WAGE AND EMPLOYMENT GROWTH IN AMERICA'S DRUG EPIDEMIC: IS ALL GROWTH CREATED EQUAL?

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The rise in drug overdose deaths in the United States since the turn of the millennium has been extraordinary. A popular narrative paints a picture whereby opioid overdoses among white, male, less-educated, rural workers have been caused by reduced economic opportunities borne by such people. In this article, we causally test the validity of this theory by using Bartik-type variables to explore the relationship between local economic conditions and county opioid overdose death rates. We add to the literature by exploring how both employment and wage growth in different types of industries are related to opioid overdose deaths for the population as a whole, as well as for rural (vs. urban), male (vs. female) and white (vs. black) populations. We find mixed evidence. Our results confirm that wage and employment growth in industries more likely to employ low-skill workers are important protective factors for rural, white males. However, we also find evidence that economic improvements in low-skill industries are just as important in protecting blacks and women against opioid overdoses, and for workers in metro counties. We also find evidence that employment growth in high-paying industries has led to increases in opioid overdoses rates.

Key words: Employment, local economic conditions, opioids, overdose, wages.

JEL codes: I15, R11.

Over the past two decades, the number of Americans who have died from drug overdoses has increased by 400% (Katz 2017), and drug overdoses are now the leading cause of death among Americans under age 50 (Katz 2017). Figure 1 plots the increase in opioid-related overdose deaths by gender and race for the United States, between 1999 and 2014 for nonmetro and metro areas. The dramatic increase in deaths has prompted questions about what underlying factors fuel the misuse of drugs and overdose. One theory that has received widespread attention in the popular

press is the idea that limited economic opportunity in some areas—especially Rust Belt states, rural areas, and communities particularly hard hit by the recession of 2007—caused individuals to turn to drugs (e.g., Hari 2017; Khazan 2017; Quinones 2015).¹ This hypothesis is informed in part by the Case and Deaton (2015) finding of rising mortality among middle-aged, white Americans. After years of consistent decreases in age-, race-, and gender-specific mortality rates, deaths due to poisoning, suicide, and liver disease—so called “deaths of despair”—have increased in white, non-Hispanic individuals under age 55. Journalistic authors have referred to shrinking economic opportunities faced by less-educated, white, working-age people—often men—in certain low-skilled industries

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¹ Other important lines of research have examined supply-side factors to help explain the rapid rise in overdose deaths. These include examinations of the role of prescription drug monitoring systems (Buchmueller and Carey 2018), physician education (Schnell and Currie 2018), and abuse-deterrent drug formulations (Alpert, Powell, and Pacula 2017).

Figure 1. Crude opioid overdose death rates by race and gender, 1999–2014

Source: CDC WONDER Multiple Cause of Death Files 1999–2014.

(i.e., manufacturing) to explain these mortality trends. Yet, limited research exists to validate that there is a causal relationship between these coinciding trends. The goal of the current article is to explicitly test the popular hypothesis linking overdose deaths to limited economic opportunity among certain demographic groups and those who work in certain industries.

The popular theory consists of three premises that we aim to test: first, that there is a causal relationship between local economic opportunities and opioid overdose deaths, such that improved employment and wages in a community result in fewer overdose deaths; second, that local employment and wage growth in industries that employ lower-skilled workers are particularly protective against opioid overdose deaths; and finally, that local employment and wage growth

reduce opioid overdose deaths more precipitously for certain demographic groups—namely, rural, white, middle-aged, male workers.

To test these three hypotheses, we use proprietary data on county-level employment and wages at the 4-digit (NAICS) industry level and restricted access mortality data. Using Bartik-style variables that capture employment and wage growth driven by national-level changes—and thus reduce potential bias from local conditions that may influence both economic growth and overdoses independently—we test for a causal relationship between local employment and wage growth and county-level opioid overdose rates. We split industries into three tiers by average industry wages, and test the second hypothesis by exploring whether employment and wage growth in low-wage

industries – which we show are more likely to employ low-skilled workers—protect against overdose deaths more strongly than similar growth in high-wage industries. Finally, we conduct our analysis by metro and nonmetro counties, as well as by race and gender, to test the third part of the theory—that local economic conditions have been particularly influential for white, rural men.

Our results confirm the popular narrative in some respects and contradict it in others. We find that employment and wage growth in lower-paying industries protect against overdoses, and we find that employment growth in particular is especially protective for males (compared to females) and whites (compared to blacks). However, we find that employment growth is just as important in metro counties as in nonmetro counties, and that the protective effects of wage growth in lower-paying industries is stronger in metro counties than in nonmetro counties. We also find that wage growth in mid-paying industries is associated with lower black and female overdose rates in metro counties. Finally, we find some evidence that in high-paying industries, increasing employment growth has led to more overdose deaths in both metro and nonmetro counties. These facts suggest that while there may be some truth to the popular narrative, the larger relationship between local economic conditions and the opioid overdose rate may be more nuanced than what is commonly portrayed.

Background and Hypotheses

Our study builds on research linking local economic conditions to health behaviors and mortality, and to drug overdose deaths in particular. Until recently, much of this work documented a pro-cyclical pattern in health behaviors and all-cause mortality. In general, studies in the United States showed that when the local county or state economy worsens people tend to decrease risky health behaviors (like smoking and binge drinking) and increase healthy ones, like exercise; mortality also decreases (for example, [Freeman 1999](#); [Ruhm 2000](#); [Ruhm and Black 2002](#); [Frijters et al. 2013](#); [Xu 2013](#)). Historically, these studies have been at odds with research that finds that individual displacements from the labor market are bad for health ([Eliason](#)

and [Storrie 2009](#); [Sullivan and von Wachter 2009](#); [Browning and Heinesen 2012](#)).

However, recent studies suggest a reversal of the all-cause mortality patterns. Namely, mortality over the past 20 years has become increasingly countercyclical ([Ruhm 2015](#); [Hollingsworth, Ruhm, and Simon 2017](#)). This reversal appears largely driven by causes associated with psychological distress such as suicide, drug overdoses, and alcohol-related deaths ([Case and Deaton 2015](#)). While suicides have always exhibited a countercyclical mortality pattern ([Ruhm 2000](#)), the relationship between accidental poisonings (of which over 90% are drug overdoses) and the unemployment rate is increasingly strong. [Ruhm \(2015\)](#) finds that a one percentage point increase in the state unemployment rate is associated with a 4% increase in poisonings—a relationship that is only present since 1991. Furthermore, there is evidence that illicit drug use increases in bad economic times ([Arkes 2007](#); [Carpenter, McClellan, and Rees 2016](#)). [Hollingsworth, Ruhm, and Simon \(2017\)](#) provide additional support for this hypothesis by investigating the relationship between county-level unemployment rates and local overdose rates, opioid overdose death rates, and emergency department visits due to drug overdose. These authors find that, controlling for county differences, a one percentage point increase in the unemployment rate is associated with a 4% increase in opioid overdose deaths, a 3% increase in all drug overdose deaths, as well as a 7% increase in overdose emergency room visits.

While [Ruhm \(2015\)](#) and [Hollingsworth, Ruhm, and Simon \(2017\)](#) both demonstrate a correlation between local employment conditions and overdose rates, and include robust county-level and time controls to help absorb confounding factors, the results from these analyses may reflect relationships other than the causal one of interest. One particularly confounding issue is the possibility of reverse causality. Decreases in the unemployment rate may stem from two sources: from more people finding jobs or from more workers dropping out of the labor force. The proportion of prime-aged men out of the labor force has steadily increased for decades ([Krause and Sawhill 2017](#)). [Krueger \(2017\)](#) shows that nearly 50% of the men who have dropped out of the labor force also have a serious health problem and take daily pain medication. If workers are leaving the labor force because of drug use, then some of the

observed relationship between unemployment rates and overdoses may reflect causation in the reverse direction, rather than the effect of unemployment on drug behavior. Indeed, when [Hollingsworth, Ruhm, and Simon \(2017\)](#) estimate their models using the state-level employment to population ratio as their macroeconomic indicator, they find smaller effects on the overdose rate, a finding that is consistent with a reverse causality story.

Reverse causality and other sources of endogeneity represent an important threat to the fundamental assumption of the popular theory that employment losses in certain areas have caused opioid overdoses. Such sources of bias could also explain why we observe high overdose rates in communities that have been historically hard hit by negative economic shocks, such as Appalachia or Rust Belt states. As such, we expand upon the above studies to test whether local economic conditions cause overdoses by using a Bartik-style instrument of employment growth. If the popular theory holds, we expect to find a significant negative relationship between local employment changes and overdoses, such that counties with improving employment and wages should exhibit lower opioid overdose rates.

The popular theory linking local economic conditions to the opioid epidemic also suggests that economic contractions in certain industries (i.e., manufacturing) may be especially detrimental. While unemployment rates have fluctuated with the business cycle across most of the country, longer-term economic forces have affected certain areas and groups more dramatically, and more negatively, than others have. Evidence is accumulating that less-educated workers are losing ground relative to well-educated workers in local labor markets due to automation ([Baily and Bosworth 2014](#); [Acemoglu and Restrepo 2017](#)) and outsourcing ([Autor, Dorn, and Hanson 2013](#)). Thus, employment and wage changes in certain industries may be more important than in others. Furthermore, because of the geographic distribution of industries across the country, more remote counties have disproportionately borne job losses ([Partridge et al. 2008](#)). Again, the fact that overdose rates are much higher for less-educated Americans provides additional support for the theory that employment effects may differ by industry ([Kolata and Cohen 2016](#);

[Snyder 2016](#); [Case and Deaton 2017](#); [Rembert et al. 2017](#)).

[Pierce and Schott \(2016\)](#) investigate this question by examining the mortality response to an important trade liberalization policy passed in 2000 charged with hurting workers in manufacturing industries in particular. These authors find that suicides, and to a lesser degree, accidental poisonings, increased in counties that were more exposed to the trade liberalization policy—the same counties that lost jobs and experienced declines in economic wellbeing as a result of the policy. While this work provides evidence that employment losses in certain industries may be especially important in predicting overdose deaths, the results of the study focus on the effects of one specific policy change, a policy that affected primarily manufacturing employment through trade alone. We further these authors' work by examining the effect of employment and wage changes across a broader set of industries—changes that have occurred over many years and may be due to other forces beyond trade liberalization (i.e., off-shoring or automation)—on local overdose mortality rates. If the popular theory is correct, we expect to find a stronger negative relationship between overdoses and employment growth in industries that disproportionately employ low-skill workers (as compared to higher-skill industries).

The labor market is also increasingly bifurcated. [Autor and Dorn \(2013\)](#) show a polarization in the U.S. labor market between 1988–2005, with growth in both high- and low-skill jobs. This seemingly contradicts the notion that low-skill workers struggle in the current economy and suggests that labor market conditions could harm less-educated workers not simply through employment, but also through a shift from better paying mid-skill manufacturing jobs to lower-paying retail and service sector jobs. Further, one of the hallmarks of the Great Recession's recovery—a recovery that has coincided with exponential increases in overdose rates—is that wages have stagnated despite consistent declines in the unemployment rate ([Mishel, Gould, and Bivens 2015](#)). The relevant question, therefore, with respect to how labor markets influence overdose rates may not only be whether workers have jobs, but *what kind* of jobs, and whether wages in those jobs are growing. To date, no studies investigate the connection between local labor market wage changes and overdose deaths. In terms

of wage growth, the popular theory requires that wage stagnation in industries that disproportionately employ low-skill workers should be especially harmful; we therefore expect that wage growth industries that disproportionately employ low-skill workers should lead to lower overdose rates, whereas wage growth in higher-skill industries should not be as strongly associated with overdose mortality rates.

Finally, overdose trends have been especially prevalent among certain demographic groups. As demonstrated in [figure 1](#) and discussed in more detail below, there are significant demographic and regional differences in the levels and changes in opioid overdose rates across demographic groups. In general, males, whites, and rural individuals saw sharper increases in opioid overdose rates since the turn of the century. The economic changes discussed above have also disproportionately affected certain demographic groups—those more likely to be employed in manufacturing and other blue-collar industries ([Autor, Dorn, and Hanson 2013](#); [Acemoglu and Restrepo 2017](#)). Furthermore, there is some evidence that males experience larger declines in subjective wellbeing when they drop out of the labor force as compared to females ([Krueger 2017](#)). These coinciding trends have led journalistic authors to paint a picture where the higher overdose rates that are especially prevalent among middle-aged white, rural males have been caused by the economic trends that have disproportionately affected them. If this is true, we would expect to find that employment and wage growth is especially protective against overdose mortality for whites, males, and rural households, and that the relationships are stronger for these groups when we consider low-skill industries as compared to higher-skill industries that have a better educated workforce. We test these hypotheses using the data and methods described below.

Data

The data for our study come from two primary sources. First, we use detailed annual individual-level death data from the Multiple Cause of Death Mortality File (MCOF) 1999–2014 maintained by the National Center for Health Statistics (NCHS) to construct our dependent variables. Every death

in the United States is categorized by underlying cause of death according to World Health Organization ICD-10 codes.² The ICD-10 codes provide detailed cause of death information and are recorded on death certificates in all 50 states. The MCOF data also include information on up to 20 conditions that contributed to the cause of death, which allow us to identify overdose deaths attributable to specific drugs, such as opioids. We use county Federal Identification Processing Standard (FIPS) codes to calculate county-level death rates attributable to opioid-related drug overdoses.³ The MCOF files contain information on deaths by gender, race, and age group, which we combine with county populations for each demographic group from the National Institutes of Health's Surveillance, Epidemiology, and End Results Program (SEER) to calculate death rates for these subpopulations. [Figure 1](#) details the rise of overdose deaths in the United States between 1999–2014 in nonmetro and metro counties. The crude opioid overdose death rate increased from around 2 per 100,000 in metro areas and 1 per 100,000 nonmetro areas in 1999 to around 8.5 per 100,000 for both in 2014. Interesting differences exist across both race and gender. In both nonmetro and metro areas, the average male overdose rate started at a higher initial level than the female rate, and also grew more rapidly over the period, although female overdose death rates also increased rapidly. Likewise, initial opioid overdose death rates for whites were higher than for blacks and diverged even more rapidly than male rates from female rates. In metro counties, the black and white rates followed roughly the same trend until about 2007, at which point the white rate continued to grow, while the black rate fell slightly before accelerating again after 2012. In nonmetro counties, the

² In 1999, the CDC switched from using ICD-9 to ICD-10 codes to categorize underlying cause of death. The change in definitions is significant enough to preclude comparison between data using the ICD-9 and ICD-10 definitions of opioid overdose deaths. Thus, our analysis is limited to years 1999 and later.

³ Following [Case and Deaton \(2015\)](#), we define overdose deaths as the sum of county deaths categorized under ICD-10 codes X40-44, X60-64, X-85, and Y10-14. Our definition of overdoses differs slightly in that we do not include poisonings attributable to alcohol in order to more closely measure opioid-related deaths as defined by the U.S. Centers of Disease Control ([CDC 2013](#)). If one of the following T-codes were listed on the death certificate as a contributing condition we categorized the death as an opioid-related overdose death: F11.0, F11.1, F11.2, F11.3, F11.4, F11.5, F11.6, F11.7, F11.8, F11.9, T40.0, T40.1, T40.2, T40.3, T40.4, T50.7, Y45.0.

divergence between the white and black rates began immediately, such that the white/black overdose death rate gap grew from 1 death per 100,000 in 1999 to 8.9 deaths per 100,000 in 2014. In our main analysis, we estimate models for these four subpopulations to determine whether changes in the labor market have had differential effects across race and gender.⁴

Figure 2 shows maps of the change in opioid overdose rates between 2001–2014 for each of our subpopulations. Together the maps demonstrate the geographic variation of changes in overdose rates over the period. Pockets of some nonmetro areas, such as most of the Appalachian region, have experienced large changes in male and white overdose rates. Conversely, nonmetro areas throughout the Midwest and Great Plains have seen smaller growth in opioid overdose death rates across all subpopulations. Female overdose rates have shown less geographic variation, with fewer counties experiencing extreme growth or modest declines in female opioid overdose death rates. Black opioid overdose death rates have risen much less dramatically over the period, but some clustering of more severe changes occurs in parts of California, Florida, and the Carolinas. Overall, there is significant variation across the country—and within states—in the growth of opioid overdose death rates for different demographic groups.

Our second key data source contains county-level employment and earnings per worker data by industry from Economic Modeling Specialists International (EMSI). We use these in constructing our key explanatory variables. EMSI compiles data from the Bureau of Labor Statistics' Quarterly Census of Employment and Wages (QCEW), supplemented by the Bureau of Economic Analysis' (BEA) Regional Economic Accounts and the U.S. Census Bureau's County Business Patterns to produce county-level employment and earnings per worker data for 323 4-digit North American Industry Classification System (NAICS) industries within the county. The advantage of these data is that they include detailed industry-specific employment and earnings information suppressed in publicly available sources. These data have been used in many county-level

economic analyses (Dorfman, Partridge, and Galloway 2011; Betz et al. 2015; Rupasingha, Liu, and Partridge 2015; Lobao et al. 2016; Tsvetkova and Partridge 2016; Tsvetkova, Partridge, and Betz 2017). The employment and earnings data span 2001–2014, which give us information on county employment and wage trends leading up to the sharp rise in overdose death rates after 2003.

We also use annual county-level data from the U.S. Census Bureau and Bureau of Economic Analysis to control for differences in total employment, population, median household income, and poverty rates across counties. Specifically, we use measures of county population from the Bureau of Economic Analysis and county-level median household income and poverty from the Census Bureau's Small Area Income and Poverty Estimates. Table 1 summarizes our key dependent and explanatory variables.

Methods

We are interested in how annual county employment and wage growth rates influence annual county opioid overdose death rates per 100,000 people. To reiterate our main hypotheses, we expect that employment and wage growth will have an inverse relationship with opioid overdose death rates. If labor market opportunity plays a significant role in individual decisions of whether or not to abuse opioids, then we would expect places with faster employment and wage growth to have lower opioid death rates. We expect the relationship to be stronger for employment and wage growth in industries that disproportionately employ high school educated workers—a group with a higher overdose death rate. Additionally, the popular theory that we test suggests that the effect should be stronger for those who have been disproportionately affected by large-scale employment losses over the past two decades—males, whites, and rural individuals.

One challenge we face in testing these hypotheses is the potentially endogenous relationship between measures of employment and opioid overdose death rates. If some unaccounted-for time-varying county factor—say human capital accumulation—were driving both employment and overdose deaths, then any estimates of the employment–overdose relationship would be biased.

⁴ We also test for differences across age groups, the results of which we include in the [supplementary online appendix, Supplementary table A3](#).

Figure 2. Change in county opioid overdose rate by gender and race, 2001-2014

Furthermore, as discussed above, reverse causality could bias estimates. To temper these potential sources of bias, we construct plausibly exogenous “Bartik” variables for employment and wage growth by calculating the inner product of the county 4-digit NAICS industry employment shares within county i in our base year (2001) with each respective industry’s national employment (or wage) growth rate. These variables take the form

$$(1) \quad E_{it,t-1}^* = \left(\sum_k E2001_{i,k} EG_{k,t,t-1} \right) \times 100$$

$$(2) \quad W_{it,t-1}^* = \left(\sum_k E2001_{i,k} WG_{k,t,t-1} \right) \times 100$$

where $E2001_{i,k}$ is the share of total employment of industry k in county i in 2001. Further, $EG_{k,t,t-1}$ is the national one-year employment growth rate of industry k between years t and $t-1$, and $WG_{k,t,t-1}$ is the national wage growth rate of industry k between years t and $t-1$. We multiply these by 100 to express the growth rates in percentage terms.

Variables that use county industry shares with national growth rates were introduced by Bartik (1991) and have long been used in the fields of labor and regional economics to estimate the effect of exogenous changes in local-level factors such as employment and

wages. In essence, these variables capture the change in county employment or wages that would have occurred if all industries within the county grew at their national growth rates over the period. The intuition behind this method is that one can decompose total industry-specific employment growth in a county into its local and national demand components. The national demand component is likely to be independent from local factors that may be driving overdose rates, yet is correlated with local employment growth. That is, it is highly unlikely that any local county-level factors in a given county are driving an industry’s national employment growth rate.^{5,6} Multiplying the independent, national growth rates by the baseline local employment share in each industry creates an exogenous proxy for local labor market conditions. Our approach rests on two main assumptions common to the long body

⁵ This assumption is potentially violated in certain cases where a particular industry is concentrated almost entirely in a single labor market. However, these situations are quite rare and we do not believe that the influence of a single concentrated industry would have enough of an impact to significantly bias our estimates. Though some counties with small populations have high industry shares of national industry employment, 99% of all county-industry shares have a value less than 0.022 over the 14-year period. The average industry share of national industry employment over all counties and all years is 0.0016.

⁶ See Broxterman and Larson (2018) and Goldman-Pinkham, Sorkin, and Swift (2018) for more complete discussions of the composition and exogeneity assumptions of the generalized Bartik variable.

Table 1. Summary Statistics of Key Variables

Variable	Mean	Standard Deviation	Minimum	Maximum
Metro Counties (N = 26,337)				
Opioid OD death rate-all	4.87	8.53	0	132.11
Opioid OD death rate-male	5.91	12.08	0	177.59
Opioid OD death rate-female	3.97	9.27	0	255.75
Opioid OD death rate-white	5.27	9.24	0	135.12
Opioid OD death rate-black	2.33	52.78	0	4,761.91
Employment growth	0.11	4.90	-74.55	309.09
Bartik employment growth	0.07	1.71	-14.54	12.10
Top-tier employment growth	-0.08	2.59	-60.95	13.54
Middle-tier employ. growth	-0.05	1.86	-17.71	5.64
Bottom-tier employ. growth	0.28	1.62	-14.49	19.83
Wage growth	0.77	8.63	-91.69	1,193.07
Bartik wage growth	0.33	1.25	-4.16	7.05
Top-tier wage growth	0.61	1.67	-10.17	16.52
Middle-tier wage growth	0.41	1.23	-4.58	7.14
Bottom-tier wage growth	0.13	1.30	-7.93	8.90
Nonmetro Counties (N=13,649)				
Opioid OD death rate-all	5.64	6.02	0	106.34
Opioid OD death rate-male	7.27	8.48	0	153.99
Opioid OD death rate-female	4.20	5.75	0	90.73
Opioid OD death rate-white	6.33	6.67	0	108.70
Opioid OD death rate-black	2.72	24.14	0	2,083.33
Employment growth	0.61	3.44	-49.38	61.18
Bartik employment growth	0.12	1.77	-12.45	4.45
Top-tier employment growth	-0.25	2.43	-44.33	8.73
Middle-tier employ. growth	-0.04	1.89	-13.90	5.03
Bottom-tier employ. growth	0.49	1.70	-13.71	8.96
Wage growth	0.29	2.92	-27.70	73.69
Bartik wage growth	0.28	1.24	-3.50	10.88
Top-tier wage growth	0.57	1.61	-7.51	7.74
Middle-tier wage growth	0.38	1.18	-3.62	4.34
Bottom-tier wage growth	0.04	1.29	-4.13	11.25

of literature that employs Bartik variables: first, after controlling for county-level fixed effects, the initial (2001) share of total county employment accounted for by each industry is independent of local overdose rates except insofar as it affects local labor conditions; and second, after controlling for year fixed effects, the year-to-year changes in national, industry-specific labor market growth is independent of changes in local overdose rates, except insofar as they affect local labor market conditions. These assumptions allow us to interpret our results as causal.

Our approach generates estimates with a different interpretation than those from past studies. While previous estimates explain variation in levels of overdose death rates with variation in *levels* of unemployment, our approach uses variation in *growth rates* of employment and wages. Thus, our approach assumes that individuals are sensitive to

changes in trend, rather than to changes in levels, of economic conditions. This distinction is important if responses to changing labor market conditions are affected by one's frame of reference: a small improvement in wages, for example, may be more meaningful in counties having experienced recent stagnation than in counties with persistently good wage growth.

Our main analysis estimates models of opioid overdose death rates that take the following form,

$$(3) \quad D_{it}^s = \beta_1 + \beta_2 E_{it,t-1}^* + \beta_3 \mathbf{X}_{it} + \delta_i + \sigma_t + \varepsilon_{its}$$

$$(4) \quad D_{it}^s = \beta_1 + \beta_2 W_{it,t-1}^* + \beta_3 \mathbf{X}_{it} + \delta_i + \sigma_t + \varepsilon_{its}$$

where D_{it}^s is the county opioid overdose death rate per 100,000 people for subpopulation s in

county i and year t . In addition to models for the entire population, we calculate county-level opioid overdose death rates for subpopulations s and estimate separate models for white, black, male, and female overdose death rates.⁷ The variable $E_{it,t-1}^*$ represents the Bartik variable for employment growth described in equation (1). County and year fixed effects are represented by δ_i and σ_t , respectively, and ε_{its} is the error term. In some models, we also control for county-level covariates, $\mathbf{X}_{it}$, which include total employment, population, median household income, and the poverty rate.⁸ Because the Bartik variable should capture exogenous changes in local labor conditions, we do not expect the inclusion of $\mathbf{X}_{it}$ to alter the main coefficient estimate, β_2 .

Equation (4) is identical to equation (3) with the exception that we replace $E_{it,t-1}^*$ with $W_{it,t-1}^*$, the Bartik variable for wage changes. We estimate separate models for rural and urban areas using the 2003 Census Metropolitan Areas definitions for each subpopulation. This results in observations for 2,024 nonmetro counties and 1,050 metro counties over 13 years for a grand total of 26,337 nonmetro observations and 13,649 metro observations. We weight our regressions by county population (and county subpopulation, for the race models) and estimate robust standard errors in all cases.

Effects by Industry Type

Our goal is to test whether employment and wage growth in industries that disproportionately employ less-educated workers are more important determinants of opioid overdose rates than employment and wage growth in higher-skill industries. However, due to data limitations, we use average industry wages as a proxy for average employee skill or educational attainment and develop models that include variables measuring employment and wage growth in high-, medium-, and low-paying industries. We do this by modifying the variables in equations (1) and (2) to reflect industry wage tiers. We order all 323 4-

digit NAICS industries according to average earnings per worker nationally in 2001 and assign each industry a rank depending on whether it is in the top-third, middle-third, or bottom-third of average industry earnings per worker. We report the industry rankings across tiers in [Supplementary table A2](#), which the interested reader may find in a [supplementary appendix](#) online. Next, we use this ranking to calculate expected county employment and wage growth in high-, medium-, and low-paying industries. The variables take the following form,

$$(5) \quad E_{it,t-1}^r = \sum_k E2001_{i,k}^r EG_{k,t,t-1}$$

$$(6) \quad W_{it,t-1}^r = \sum_k E2001_{i,k}^r WG_{k,t,t-1}.$$

All of the variables and subscripts remain the same as in equations (1) and (2), except for the inclusion of industry rank r representing high-, medium, and low-paying industry tiers.⁹ We calculate top-tier, middle-tier, and bottom-tier expected employment and wage growth for each county and substitute $E_{it,t-1}^r$ for $E_{it,t-1}^*$ and $W_{it,t-1}^r$ for $W_{it,t-1}^*$ into equations (3) and (4), respectively, and estimate the models reflecting the effects of employment and wage growth across different industry compensation tiers.

This approach will only allow us to test for heterogeneous effects for lower-skill workers if lower-wage industries tend to employ less-educated workers. We test this assumption using data from the American Community Survey microdata from IPUMS and the March supplement of the Current Population Survey on the average educational attainment of workers in 4-digit industries. While these data are not available for all industries—hence our need to proxy with wage—we are able to explore average worker education for 170 of our 323 total industries. For the industries we observe, we calculate the average share of workers in each wage-tier with a high school diploma or less in 2001, 2007, and 2014. [Table 2](#) shows that among industries in the low- and middle-wage tiers, approximately 50% of employees had a high school degree or less in 2001 and 2007; in the higher-wage tier, by contrast,

⁷ We also test for differences across age groups, the results of which we include in the [supplementary online appendix](#), [Supplementary table A3](#).

⁸ In sensitivity tests, we also include the share of the county population receiving Social Security Disability Insurance from the Old Age and Survivors Disability Insurance (OASDI) program, but they had little effect on our estimates of the employment and wage growth coefficients.

⁹ $E_{i,k,2001}^r$ is employment in industry k divided by sum of total county employment of all industries of rank r .

Table 2. Average Share of Industry Employees with a High School Degree or Less, by Industry, Years 2001, 2007, and 2014

Industry tier	2001	2007	2014
Top-tier	38.5	35.1	31.5
Middle-tier	50.3	47.1	43.5
Bottom-tier	52.9	51.0	43.8

only 39% of workers had a high school degree or less. By 2014, the average proportion of workers in any tier without a college degree had dropped, but such workers remain over-represented in the lower-wage industries as compared to the high-wage industries. The differences between middle- and top-tier educational attainment are significant at the 5% level for all years, as are the bottom-to-top tier differences. We also acknowledge that there is a distribution of occupations within industries that sometimes results in large variances in pay across a single industry, and our results are subject to this limitation.

We also consider the possibility that high-, medium-, and low-tier industries may be distributed differently across metro and nonmetro counties. In this case, we might be concerned that significant differences in effects between metro and nonmetro areas could be due to, for example, the fact that top-tier industries are drastically more important to the overall economy in metro areas. We compare the proportion of total employment in each wage tier represented in metro and nonmetro counties, and find there is little difference. Table 3 shows the share of county total employment for each wage tier in metro and nonmetro counties. Metro counties have slightly more top- and bottom-tier industry employment, and nonmetro counties have slightly more middle-tier industry employment, but overall differences are minimal. Finally, we explore the extent to which industries travel across wage tiers over time. We find that the three tiers are relatively stable. Over the entire 13-year period, 91% of bottom-tier industries, 84% of middle-tier industries, and 93% of top-tier industries remained in their initial wage tier. No industries moved from the top to the bottom, or vice versa.

Results

Table 4 displays our regression results for the population as a whole. Each column shows

Table 3. Industry Tier Share of Local County Employment, 2014

	Mean	Standard Dev.	Min.	Max.
Nonmetro Counties				
Top-tier	17.99	9.75	1.59	100.00
Middle-tier	38.10	8.33	4.83	82.40
Bottom-tier	43.95	9.63	3.52	83.95
Metro Counties				
Top-tier	19.64	7.68	3.41	56.89
Middle-tier	36.20	6.80	3.90	75.17
Bottom-tier	44.16	7.34	13.83	88.46

results from a different model, and all specifications include county- and time-fixed effects, while even-numbered columns also contain the additional controls for county-specific observable characteristics outlined in the data and methods sections. In panel A of table 4, we show the results of estimating equations (3) and (5) using the employment growth Bartik variables. Looking across the first row of panel A, we see that when we consider all industry tiers combined, employment growth rates are not significantly related to county opioid overdose rates in nonmetro or metro counties.

However, the results in columns 3, 4, 7, and 8 of table 4—which disaggregate overall employment growth into growth in industries in each wage tier—show that the overall insignificant effect masks heterogeneity across industry pay tiers. Columns 3 and 4 show results for nonmetro counties. We find that variation in bottom- and middle-tier employment growth rates is negatively related to the opioid overdose death rate, although only the estimate for middle-tier growth is statistically significant. This suggests that when industries that are more likely to employ less-educated workers grew faster than the previous year, opioid overdose death rates declined. We find that a one- percentage point increase in the middle-tier employment growth rate results in about 0.13 fewer overdose deaths per 100,000 people. Interpreting this effect shows that a 1 standard deviation (SD) increase in middle-tier employment growth results in a 0.04 SD decrease in the opioid overdose rate in nonmetro counties. These results imply that middle-tier employment growth changes could produce significant differences in overdose rates between counties with fast and slow growth, respectively. For instance, if the year-to-year middle-tier employment growth rate in County A increased

Table 4. Effects of Employment and Wage Growth on All Population Opioid Overdose Rates, 2001–2014

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Nonmetro Counties				Metro Counties			
Panel A—Employment growth								
Employment growth rate	−0.04 (−0.58)	−0.05 (−0.74)			−0.05 (−0.61)	−0.10 (−1.34)		
Top-tier employment growth rate			0.06* (1.83)	0.06* (1.82)			0.08** (2.07)	0.06 (1.50)
Middle-tier employment growth rate			−0.13** (−2.15)	−0.15** (−2.40)			0.02 (0.24)	−0.07 (−0.85)
Bottom-tier employment growth rate			−0.09 (−1.27)	−0.09 (−1.32)			−0.20** (−2.57)	−0.18** (−2.32)
County and Year FE	X	X	X	X	X	X	X	X
Controls		X		X		X		X
Observations	26,337	26,337	26,337	26,337	13,649	13,649	13,649	13,649
Panel B—Wage growth								
Wage growth rate	−0.05 (−0.42)	−0.08 (−0.73)			−0.41*** (−3.56)	−0.30*** (−2.78)		
Top-tier wage growth rate			0.04 (0.65)	0.03 (0.53)			−0.09* (−1.88)	−0.04 (−1.03)
Middle-tier wage growth rate			−4.50E-03 (−0.05)	−0.02 (−0.16)			−0.66*** (−4.45)	−0.41*** (−3.18)
Bottom-tier wage growth rate			−0.23** (−2.08)	−0.25** (−2.28)			−0.04 (−0.33)	−0.05 (−0.44)
County and Year FE	X	X	X	X	X	X	X	X
Controls		X		X		X		X
Observations	26,337	26,337	26,337	26,337	13,649	13,649	13,649	13,649

Note: The t-statistics appear in parentheses. Asterisks indicate the following: * $p < 0.10$, ** $p < 0.05$, and *** $p < 0.01$. Controls include total employment, poverty rate, median household income, and log of population. Robust standard errors are estimated for all models; death rates are deaths per 100,000.

by 1 SD (about 1.9% points), while County B saw a similar reduction in their year-to-year growth rate, we would expect to see about 0.5 more opioid overdoses per 100,000 in County B relative to County A, which would account for roughly 10% of all opioid overdose deaths. We also estimate a significant effect of top-tier employment growth on opioid overdose rates, although the estimated coefficient is positive (0.06). We find that a 1 SD increase in top-tier employment growth leads to a 0.02 SD increase in the local opioid overdose rate in nonmetro counties.

In metro areas (columns 7 and 8), we find a similar pattern. Increases in bottom-tier employment growth are negatively related to opioid overdose death rates (coeff.= −0.20), while higher growth in top-tier

employment increases the overdose death rate (coeff.= 0.08). We estimate that a 1 SD increase in bottom-tier employment growth leads to a 0.04 SD reduction in the local opioid overdose death rate (or about 0.3 fewer overdose deaths per 100,000 people); and a 1 SD increase in top-tier employment growth leads to a 0.02 SD increase in the overdose death rate (about 0.2 more overdose deaths per 100,000). It is also noteworthy that for all the employment growth models, our results are barely impacted by the addition of county-level covariates (i.e., columns 2, 4, 6, and 8). This suggests that the Bartik measures are capturing exogenous variation in local employment growth.

Turning to panel B, we show the results of estimating equations (4) and (6) using our

wage growth treatment variables. In nonmetro counties, we find that aggregate wage growth has no relationship with overdose rates (top row). When we disaggregate by wage tier, we find that increases in bottom-tier wage growth are associated with decreases in the overdose rate for the general population. A 1 SD increase in wage growth among bottom-tier industries leads to a 0.05 SD reduction in the local opioid overdose rate in nonmetro counties (or about 0.3 fewer overdoses per 100,000 people). Again, the inclusion of covariates does not impact our estimates.

In metro counties, we find that the aggregate wage growth measure is negatively associated with overdose rates, such that a 1 SD increase in wage growth reduces the opioid overdose rate by 0.06 SD. The aggregate effect is driven by growth in middle- and—to a lesser extent—top-tier industries. We find that a 1 SD increase in middle- (top-) tier wage growth leads to a 0.10 (0.02) SD reduction in the local opioid overdose rate. The large estimated effect of wage growth in middle-tier industries is noteworthy: if County A experienced a 1 SD year-to-year increase middle-tier wage growth while County B experienced a 1 SD decrease, County A's opioid overdose rate would decrease by 1.6 overdoses per 100,000 people relative to County B's. This figure represents a 20% difference relative to the overall overdose rate in metro counties of 8.53 per 100,000 people. However, one important caveat of these results is that the inclusion of additional, county-level covariates in the wage growth models for metro counties affects the results. We may therefore be concerned that the Bartik variables are not independent of other factors that could impact opioid overdoses in the metro wage models.¹⁰

Effects by Gender

The results for our overdose rate models by gender are in [table 5](#), which is organized similarly to [table 4](#). However, since our parsimonious results differ little from our models that include county controls, we only present the latter. As in [table 4](#), the employment growth results are presented in panel A and the wage growth results are presented in panel B.

Employment growth rates (both disaggregated and in the aggregate) are not statistically related to the female opioid overdose death rate in nonmetro counties, although the estimated coefficients reflect a similar pattern to the overall population. For men, we also find a similar pattern: increases in middle- and bottom-tier employment growth are both associated with decreases in male overdose rates, although—just as with the full sample—only the middle-tier growth effect is statistically significant. An increase in top-tier growth increases male overdose rates in nonmetro counties. We estimate that a 1 SD increase in employment growth in middle- and top-tier industries results in a 0.05 reduction and a 0.03 increase in the nonmetro male opioid overdose rate, respectively. In sum, the patterns in the gender-specific opioid overdose death rates in nonmetro counties parallel the overall pattern and are more pronounced for men than women.

Turning to metro counties, we find that a 1 SD increase in the aggregate employment growth rate leads to a 0.03 SD reduction in the male opioid overdose death rate, and an insignificant, near-zero change in the female rate. However, when disaggregated by industry tier, interesting heterogeneity becomes apparent. For men, we find that variation in employment growth in bottom-tier industries drive the aggregate effect. A 1 SD increase in bottom-tier employment growth leads to a 0.04 SD decrease in the male opioid overdose rate (or about 0.5 fewer male overdose deaths per 100,000 men). For women, we estimate insignificant, negative relationships between changes in middle- and bottom-tier employment growth and the opioid overdose death rate. However, we find that the positive association between top-tier employment growth and the full population overdose death rate is driven by women: a 1 SD increase in employment growth in high-paying industries leads to a 0.02 SD increase in the female opioid overdose rate (or about 0.2 more female overdoses per 100,000 women).

We consider the impact of variation in wage growth rates on variation in gender-specific overdose rates in panel B of [table 5](#). In nonmetro counties, we find that variation in the aggregate wage growth rate is statistically associated with variation in only the female overdose rate, although the estimated coefficient for men is positive and rather large in magnitude (0.14). We estimate that a 1 SD increase in wage growth across all

¹⁰ After including our control variable one at a time, we find that inclusion of total population drives the large change to our results. This is true even though our regressions are population weighted.

Table 5. Effects of Employment and Wage Growth on Gender-Specific Opioid Overdose Rates, 2001–2014

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Nonmetro Counties				Metro Counties			
	Male		Female		Male		Female	
Panel A—Employment growth								
Employment growth rate	−0.06 (−0.61)		−0.05 (−0.70)		−0.21** (−1.98)		−2.60E-03 (−0.04)	
Top-tier employment growth rate		0.11** (2.37)		0.01 (0.26)		0.05 (0.87)		0.07** (2.16)
Middle-tier employment growth rate		−0.24*** (−2.59)		−0.06 (−1.00)		−0.09 (−0.72)		−0.06 (−0.96)
Bottom-tier employment growth rate		−0.11 (−1.09)		−0.07 (−1.02)		−0.29*** (−2.65)		−0.08 (−1.24)
County and Year FE	X	X	X	X	X	X	X	X
Controls	X	X	X	X	X	X	X	X
Observations	26,337	26,337	26,337	26,337	13,649	13,649	13,649	13,649
Panel B—Wage growth								
Wage growth rate	0.14 (0.81)		−0.30** (−2.45)		−0.43*** (−2.75)		−0.18** (−2.02)	
Top-tier wage growth rate		0.13 (1.47)		−0.06 (−1.10)		−0.04 (−0.57)		−0.05 (−1.45)
Middle-tier wage growth rate		0.08 (0.55)		−0.10 (−1.00)		−0.71*** (−3.76)		−0.13 (−1.24)
Bottom-tier wage growth rate		−0.28* (−1.80)		−0.24** (−2.12)		−0.02 (−0.12)		−0.08 (−0.87)
County and Year FE	X	X	X	X	X	X	X	X
Controls	X	X	X	X	X	X	X	X
Observations	26,337	26,337	26,337	26,337	13,649	13,649	13,649	13,649

Notes: t-statistics in parenthesis; *p < 0.10, **p < 0.05, ***p < 0.01; robust standard errors estimated for all models; death rates are deaths per 100,000.

industries is associated with a 0.15 SD reduction in the female opioid overdose death rate (or about 0.9 fewer female overdoses per 100,000 women). When we disaggregate into wage tiers, we find that a 1 SD increase in wage growth in the lowest-paying industries is associated with a 0.04 SD reduction in the male opioid overdose rate and a 0.05 SD reduction in the female rate.

In metro areas, increases in aggregate wage growth are negatively associated with both the male and female opioid overdose rates. A 1 SD increase in the aggregate wage growth rate leads to a 0.05 SD reduction in the male overdose rate, and a 0.02 SD reduction in the female rate (or 0.5 fewer male overdoses per 100,000 men and 0.2 fewer female overdoses per 100,000 women). When we disaggregate

by industry tier, we find that the protective effects are strongest for middle-tier industries, for both men and women, though none of the disaggregated coefficients are significant for women.

Effects by Race

Table 6 contains regression results for models explaining variation in the white and black opioid overdose death rates. In panel A, we find that in nonmetro areas, aggregate employment growth affects neither the white nor the black opioid overdose rate. When we disaggregate, we find a pattern of results among whites that parallels the results for the overall overdose death rate: increases in middle- and bottom-tier growth rates are

Table 6. Effects of Employment and Wage Growth on Race-Specific Opioid Overdose Rates, 2001-2014

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Nonmetro Counties				Metro Counties			
	White		Black		White		Black	
Panel A—Employment growth								
Employment growth rate	−0.08 (−1.03)		0.01 (0.13)		−0.07 (−0.79)		−0.31* (−1.69)	
Top-tier employment growth rate		0.05 (1.39)		−0.18 (−1.02)		0.06 (1.40)		0.05 (0.73)
Middle-tier employment growth rate		−0.17** (−2.52)		0.01 (0.02)		−0.06 (−0.64)		−0.20 (−1.33)
Bottom-tier employment growth rate		−0.11 (−1.45)		0.03 (0.08)		−0.17* (−1.78)		2.80E-03 (0.03)
County and Year FE	X	X	X	X	X	X	X	X
Controls	X	X	X	X	X	X	X	X
Observations	26,337	26,337	26,196	26,196	13,649	13,649	13,649	13,649
Panel B—Wage growth								
Wage growth rate	−0.10 (−0.80)		−0.38** (−2.25)		−0.37*** (−2.93)		−0.22 (−1.50)	
Top-tier wage growth rate		0.04 (0.58)		−0.42 (−1.29)		−0.03 (−0.62)		0.07 (0.76)
Middle-tier wage growth rate		−3.40E-03 (−0.03)		0.15 (0.39)		−0.43*** (−3.08)		−0.44* (−1.85)
Bottom-tier wage growth rate		−0.35*** (−2.73)		−1.00*** (−2.67)		−0.13 (−0.99)		−0.21 (−1.30)
County and Year FE	X	X	X	X	X	X	X	X
Controls	X	X	X	X	X	X	X	X
Observations	26,337	26,337	26,196	26,196	13,649	13,649	13,649	13,649

Note: The t-statistics appear in parenthesis. Asterisks indicate the following: *p < 0.10, **p < 0.05, and ***p < 0.01. Robust standard errors are estimated for all models; death rates are deaths per 100,000.

associated with reductions in opioid overdose rates, while top-tier increases in employment growth are associated with increases in overdose death rates (although only the coefficient for middle-tier industries is significant). We estimate that a 1 SD increase in employment growth in middle-tier industries leads to a 0.05 SD reduction in the white overdose rate (or 0.3 fewer overdose deaths per 100,000 white inhabitants). We estimate no significant coefficients for the black overdose rates, possibly because of relatively smaller black populations in nonmetro counties.

Turning to metro counties, we again find a pattern of results among whites that parallels the overall results: a positive association between employment growth in high-paying industries and the opioid overdose death rate,

and a negative association between employment growth rates in lower-paying industries and the opioid overdose death rate. Here, we only estimate a significant coefficient for growth in bottom-tier industries. We find that a 1 SD increase in bottom-tier employment growth leads to a 0.03 SD reduction in the white opioid overdose death rate. For black opioid overdose death rates, in contrast to nonmetro counties, we also estimate significant effects of employment growth on opioid overdose death rates. We find that a 1 SD increase in aggregate employment growth leads to a 0.01 SD reduction in the black overdose rate (or 0.4 fewer overdoses per 100,000 black inhabitants). While we find no significant associations between the disaggregated growth measures and black rates, it does

appear that the overall effect is primarily driven by employment growth in middle-tier industries.

In panel B of [table 6](#), we explore the relationship between wage growth and opioid overdose death rates by race. In nonmetro counties, we find relatively similar results by race: negative associations between wage growth and opioid overdose death rates, primarily driven by wage growth in lower-tier industries. Our results show that a 1 SD increase in wage growth in bottom-tier industries is associated with a 0.07 SD reduction in the white overdose rate, and a 0.05 reduction in the black overdose rate.¹¹ The strong effect on the black rate is also apparent when we consider aggregate wage growth, where we estimate a statistically significant, negative relationship between wage growth and black overdose rates (coeff. = -0.38).

In metro counties, we estimate negative coefficients for aggregate wage growth in the models explaining both the black and white opioid overdose death rates, although only the estimate for whites is significant. We find that a 1 SD increase in aggregate wage growth is associated with a 0.05 SD reduction in the white opioid overdose death rate. The aggregate effect is primarily driven by changes in middle-tier wage growth, where a 1 SD increase in the growth rate leads to a 0.06 SD reduction in the white opioid overdose death rate (or 0.5 fewer overdoses per 100,000 white inhabitants). We also find that increased wage growth in middle-tier industries is significantly associated with a lower opioid overdose death rate among blacks. A 1 SD increase in the middle-tier wage growth leads to 0.5 fewer overdoses per 100,000 black individuals.

Conclusions

The pattern of results we uncover in our analyses paints an interesting picture, providing empirical evidence to support some popular media narratives, and evidence against others. In terms of our hypotheses, we find limited evidence that improving employment opportunities in general are related to lower opioid overdose death rates. However, when

we disaggregate by industry type, we find strong support for the theory that growth in industries more likely to employ less-skilled workers protects against increasing opioid overdose deaths. We also find evidence that wage growth—especially in mid-paying industries—may be just as important as overall employment growth. We confirm that the protective effects of employment growth in lower-tier industries are important for males and for whites. This finding generally aligns with the popular press story of predominantly white, male workers with less education turning to drug use as a means of coping with reduced economic opportunity.

However, our results also reveal relationships that challenge the popular narrative in several important ways. Firstly, while the popular theory paints a picture of job losses in predominantly rural areas as a causal factor, we uncover protective effects of employment and wage growth in both rural and urban counties. Increased employment growth in bottom-tier industries in metro counties reduces the overall overdose rate, as well as the male and white overdose rates. Furthermore, the protective effects of wage growth against opioid overdose are even stronger in metro counties than in nonmetro counties. For the overall opioid overdose death rate in metro areas, increased middle- and (to a lesser extent) top-tier wage growth are associated with declines in opioid overdose deaths.

Second, while we do find evidence that employment effects are stronger for males and whites, we also find important relationships between local economic conditions and the black and female overdose rates. Increasing aggregate wage growth in nonmetro counties protects both women and blacks against overdose, effects that are driven by wage growth in the lowest-paying industries. In metro counties, wage growth in middle-tier industries is just as important for blacks as it is for whites in protecting against overdose.

Finally, we uncover one particularly unexpected result: increasing employment growth in high-paying industries is associated with *growth* in opioid overdose death rates for the general population. We find evidence of this effect in both rural and urban counties. We also uncover differential response by gender. While the nonmetro effect is driven primarily by the male overdose rate, we find the opposite in metro counties where only the female opioid overdose death rate increases with

¹¹ Standard deviations for black overdose rates in nonmetro areas are roughly 6–8 times larger than those for whites, males, and females.

increasing top-tier employment growth. One possible explanation for this result is that employment growth in top-tier industries indirectly harms lower-educated workers by compromising their labor market opportunities—either decreasing wages or changing the nature of jobs available to such workers. Another possibility is that increasing job availability indirectly harms low-tier industry workers by increasing opportunity inequality (Lillard et al. 2015; Pickett and Wilkinson 2015). While we are unable to directly test these hypotheses—due to the fact that overdose death rate data by industry is not available—we do not find a strong correlation between top-tier employment growth and lower-tier employment or wage growth.

A third hypothesis is that employment growth in better-compensated sectors increases access to employer-provided health insurance, thereby increasing access to prescription opioids. Powell, Pacula, and Taylor (2016) show that the introduction of Medicare Part D, which dramatically increased insurance rates for older Americans, led to an influx of prescription opioids in affected areas; this, in turn, created spillovers that increased the overdose rate among younger Americans. Access to insurance could therefore have directly increased overdose rates for workers in top-tier industries, or could have increased death rates for workers in other industries by increasing the overall supply of prescription opioids in a county. While we cannot differentiate between these theories, what is certain is that this evidence runs counter to the popular narrative wherein improved employment opportunities always protect against overdose.

Our results are consistent with other investigations of labor market influences on overdose death rates (Ruhm 2015; Hollingsworth, Ruhm, and Simon 2017) in that we find relationships between local economic conditions and overdose death rates. One important difference, however, is that our analyses show that using aggregate measures masks important nuance that becomes clear when we break measures down by wage tier. Like Pierce and Schott (2016), we find that workers at the low end of the wage distribution—and workers who are more likely to have a high school diploma or less—are disproportionately affected by changes to wage and employment growth.

Another important difference is that our use of the Bartik-style instrument appears

important in estimating effects. In naive regressions where we use standard employment growth and wage growth measures without the Bartik adjustment, we find significant results in nearly all of our specifications, even the aggregate measure models that generally produce null effects when we use the Bartik instrument (see results in [Supplementary table A1](#), which the interested reader may find in a [supplementary appendix](#) online). This suggests the presence of unobservable local characteristics that influence the relationship between employment growth and opioid overdose death rates, which would bias our results if we did not account for them.

Our study is limited in several ways. Most notably, we do not have access to data on opioid overdose death rates by industry. Thus, while we can link local economic fluctuations in different types of industries to variation in overdose rates across the general population, we cannot distinguish between direct or indirect effects of the changes: that is, whether changing employment conditions in one segment of industries affects employees in that industry or spills over to other parts of the economy. Furthermore, because we can only group industries, and not occupations, by average pay, it is difficult to distinguish whether our estimated effects reflect direct or indirect relationships with overdose rates. Despite these limitations, our results add to the growing body of literature intended to explain the meteoric rise in drug overdoses in the United States.

How large are our estimated effects? To put them into context, we calculate the percentage of total variation in annual county-level opioid overdose rates that is explained by our measures of employment and wage growth in each tier. For the overall overdose rate, we find that in nonmetro counties, about 7% of the total variation is explained by employment growth across all three tiers, while about 10% is explained in metro counties. We also find that a small portion (<5%) of total variation in opioid overdose death rates is explained by wage growth in nonmetro counties, while 10% is explained by wage growth in metro counties. These estimates align with a new working paper where the author finds that after controlling for many county-level covariates, variation in local economic conditions explains less than 10% of total variation in drug overdoses (Ruhm 2018). As such, while we do find evidence to support the popular narrative, we also find that the theory

may account for relatively little of the large increase in overdoses over the past decades.

Supplementary Material

Supplementary material are available at *American Journal of Agricultural Economics* online.

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