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Debts of despair: Education, financial losses, and precursors of deaths of despair



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ABSTRACT

Recent deaths of despair literature hypothesizes that financial losses are a key mechanism through which education is associated with higher risk for drug use, alcohol abuse, and suicidal ideation. However, few studies have empirically assessed the significance of this harmful pathway or compared it to other hypothesized explanations. Drawing on data from over 8000 respondents in the National Longitudinal Study of Adolescent to Adult Health, this paper finds that lower education-levels are associated with heightened risk of drug use, painkiller use, frequent binge drinking, and suicidal ideation; in turn, decompositions reveal that financial losses mediate about 20 percent of the association between education with drug use and suicidal ideation. The results support a core assumption of the deaths of despair hypothesis—that financial losses among those with low education-levels drive the increase in harmful despair-associated behaviors, which often precede disease and mortality. Future research should extend this work by linking individual-level socioeconomic and health patterns with broader economic changes to better understand how individuals' educational attainment interacts with macro-level structural factors to shape their vulnerability to despair-associated disease and death.

1. Introduction

Recent trends have shown a substantial and unexpected increase in midlife mortality among disadvantaged US populations in the past 20 years (Case & Deaton, 2015; Curtin & Arias, 2019; Miech et al., 2011), accounting for stagnation and declining life expectancy in the United States over the past four years (Kochanek et al., 2017; Xu et al., 2020). A disproportionate amount of deaths are attributable to drug poisoning, alcohol poisoning and alcohol-related diseases, and suicide. These deaths have been collectively dubbed as "deaths of despair" (Case & Deaton, 2015; Rudd et al., 2016; Stone et al., 2018)—and some have referred to the health conditions and behaviors preceding them as "diseases of despair" (Shanahan et al., 2019)—as these causes of morbidity and mortality are proposed to stem from growing psychosocial despair related to social and economic adversity among middle-aged adults in the United States (Bor et al., 2017; Cantu et al., 2019; Case & Deaton, 2015, 2020; Chetty et al., 2016; Goldman et al., 2018).

Indeed, economic adversity has been central to this troubling downturn in population health, as many have observed increasing financial instability and insecurity among the most socioeconomically disadvantaged members of society (Acemoglu & Autor, 2011; Howell & Kalleberg, 2019; Piketty et al., 2018). These trends are particularly notable among those with low levels of education as they are both most vulnerable to economic adversity due to the growing precariousness of employment (Kalleberg & Vallas, 2017), and least likely to recover from economic shocks, such as unemployment or financial downturns (Cutler et al., 2015; Glei et al., 2019; Kirsch & Ryff, 2016).

Amid the continued impact of drug overdoses, alcohol-related deaths, and suicide on US mortality rates and life expectancy, extant literature has provided valuable insights on these trends through the use of vital statistics data to document the association between low socioeconomic status and higher risks for deaths of despair (Case & Deaton, 2015, 2020; Masters et al., 2018). However, relatively few studies have leveraged survey data to explore the significance of different individual-level mechanisms at work (Gaydosh et al., 2019). The dearth of research is understandable given the difficulty of studying *deaths* of despair in survey data, as these causes of death are too infrequent to obtain stable estimates. Nevertheless, rich, longitudinal data provide an opportunity to study precursors to mortality in the form of various harmful behaviors associated with these outcomes (Shanahan et al., 2019). Consequently, this study uses longitudinal data from young and middle-aged adults surveyed in recent years to examine the relationship

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between educational attainment, financial losses, and despair-associated behaviors and thought-patterns like drug and opioid use, alcohol abuse, and suicidal ideation. Examining these pathways is an important step for evaluating the significance of financial loss in the ongoing deaths of despair narrative, and thus developing public policy to reduce inequity in US population health.

Moreover, it is important to contextualize financial losses as one of multiple plausible pathways connecting education and health. Link and Phelan's Fundamental Cause Theory (1995) contends that socioeconomic status-often measured by one's education-is associated with poor health and mortality via a multiplicity of mechanisms, which may change across contexts. Indeed, Shanahan and colleagues (2019) explicitly emphasize the need for using longitudinal data to better understand the multitude of sociodemographic and psychosocial stressors mediating the association between individuals' socioeconomic status and harmful, despair-associated behaviors. In keeping with this suggestion-and in light of the emphasis on "despair" and psychological distress as key driving mechanisms of recent population health trends—we also examine baseline income and wealth (Elo, 2009; Link & Phelan, 1995; Miech et al., 2011), stress (Lantz et al., 2005; Thoits, 2010), and divorce (Bramlett & Mosher, 2002; Cherlin, 2020) as alternative mechanisms that are contributing to educational disparities in drug and opioid use, alcohol abuse, and suicidal ideation.

In this article, we evaluate the role of financial losses in the ongoing despair narrative in population health-namely that financial loss among those with low education-levels is a key risk factor for increases in despair-associated behaviors that precede diseases and deaths resulting from drug use, excessive drinking, and suicidal ideation (Case & Deaton, 2015). We evaluate these patterns using data from the National Longitudinal Study of Adolescent to Adult Health to estimate logistic regressions and decomposition analyses. We examine the baseline relationship between education and drug use, painkiller use, frequent binge drinking, and suicidal ideation, provide estimates adjusted for adolescent health, demographic background and personality, and, lastly, explore mechanisms for the relationship between education and harmful health behaviors. We disentangle the contributions of mediating variables, comparing the relative importance of financial losses with individuals' existing assets and income, stress exposure, and marriage dissolution.

2. Data

The paper draws on data from the National Longitudinal Study of Adolescent to Adult Health (Add Health). Add Health has followed respondents from adolescence (Waves I and II) through young adulthood (Waves III and IV) and early midlife (Wave V). We use data from Waves I, IV, and V: Wave I's in-home survey was obtained in 1994–1995, Wave IV was collected in 2007–2008, and Wave V was collected in 2016–2018 (mean age 38, ranging from 33 to 44, with the majority ages 36-40). Several attributes of Add Health make it ideal for this study: (1) Add Health has comprehensive health and socioeconomic information on respondents at each survey wave; (2) Add Health's large sample size aids in the analysis of relatively rare outcomes, such as frequent binge drinking and suicidal ideation; and (3) the most recent Add Health data directly precede the age range exhibiting some of the most troubling health trends in the deaths of despair literature (Case & Deaton, 2015; Masters et al., 2018), and represent a key stage in the life course, when educational attainment is complete for most respondents and the importance of individual financial resources and assets is increasingly salient.

The Add Health sample begins with 20,745 total cases in Wave I; after attrition in Wave IV 15,701 cases remain. With additional attrition by Wave V, the sample of complete cases with information from Waves I, IV, and V is 10,914. We also dropped cases missing information on the treatment variables—constructed from Wave IV and V income and assets (N = 9417). Due to the relatively low missingness rate for covariates,

listwise deletion is used in the primary analyses (N = 8377). No cases exceed 5 percent missing; the Wave IV estimation of positive assets has the highest missingness rate at 4.3 percent for estimation of positive assets. Critically, this final sample represents over 75 percent of the total cases with information from Waves I, IV, and V. The final analysis sample size varies somewhat by the drug use (N = 8201), painkiller use (N = 8340), frequent binge drinking (N = 8366), and suicidal ideation outcomes (N = 8231), as seen in the descriptive statistics in Table A.1.

Traditional multiple imputation methods are difficult to implement in these analyses, as the disentangling function—which compares the contributions of mediators—of the khb (Kohler, Karlson, and Holm 2011) decomposition command is not compatible with Stata's multiple imputation procedure. Nevertheless, we compare the baseline models using multiple imputation to those based on listwise deletion and find no meaningful differences (Table B.6-B.7). Weight association tests (Bollen et al., 2016) and comparison of unweighted and weighted estimates revealed no meaningful bias in unweighted estimates relative to weighted estimates. Thus, unweighted estimates are used to provide tighter standard errors.

3. Measures

The three key outcomes for the analysis are use of illicit or nonprescribed medical drugs in the last 30 days (drug use), binge drinking three or more days a week (frequent binge drinking) in the past year, and suicidal ideation in the past year. A fourth outcome, use of nonprescribed painkillers in the last 30 days, is included to approximate the concern for the abuse of opioids and other similar drugs. All outcomes are from Wave V.

The drug use indicator is dichotomized: (1) use of non-prescribed sedatives, tranquilizers, stimulants, painkillers or opioids, cocaine, crystal meth, heroin, or other drugs (e.g., LSD, PCP, ecstasy, mushrooms, or inhalants) or (0) no use of these drugs in the past 30 days. We do not count marijuana towards this indicator, given the greater heterogeneity

Table 1

Cross-tabulation of the despair-associated behaviors and thought-processes and financial losses by education.

	<hs< th=""><th>HS</th><th>SC</th><th>BA</th><th>>BA</th></hs<>	HS	SC	BA	>BA
Outcomes					
Drug Use					
No	80.0	86.9	85.8	90.3	93.1
Yes	20.0	13.1	14.2	9.7	6.9
Painkiller Use					
No	88.1	92.0	92.0	95.4	97.2
Yes	11.9	8.0	8.0	4.6	2.8
Frequent Binge	Drinking				
No	91.6	94.2	95.6	96.4	98.2
Yes	8.4	5.8	4.4	3.6	1.8
Suicidal Ideation	n				
No	89.6	93.2	92.6	95.8	95.8
Yes	10.4	6.8	7.4	4.2	4.2
Treatment					
Any Income Los	s				
None	64.9	70.6	76.5	87.6	90.4
<25%	4.2	3.2	2.4	0.5	0.4
25-50%	11.5	14.0	12.9	8.4	6.8
50-75%	11.0	7.1	4.8	2.0	1.4
75%+	8.4	5.1	3.5	1.6	1.0
Any Asset Loss					
None	68.2	75.6	76.8	87.4	88.4
+ to 0	11.3	9.9	8.3	5.1	4.0
+/0 to -	20.5	14.5	14.8	7.6	7.6

N = 8377.

Notes: Sample sizes vary by outcome.

Source: National Longitudinal Study of Adolescent to Adult Health

in motivation for its use, and variation in its legality/availability across the US. The binge drinking variable was obtained from an ordinal indicator the frequency of drinking four (female) or five (male) drinks in a row. This variable was dichotomized: drinking three or more days week (1) or binge drinking less than three days a week (0). The binary indicator reflects the threshold-type association between between alcohol consumption and related mortality, with steep increases in the mortality risk above 200 grams of alcohol per week (Wood et al., 2018). Moreover, midlife death from alcohol poisoning or chronic liver disease or cirrhosis may be correlated with frequent high doses of alcohol. Suicidal ideation is also dichotomized: (1) respondents who report having "seriously thought about committing suicide" in the past 12 months or (0) those who have not thought about committing suicide the past 12 months.

Educational attainment is obtained from Wave IV. The indicator is divided into five categories: less than high school, high school, some college, bachelor's degree, more than a bachelor's degree (referent). Education is completed by most respondents before Wave IV, with many completing their education by Wave III (late teens and early 20s).

A key mediator of interest is loss of income, which is defined as any decline in household income bracket between Wave IV and V. Both Wave IV and V are divided into bracket, and coded based on their midpoint values (in parentheses): less than \$5000 (\$2500), \$5000 to \$9999 (\$7500), \$10,000 to \$14,999 (\$12,500), \$15,000 to \$19,999 (\$17,500), \$20,000 to \$24,999 (\$22,500), \$25,000 to \$29,999 (\$27,500), \$30,000 to \$39,999 (\$35,000), \$40,000 to \$49,999 (\$45,000), \$50,000 to \$74,999 (\$62,500), \$75,000 to \$99,999 (\$87,500), \$100,000 to \$149,999 (\$125,000), \$150,000 to \$199,999 (\$175,000), and \$200,000 or more (\$250,000), with the last category only available in Wave V. To reflect income loss—rather than income change—a five-category indicator of income loss is used: none (referent), <25% decline, 25–50% decline, 50–75% decline, and 75+% decline. Wave IV income is also included in the model, accounting for right skew with a log transformation.

Our other key measure of financial loss is based on assets, and is defined as any downward shift in asset category between Wave IV and V. Unfortunately, Add Health does not give more detailed information on assets, such as a measure of magnitude akin to the income categories above. In both waves, compatible assets variables are defined as positive, zero, or negative. Thus, a three-category indicator for asset loss is used: no reduction in categories (i.e., none) (referent), positive to zero assets (+to 0), and falling into debt (+/0 to -). Wave IV—but not Wave V—includes an indicator for a respondents' guess of the value of their positive assets, which we include as an independent indicator of baseline assets. Thus, a log transformed indicator of Wave IV positive assets is also included as a measure of baseline assets. Because of the similarity in these financial indicators, we conduct tests for collinearity, but find no meaningful multicollinearity.

To contextualize financial loss, we also consider mediation due to stress and divorce. Perceived stress is measured using Cohen's Stress Index (0–16) (Cohen et al., 1983). The stress index was constructed by the Add Health team and is left as a continuous indicator. Stress is an inherently subjective process and may omit important information about a person's resulting stress *response*; in supplemental analyses, we examine C-reactive protein as an objective measure of stress but find no change in our results (Table B.1). Divorce is constructed using information from both waves, to ascertain changes in one's marital status. The indicator is dichotomized: (1) divorce between Waves IV and V and (0) no divorce between Waves IV and V. The variable focuses on the time period between the two Waves because divorce may be correlated with financial losses and the despair-associated outcomes of interest.

Finally, we account for potential biases or confounding associated with issues of "selection," as low levels of education and poor health are not random phenomena in the United States, and are often linked to early life circumstances (Kawachi et al., 2010). To help mitigate selection on health—especially for these despair-associated behaviors—multiple adolescent covariates are obtained from Wave I. Self-rated health ranges from 1 through 5 and is treated as continuous. Depression is based on a CESD scale and ranges from 0 through 15 and is treated as continuous. Smoking, drug use, and marijuana use during the last 30 days, and suicidal ideation in the past year are dichotomous indicators. Adolescent drinking is divided into three categories: never, once a month or less, 2–3 days per month to 1–2 days/week, and 3+ days each week. The ordinal indicator focused on drinking rather than binge drinking is preferred because the (un)availability of alcohol to adolescents may inhibit frequent binge drinking.

We also incorporate personality characteristics are from Wave IV (young adulthood), which may also confound the association between education and health (Conti et al., 2010). The "Big-Five" personality characteristics (Gosling et al., 2003)—extroversion, neuroticism, agreeableness, conscientiousness, and openmindedness—were constructed by the Add Health staff. Risk taking propensity is obtained from a three-category ordinal indicator asking if respondents like to take risks: agree, neutral, and disagree.

Background demographic characteristics are obtained from Wave I. Parental education is obtained from the highest level of parental education between two resident parents. The indicator has five categories: less than high school, high school, some college, bachelor's degree, and more than a bachelor's degree. Family structure is divided into five categories (Harris, 1999): two biological parents, two parents, single mother, single father, and other. Race/ethnicity is divided into 5 categories: White, Black, Hispanic, Asian, and Other. Gender is dichotomized: (0) male and (1) female.

4. Methods

The analysis uses logistic regression to model the relationship between education and four despair-associated health behaviors: drug use, painkiller use, frequent binge drinking, and suicidal ideation. Bivariate (1) and adjusted (2) models are estimated. Additional models for all four outcomes include hypothesized mediators of loss of income and assets between Waves IV and V (3), and all mediators—baseline income and assets in Wave IV, stress in Wave IV, divorce between Waves IV and V—and all covariates (4).

The logistic regressions are used to calculate average marginal effects (AME). Not only are AME easier to interpret than odds ratios—reflecting discrete changes in probability relative to the reference group—but they also allow for comparisons of nested models because they evade logistic regression's problems of changing scale parameters across models (Mood, 2010). The AME are multiplied by 100 to be interpreted as percentage point changes. We also display estimates as log odds ratios.

The third part of the analysis uses Karlson, Holm, and Breen's (KHB) (2012; Kohler et al., 2011) decomposition to formally test mediation and disentangle the mediators' contributions to the indirect effect of education on the outcomes. Their approach corrects the issue of changing variance across different logistic regression models (please see Karlson, Holms, and Breen [2012] for more detail on this approach).

In the case of our model, we evaluate the confounding role of a series of mediators (changes in income, changes in assets, baseline income, baseline positive assets, assets (categorical), stress, and divorce) for education's association with the drug use, painkiller use, frequent binge drinking, and suicidal ideation—in four separate models. Using Stata's khb command (Kohler et al., 2011), we disentangle the contribution of each mediator to the indirect effect, net of covariates for sociodemographic characteristics, health, and personality.

5. Results

5.1. Descriptive results

Table 1 displays cross-tabulations of the association between education and the health behavior outcomes and the treatments. Higher

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levels of education are consistently associated with lower rates of harmful behaviors. For example, 20 percent of respondents with less than a high school degree use drugs, while 6.9 percent of respondents with more than bachelor's degree use drugs. Similarly, higher education is associated with lower rates of income and asset loss. For example, 35.1 percent of respondents with less than a high school degree had any income loss between Waves IV and V. On the other hand, only 9.6 percent of respondents with more than a bachelor's degree had an income reduction between Waves IV and V. In short, lower education has a consistent inverse association with both despair-associated health behaviors and financial decline.

5.2. Logistic regression results

Second, AME and log odds ratios from models of drug use, painkiller use, frequent binge drinking, and suicidal ideation are shown in Table 2 (see predicted probabilities in Table B.8 and full models in Tables C.1-C.4). Again, education is associated with elevated rates of drug use. For example, in Model 1, the bivariate model, those with less than a high school degree have 13.1 percentage points higher rate of drug use than those with more than bachelor's degree. Adjustment in Model 2 leads to attenuation (a 4.1 percentage point reduction in AME) of differences for those a high school degree or less. Interestingly, differences between those with more than bachelor's degree and those with some college or a bachelor's degree remain stable or even slightly increase. Model 3 introduces a variable for financial losses, attenuating the AME for less than a high school degree by 1.9 percentage points relative to Model 2. Inclusion of all mechanisms in Model 4 further reduces less than high school degree's AME to 5.6 percentage points higher likelihood of drug use than those with more than a bachelor's degree, net of other factors.

Quite similar patterns are observed in the results from painkiller use models although their initial differences are less wide. In general, results from the drug and painkiller use models show considerable education disparities. Although they are partially negated by adjusting for covariates, the association between low education and heightened risk of drug use remains. The results suggest that financial losses partially account for these education disparities.

Results from the frequent binge drinking models also reveal education disparities. For example, those with less than a high school degree have a 6.6 percentage point higher rate of frequent binge drinking than those with more than bachelor's degree (Model 1). Adjusting for covariates has no meaningful impact on the estimates (Model 2). Minor estimate reductions are observed when including information on financial losses (Model 3). No meaningful change is observed from adding more mechanisms (Model 4). Although results from the frequent binge drinking models show educational inequality, there is less evidence for financial losses as a meaningful mechanism.

Lastly, results from suicidal ideation models are displayed, revealing meaningful education gaps in suicidal ideation. For example, those with less than a high school degree have 6.2 percentage points higher rate of suicidal ideation than those with more than a bachelor's degree (Model 1). Adjusting for covariates modestly reduces the AMEs from 6.2 to 4.2

Table 2

Estimates from logistic regressions of drug use, painkiller use, frequent binge drinking, and suicidal ideation on education.

	Drug Use		Painkiller	Painkiller Use		Frequent Binge Drinking		Suicidal Ideation	
	AME	B (SE)	AME	B (SE)	AME	B (SE)	AME	B (SE)	
Model 1 (Biv	variate)								
Education (>	>BA)								
BA	2.84	0.38 (13)**	0.00	0.51 (0.20)*	1.74	0.69 (0.24)**	-0.04	-0.01 (0.18)	
SC	7.33	0.81 (0.12)***	5.21	1.10 (0.18)***	2.55	0.90 (0.23)***	3.18	0.59 (0.16)***	
HS	6.21	0.71 (0.13)***	5.18	1.10 (0.19)***	3.95	1.19 (0.23)***	2.54	0.50 (0.17)**	
<hs< td=""><td>13.10</td><td>1.22 (0.16)***</td><td>9.05</td><td>1.54 (0.22)***</td><td>6.59</td><td>1.60 (0.27)***</td><td>6.16</td><td>0.97 (0.21)***</td></hs<>	13.10	1.22 (0.16)***	9.05	1.54 (0.22)***	6.59	1.60 (0.27)***	6.16	0.97 (0.21)***	
Model 2 (Ad	justed)								
Education (>	>BA)								
BA	2.95	0.36 (0.14)**	1.91	0.47 (0.20)*	1.57	0.64 (0.24)**	0.06	0.01 (0.18)	
SC	6.16	0.67 (0.13)***	4.36	0.88 (0.19)***	2.52	0.89 (0.24)***	2.56	0.49 (0.17)**	
HS	4.32	0.50 (0.14)***	3.68	0.78 (0.20)***	3.88	1.19 (0.25)***	1.88	0.38 (0.19)*	
<HS	8.75	0.87 (0.18)***	5.88	1.08 (0.24)***	6.71	1.63 (0.30)***	4.22	0.73 (0.23)**	
Model 3 (Ad	justed + Financia	al Losses)							
Education (>	>BA)								
BA	2.93	0.34 (0.14)**	1.95	0.45 (0.20)*	1.60	0.63 (0.24)*	0.01	0.00 (0.18)	
SC	5.37	0.57 (0.13)***	4.03	0.80 (0.19)***	2.41	0.85 (0.24)***	2.20	0.42 (0.17)*	
HS	3.14	0.36 (0.14)**	3.17	0.67 (0.20)***	3.67	1.12 (0.25)***	1.44	0.29 (0.19)	
<hs< td=""><td>6.86</td><td>0.70 (0.18)***</td><td>4.95</td><td>0.93 (0.24)***</td><td>6.13</td><td>1.53 (0.30)***</td><td>3.49</td><td>0.61 (0.24)*</td></hs<>	6.86	0.70 (0.18)***	4.95	0.93 (0.24)***	6.13	1.53 (0.30)***	3.49	0.61 (0.24)*	
Model 4 (Ad	justed + All Med	liators)							
Education (>	>BA)								
BA	3.20	0.37 (0.14)**	2.15	0.49 (0.20)*	1.58	0.62 (0.24)*	0.13	0.03 (0.18)	
SC	5.12	0.55 (0.13)***	3.94	0.78 (0.19)***	2.32	0.82 (0.24)**	1.83	0.35 (0.17)*	
HS	2.81	0.33 (0.15)*	3.00	0.64 (0.21)**	3.73	1.13 (0.25)***	1.05	0.21 (0.19)	
<hs< td=""><td>5.59</td><td>0.59 (0.19)**</td><td>4.03</td><td>0.79 (0.25)**</td><td>6.26</td><td>1.55 (0.31)***</td><td>2.10</td><td>0.39 (0.25)</td></hs<>	5.59	0.59 (0.19)**	4.03	0.79 (0.25)**	6.26	1.55 (0.31)***	2.10	0.39 (0.25)	
	8201		8340		8366		8231		

N = 8377.

Notes: Sample sizes vary by outcome. The logistic regressions adjust for adolescent drug use, adolescent alcohol use, adolescent suicidal ideation, self-rated health, smoking, marijuana use, and depression, extroversion, neuroticism, agreeableness, conscientiousness, openmindedness, risk-taking propensity, parental education, family structure, race/ethnicity, and gender. The mediators are Wave IV income, assets (categories), and positive assets, income losses and asset losses between Waves IV and V (financial losses), stress, and divorce.

Source: National Longitudinal Study of Adolescent to Adult Health

from Model 1 to Model 2, respectively. Adjustment for financial losses further reduces the AME to 3.5 percentage points (Model 3). Inclusion of additional mechanisms for income, assets, stress, and divorce further attenuate the AME to overlap with zero (Model 4). Again, results from suicidal ideation models suggest that educational inequality is partially mediated by financial losses and other mechanisms.

5.3. Decomposition results

Next, estimates from the KHB decompositions are shown (Table 3). Each model disaggregates estimates into total, direct, and indirect effects, and disentangles the indirect effects into individual components. No meaningful indirect effects are observed for bachelor's and more than bachelor's contrasts for drug use. The mechanisms account for a considerable portion of confounding for those with a high school degree or less, however. For example, 32.4 percent of the total effect of having less than a high school degree relative to a bachelor's degree or more on drug use are indirect effects. Among these indirect effects, only log(income) and losses of income and assets have associations when the indirect effects are disentangled. These financial losses account for 20.8 percent of the total effect. Similar patterns are observed at the high school degree level. A similar pattern is observed in the decomposition of painkiller use. Note that financial losses account for a slightly smaller percentage of the total effect (16% for < HS) than for drug use. In short, financial losses account for a meaningful portion of education's relationship with drug use (generally) and—specifically—painkiller use.

In contrast, the results from frequent binge drinking models reveal no clear evidence of indirect effects. However, disentangled estimates suggest that loss of assets and stress—when separated—account for a small portion of the total effects of education on frequent binge drinking. Thus, results from frequent binge drinking models do not fit the despair narrative in which financial losses meaningfully mediate its relationship with education.

Lastly, estimates are shown for suicidal ideation. Like the other results, no meaningful indirect effect is observed for the bachelor's and more than bachelor's contrast. However, indirect effects are observed for respondents with some college, high school, and less than a high school degree relative to those with more than a bachelor's degree. For example, the indirect effect accounts for 45.7 percent of the total effect of having less than a high school degree relative to having more than a bachelor's degree on suicidal ideation. Disentangling the indirect effect reveals the roles of income and asset losses, stress, and divorce. Financial losses account for around for 19.1 percent of the total effect for having less than a high school degree relative to completing more than a bachelor's degree on suicidal ideation. Together these results support a key "deaths of despair" hypothesis that financial losses partially account for the relationship between education and suicidal ideation, while also providing some support for the roles of stress and divorce.

6. Extensions and sensitivity analyses

We conduct a series of sensitivity analyses to address potential concerns and complexities in our primary findings. A detailed description of these sensitivity analyses is in Appendix B of the online supplemental file. First, we estimate models with an estimated debt measure and a biological indictor of elevated stress response (C-reactive protein). Second, we use Wave IV covariates in place of Wave I covariates to address potential reverse causality. Third, we carefully consider potential issues from temporal ordering in the analyses, and estimate decompositions without divorce, through which financial losses could impact health outcomes. Fourth, we estimate models which allow baseline financial indicators (Wave IV) to interact with education. In general, our results are robust to alternative specifications, but we acknowledge that the Add Health data and methods used cannot completely resolve these concerns.

7. Discussion

This paper tests a key aspect of Case and Deaton's (2015, 2020) hypothesis tying education inequalities to precursors of deaths of despair; namely that financial losses among those with low education levels are a key explanatory mechanism. Using data from the National Longitudinal Study of Adolescent to Adult Health, the analysis reveals strong associations between low education-levels and financial losses-measured as income and asset losses-with drug use, painkiller use, frequent binge drinking, and suicidal ideation. Financial losses account for a meaningful portion of the relationship between education with drug use and suicidal ideation, but not with frequent binge drinking. Specifically, financial losses account for around 20 percent of the gap in drug use and suicidal ideation between those with less than a high school degree and those more than a bachelor's degree. These results provide strong evidence for Case and Deaton's explanation of how education, despair, and mortality are interconnected among those with low levels of education. Consistent with their theory (2020), financial losses are only meaningful mechanisms among those with less than a college degree relative to those with a graduate degree.

We also test the alterative hypotheses about the importance of baseline income and assets, stress, and divorce, as additional mechanisms tying individuals' socioeconomic status these different health outcomes (Link & Phelan, 1995; Shanahan et al., 2019). We find some support for the role of baseline income. There is also some evidence of the important roles of stress and divorce as mechanisms for suicidal ideation—at magnitudes smaller than those for financial losses. At the same time, it is possible that these other mechanisms operate *through* financial losses to influence these harmful behaviors. Such an explanation would still support Case and Deaton's hypothesis on financial losses, as a key mechanism that is impacted by multiple aspects of individuals' social lives.

In general, we provide evidence for Case and Deaton's argument in the Add Health cohort, which covers an age range approximately one decade younger than the "middle-aged" adults that have been the focus of recent trends in population health (Bor et al., 2017; Cantu et al., 2019; Chetty et al., 2016). Future research will benefit from linking macro-level economic and demographic patterns with individual-level behavior to determine if these health patterns relate to diverging circumstances across education, as speculated by many researchers examining these trends. Furthermore, this study would benefit from examination of patterns across cohorts and periods, given Case and Deaton's argument that those with high school degrees or less have been increasingly left behind in the current economic market, and as echoed by extant sociological research on rising financial and labor market precarity among this large segment of the working-age population (Howell and Kalleberg 2019). A more complete model would incorporate information on these macro-level economic changes over period, cohort change, and mortality across midlife.

We demonstrate the plausibility of the education-finances-deaths of despair pathway outlined by Case and Deaton. Nevertheless, we cannot necessarily disconfirm many counterarguments to Case and Deaton's theory. For example, other work (Geronimus et al., 2019; Masters et al., 2018) contends that the mortality increases are primarily attributable to drug overdoses, arguing that drug and alcohol use and suicidal ideation are not necessarily driving the same pattern. Given that the indirect effect sizes of financial losses on drug use and suicidal ideation are somewhat larger than those for frequent binge drinking, the results are somewhat consistent with this claim. It is also possible that binge drinking is distinct from drug use and suicidal ideation in reflecting a mix of underlying etiologies, associated with both increased distress and despair, but also a more 'social' attitude towards drinking (Halim et al., 2012), which is independent of financial loss mechanisms.

These results provide several important implications for policymakers. First, the results suggest that focusing on reducing educational inequities would benefit population health in reducing the prevalence of

Table 3

Estimates from decompositions of logistic regressions of drug use, painkiller use, frequent binge drinking, and suicidal ideation on education.

	Drug Use		Painkiller Use		Frequent Binge Drinking		Suicidal Ideation	
	В	% Red.	В	% Red.	В	% Red.	В	% Red.
Education (>BA)								
BA								
Total Effect (TE)	0.36 (0.14)**		0.47 (0.20)*		0.63 (0.24)**		0.01 (0.18)	
Direct Effect (DE)	0.37 (0.14)**		0.49 (0.20)*		0.62 (0.24)*		0.03 (0.18)	
Indirect Effect (IE) Decomposition of IF	0.00 (0.03)	-1.20	-0.02 (0.03)	-3.54	0.01 (0.03)	1.89	-0.02 (0.04)	-249.09
Log (Income)	0.00 (0.00)	-0.55	0.00 (0.00)	-0.51	0.00 (0.01)	0.49	0.00 (0.00)	-38.51
Log (Assets)	0.00 (0.00)	-0.50	0.00 (0.00)	-0.72	0.00 (0.00)	0.74	0.00 (0.00)	-38.38
Asset Category (+)	0.01 (0.00)	-0.71	0.01 (0.01)	1.02	0.00 (0.00)	0.00	0.00 (0.00)	00.40
0	0.01 (0.00)	1 48	0.01 (0.01) -0.04 (0.01)**	1.93 	-0.00(0.00)	0.09 -1.48	0.00 (0.00) -0.04 (0.01)**	23.48
Loss of Income (None)	-0.03 (0.01)	-7.40	-0.04 (0.01)	-0.51	-0.01 (0.02)	-1.40	-0.04 (0.01)	-473.29
<25%	0.00 (0.00)		0.00 (0.00)	-0.12	0.00 (0.00)	-0.06	0.00 (0.00)	16.89
25–50%	0.01 (0.00)	0.00	0.01 (0.00)	1.15	0.00 (0.00)	-0.3	0.00 (0.00)	54.17
50–75%	0.00 (0.00)	1.39	0.00 (0.00)	0.67	0.00 (0.00)	0.05	0.00 (0.00)	32.53
75%+	0.01 (0.00)	1.19	0.01 (0.01)	1.21	0.00 (0.00)	0.72	0.00 (0.00)	28.67
Loss of Assets (None)	0.00 (0.00)	1.47	0.00 (0.00)	0.00	0.00 (0.00)	0.07	0.00 (0.00)	17.00
+ to 0	0.00 (0.00)	1 19	0.00 (0.00)	0.93	0.00 (0.00)	0.37	0.00 (0.00)	17.03
+/0 10 -	0.00 (0.00)	0.17	0.00 (0.00)	0.25	0.00 (0.01)	0.25	0.00(0.00)	20.45
Divorce	0.00 (0.00)	0.17	0.00 (0.00)	-0.26	0.01 (0.01)	0.84	0.01 (0.01)	24.07
Divolce	0.00 (0.00)	0.40	0.00 (0.00)	-0.20	0.00 (0.00)	0.19	0.00 (0.00)	24.07
SC								
Total Effect (TE)	0.66 (0.13)***		0.87 (0.19)***		0.88 (0.24)***		0.47 (0.17)**	
Direct Effect (DE)	0.55 (0.13)***		0.78 (0.19)***		0.82 (0.24)***		0.35 (0.17)*	
Indirect Effect (IE) Decomposition of IE	0.11 (0.03)**	16.95	0.09 (0.04)*	10.19	0.06 (0.05)	6.77	0.13 (004)**	26.57
Log (Income)	0.03 (0.01)*	4.18	0.03 (0.02)*	4.02	-0.05 (0.02)*	-5.55	0.03 (0.02)*	7.32
Log (Assets)	-0.01 (0.01)	-1.70	-0.02 (0.01)	-1.76	0.02 (0.02)	2.37	-0.01 (0.01)	-3.08
Asset Category (+)	0.01 (0.01)*	0.00	-0.04 (0.01)**	0.70	0.00(0.01)	0.16	0.01 (0.01)	1.16
0	0.01 (0.01)*	2.02	0.02 (0.01)**	2.73	-0.00(0.01)	0.16	0.01 (0.01)	1.16 _8 79
Loss of Income (None)	-0.03 (0.01	-4.20	-0.04 (0.01)	-4.01	-0.01 (0.02)	-1.11	-0.04 (0.01)	-0.79
<25%	0.00 (0.01)	-0.02	0.00 (0.01)	-0.49	0.00 (0.01)	-0.33	0.01 (0.01)	2.16
25-50%	0.02 (0.01)**	2.98	0.02 (0.01)*	2.26	-0.01 (0.01)	-0.76	0.02 (0.01)	3.28
50-75%	0.02 (0.01)**	2.90	0.02 (0.01*	1.73	0.00 (0.01)	0.16	0.01 (0.01)	2.65
75%+	0.02 (0.01)**	2.59	0.02 (0.01)**	2.12	0.01 (0.01)*	1.67	0.01 (0.01)	1.48
Loss of Assets (None)	0.00 (0.01)							
+ to 0	0.02 (0.01)**	2.81	0.02 (0.01)*	1.93	0.01 (0.01)	1.07	0.01 (0.01)	1.17
+/0 to -	0.02 (0.01)**	3.07	0.03 (0.01)**	2.92	0.03 (0.01)**	3.34	0.03 (0.01)**	5.34
Divorce	0.01 (0.01)	1.67	0.01(0.01)	1.4/	$0.03(0.01)^{\circ}$	3.40 2.20	0.04 (0.01)**	7.99
Divolce	0.00 (0.01)	0.03	-0.02 (0.01)	-1.95	0.02 (0.01)	2.29	0.03 (0.01)	5.69
HS								
Total Effect (TE)	0.48 (0.14)***		0.76 (0.20)***		1.18 (0.25)***		0.36 (0.19)	
Direct Effect (DE)	0.33 (0.15)*		0.64 (0.21)**		1.13 (0.25)***		0.21 (0.19)	
Indirect Effect (IE)	0.15 (0.04)***	31.77	0.12 (0.05)*	16.40	0.05 (0.06)	3.98	0.15 (0.05)**	41.13
Decomposition of IE								
Log (Income)	0.04 (0.02)*	8.24	0.05 (0.02)*	6.66	-0.07 (0.03)*	-6.01	0.05 (0.02)*	14.32
Log (Assets)	-0.01 (0.01)	-2.89	-0.02 (0.02)	-2.48	0.03 (0.02)	2.18	-0.02 (0.02)	-4.89
Asset Category (+)	0.02 (0.01)*	3.61	0.03 (0.01)**	3 01	0.00(0.01)	0.15	0.01 (0.01)	1.95
-	-0.04 (0.01)**	-7.62	-0.05 (0.02)***	-7.15	-0.01(0.02)	-1.08	-0.05 (0.02)**	-15.08
Loss of Income (None)	0101 (0101)	,102	0100 (0102)	,110	0101 (0102)	1100	0100 (0102)	10100
<25%	0.00 (0.01)	-0.03	-0.01 (0.01)	-0.78	0.00 (0.01)	-0.36	0.02 (0.01)	4.21
25–50%	0.02 (0.01)**	4.93	0.02 (0.01)*	3.04	-0.01 (0.01)	-0.67	0.02 (0.01)	5.37
50-75%	0.03 (0.01)***	7.14	0.03 (0.01)*	3.38	0.00 (0.01)	0.20	0.02 (0.01)*	5.85
75%+	0.03 (0.01)***	5.90	0.03 (0.01)***	4.07	0.02 (0.01)*	2.05	0.01 (0.01)	3.22
Loss of Assets (None)								
+ to 0	0.03 (0.01)**	5.45	0.02 (0.01)	3.09	0.01 (0.01)	1.12	0.01 (0.01)	2.18
+/0 to -	0.02 (0.01)**	4.06	0.02 (0.01)**	3.19	0.03 (0.01)*	2.39	0.02 (0.01)*	6.70
Stress	0.01(0.01)	2.16	0.01 (0.01)	1.57	0.03 (0.01)*	2.45	0.04 (0.01)***	10.08
Divolce	0.00 (0.01)	0.82	-0.02 (0.01)	-2.09	0.02 (0.01)	1.20	0.03 (0.01)^^	/.21
<hs< td=""><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></hs<>								
Total Effect (TE)	0.87 (0.18)***		1.07 (0.24)***		1.62 (0.30)***		0.72 (0.24)**	
Direct Effect (DE)	0.59 (0.19)***		0.79 (0.25)**		1.55 (0.31)***		0.39 (0.25)	

(continued on next page)

Table 3 (continued)

	Drug Use		Painkiller Use	Painkiller Use		Frequent Binge Drinking		Suicidal Ideation	
	В	% Red.	В	% Red.	В	% Red.	В	% Red.	
Indirect Effect (IE)	0.28 (0.06)***	32.36	0.28 (0.07)***	26.06	0.07 (0.09)	4.45	0.33 (0.08)***	45.71	
Decomposition of IE									
Log (Income)	0.10 (0.05)*	11.08	0.13 (0.06)*	11.65	-0.17 (0.08)*	-10.65	0.13 (0.06)*	17.55	
Log (Assets)	-0.03 (0.03	-3.37	-0.04 (0.04)	-3.85	0.06 (0.04)	3.42	-0.04 (0.04)	-5.33	
Asset Category (+)									
0	0.02 (0.01)*	2.51	0.04 (0.01)**	3.42	0.00 (0.02)	0.13	0.01 (0.01)	1.21	
-	-0.02 (0.01)	-2.09	-0.03 (0.01)*	-2.33	-0.01 (0.01)	-0.34	-0.02 (0.01)	-3.15	
Loss of Income (None)									
<25%	0.00 (0.01)	-0.02	-0.01 (0.01)	-0.72	-0.01 (0.01)	-0.33	0.02 (0.01)	2.64	
25–50%	0.01 (0.01)	1.48	0.01 (0.01)	1.18	0.00 (0.01)	-0.29	0.01 (0.01)	1.66	
50-75%	0.05 (0.01)***	6.27	0.04 (0.02)*	3.92	0.00 (0.02)	0.25	0.03 (0.02*	4.79	
75% +	0.05 (0.01)***	5.29	0.05 (0.01)***	4.65	0.04 (0.02)*	2.53	0.02 (0.01)	2.58	
Loss of Assets (None)									
+ to 0	0.03 (0.01)**	3.85	0.03 (0.01)*	2.75	0.02 (0.02)	1.02	0.01 (0.01)	1.25	
+/0 to -	0.03 (0.01)**	3.96	0.05 (0.02)**	4.20	0.05 (0.02)**	3.20	0.04 (0.02)**	6.20	
Stress	0.03 (0.02)	2.92	0.03 (0.02)	2.75	0.07 (0.07)*	4.33	0.09 (0.03)***	12.54	
Divorce	0.00 (0.01)	0.47	-0.02 (0.01)	-1.56	0.02 (0.01)	1.18	0.03 (0.01)*	3.79	
Observations	8201		8340		8366		8231		

N = 8377.

Notes: Sample sizes vary by outcome. The decompositions adjust for adolescent drug use, adolescent alcohol use, adolescent suicidal ideation, self-rated health, smoking, marijuana use, and depression, extroversion, neuroticism, agreeableness, conscientiousness, openmindedness, risk-taking propensity, parental education, family structure, race/ethnicity, and gender.

Source: National Longitudinal Study of Adolescent to Adult Health

key despair-associated health behaviors, and thus potentially despairassociated morbidity and mortality. Critically, education may impart important resources—like robust social support networks, a sense of control over one's life, and knowledge of health positive health behaviors and coping mechanisms (Link and Phelan 1995)—which reduce stress and the likelihood of despair by facilitating greater resilience in the face of unexpected and difficult challenges, like financial loss.

To that end, our results suggest that direct intervention in finances among those with low education-levels may also serve to reduce rates of the harmful behaviors associated with deaths of despair. Progressive tax rates, in the form of lower tax-rates among this segment of the population or providing higher minimum wages could reduce the health-toll of educational inequality on the US population. Such progressive policies are generally associated with better health outcomes, but there are exceptions. For example research shows that increases in minimum wage are associated with reduced low birthweight and infant mortality and better mental health care outcomes (Reeves et al., 2017; Wehby et al., 2020). Moreover, this form of more robust social support and/or welfare helps to explain the superior health outcomes of lower-SES adults in other high-income nations, where the impact of financial loss and/or instability on lower-educated adults is mitigated by economic policies that provide assistance in challenging economic circumstances (National Research Council & Committee on Population, 2013).

7.1. Limitations

The analysis herein has several limitations. First, the models do not account for selection on unobserved characteristics, such as health, personality attributes, or peers' health behaviors not included in Add Health. One proposed solution is longitudinal fixed effects models to model financial losses' relationship with these health outcomes. This approach has potential problems from aging directionality (i.e., changes across the life course vs. changes within-person), the likelihood that increases in finances may not benefit health as much as financial losses hurt health (Benzeval & Judge, 2001). Most importantly for our analyses, it cannot be used to evaluate education's time invariant relationship with the outcomes.

Second, the results pertain specifically to the Add Health cohort and the ages which Add Health Waves IV and V cover. Thus, the results primarily apply to the association between financial losses between young adulthood and middle adulthood and despair-associated behaviors, and do not necessarily pertain to the same association at older ages. In addition, this specific cohort may have its economic and health outcomes meaningfully impacted by the 2008 recession.

Third, trends observed in these analyses may not necessarily apply to deaths. For example, Geronimus and colleagues (2019) found that drug overdoses contributed to increased White educational inequality in mortality in the United States, but did not contribute for Blacks. Thus, future research will need to examine if these increases in harmful, despair-associated behaviors translate into deaths with population data with enough cases for racial/ethnic disaggregation.

8. Conclusion

The current paper evaluates Case and Deaton's hypothesis that education influences despair-associated health behaviors—drug use, frequent binge drinking, and suicidal ideation—via financial losses among those with low education levels. The analysis supports this hypothesis. It reveals that education is associated with these harmful health behaviors. Decompositions show that financial losses account for a significant portion of the relationship between education and these behaviors—especially drug use and suicidal ideation. These results provide empirical support for the financial mechanisms tying lower levels of education to increased mortality from deaths of despair, suggesting the benefits of educational and financial interventions to reduce drug and suicide-related mortality in the United States.

Future work should examine if these health patterns relate to diverging circumstances across education. Furthermore, this research would benefit from examination of patterns across cohorts and periods, given Case and Deaton's argument that those with high school degrees or less have been increasingly left behind in the current economic market. A more complete model would incorporate information on macro-level economic changes over period, cohort change, and mortality across midlife.

CRediT authorship contribution statement

Samuel H. Fishman: Writing - original draft, Formal analysis, Conceptualization, Supervision. **Iliya Gutin:** Writing – review & editing, Conceptualization.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ssmph.2021.100759.

Ethical statement

No data were collected for this research. The study was approved by the IRB at Duke University.

The authors have no conflicts of interest.

References

- Acemoglu, D., & Autor, D. (2011). Skills, tasks and technologies: Implications for employment and earnings. In, Vol. 4. Handbook of labor economics (pp. 1043–1171). Elsevier.
- Benzeval, M., & Judge, K. (2001). Income and health: The time dimension. Social Science & Medicine, 52(9), 1371–1390.
- Bollen, K. A., Biemer, P. P., Karr, A. F., Tueller, S., & Berzofsky, M. E. (2016). Are survey weights needed? A review of diagnostic tests in regression analysis. *Annual Review of Statistics and Its Application, 3*, 375–392.
- Bor, J., Cohen, G. H., & Galea, S. (2017). Population health in an era of rising income inequality: USA, 1980–2015. The Lancet, 389(10077), 1475–1490.
- Bramlett, M. D., & Mosher, W. D. (2002). Cohabitation, marriage, divorce, and remarriage in the United States. National Center for Health Statistics.
- Cantu, P. A., Sheehan, C. M., Sasson, I., & Hayward, M. D. (2019). Increasing educationbased disparities in healthy life expectancy among US non-hispanic whites, 2000–2010. The Journals of Gerontology: Series B.
- Case, A., & Deaton, A. (2015). Rising morbidity and mortality in midlife among white non-Hispanic Americans in the 21st century. *Proceedings of the National Academy of Sciences*, 112(49), 15078–15083.
- Case, A., & Deaton, A. (2020). Deaths of despair and the future of capitalism. Princeton University Press.
- Cherlin, A. J. (2020). Degrees of change: An assessment of the deinstitutionalization of marriage thesis. Journal of Marriage and Family, 82(1), 62–80.
- Chetty, R., Stepner, M., Abraham, S., Lin, S., Scuderi, B., Turner, N., Bergeron, A., & Cutler, D. (2016). The association between income and life expectancy in the United States, 2001-2014. Jama, 315(16), 1750–1766.
- Cohen, S., Kamarck, T., & Mermelstein, R. (1983). A global measure of perceived stress. Journal of Health and Social Behavior, 24(4), 385–396.
- Conti, G., Heckman, J., & Urzua, S. (2010). The education-health gradient. *The American Economic Review*, 100(2), 234–238.
- Curtin, S. C., & Arias, E. (2019). Mortality trends by race and ethnicity among adults aged 25 and over: United States, 2000–2017.
- Cutler, D. M., Huang, W., & Lleras-Muney, A. (2015). When does education matter? The protective effect of education for cohorts graduating in bad times. *Social Science & Medicine*, 127, 63–73.
- Elo, I. T. (2009). Social class differentials in health and mortality: Patterns and explanations in comparative perspective. Annual Review of Sociology, 35, 553–572.

- Gaydosh, L., Hummer, R. A., Hargrove, T. W., Halpern, C. T., Hussey, J. M., Whitsel, E. A., Dole, N., & Harris, K. M. (2019). The depths of despair among US adults entering midlife. *American Journal of Public Health*, 109(5), 774–780.
- Geronimus, A. T., Bound, J., Waidmann, T. A., Rodriguez, J. M., & Timpe, B. (2019). Weathering, drugs, and whack-a-mole: Fundamental and proximate causes of widening educational inequity in US life expectancy by sex and race, 1990–2015. *Journal of Health and Social Behavior*, 60(2), 222–239.
- Glei, D. A., Goldman, N., & Weinstein, M. (2019). A growing socioeconomic divide: Effects of the Great Recession on perceived economic distress in the United States. *PloS One*, 14(4), Article e0214947.
- Goldman, N., Glei, D. A., & Weinstein, M. (2018). Declining mental health among disadvantaged Americans. Proceedings of the National Academy of Sciences, 115(28), 7290–7295.
- Gosling, S. D., Rentfrow, P. J., & Swann, W. B., Jr. (2003). A very brief measure of the Big-Five personality domains. *Journal of Research in Personality*, 37(6), 504–528.
- Halim, A., Hasking, P., & Allen, F. (2012). The role of social drinking motives in the relationship between social norms and alcohol consumption. *Addictive Behaviors*, 37 (12), 1335–1341.
- Harris, K. M. (1999). The health status and risk behaviors of adolescents in immigrant families. Children of Immigrants: Health, Adjustment, and Public Assistance, 286–347.
- Howell, D. R., & Kalleberg, A. L. (2019). Declining job quality in the United States: Explanations and evidence. RSF: The Russell Sage Foundation Journal of the Social Sciences, 5(4), 1–53.
- Kalleberg, A. L., & Vallas, S. P. (2017). Precarious work. Emerald Group Publishing.
- Karlson, K. B., Holm, A., & Breen, R. (2012). Comparing regression coefficients between same-sample nested models using logit and probit: A new method. *Sociological Methodology*, 42(1), 286–313.
- Kawachi, I., Adler, N. E., & Dow, W. H. (2010). Money, schooling, and health: Mechanisms and causal evidence. *Annals of the New York Academy of Sciences*, 1186, 56–68.
- Kirsch, J. A., & Ryff, C. D. (2016). Hardships of the great recession and health: Understanding varieties of vulnerability. *Health Psychology Open*, 3(1), 2055102916652390.
- Kochanek, K. D., Murphy, S. L., Xu, J., & Arias, E. (2017). Mortality in the United States, 2016. National Center for Health Statistics.
- Kohler, U., Karlson, K. B., & Holm, A. (2011). Comparing coefficients of nested nonlinear probability models. STATA Journal, 11(3), 420–438.
- Lantz, P. M., House, J. S., Mero, R. P., & Williams, D. R. (2005). Stress, life events, and socioeconomic disparities in health: Results from the Americans' Changing Lives Study. Journal of Health and Social Behavior, 46(3), 274–288.
- Link, B. G., & Phelan, J. (1995). Social conditions as fundamental causes of disease. Journal of Health and Social Behavior, 80–94.
- Masters, R. K., Tilstra, A. M., & Simon, D. H. (2018). Explaining recent mortality trends among younger and middle-aged White Americans. *International Journal of Epidemiology*, 47(1), 81–88.
- Miech, R., Pampel, F., Kim, J., & Rogers, R. G. (2011). The enduring association between education and mortality: The role of widening and narrowing disparities. *American Sociological Review*, 76(6), 913–934.
- Mood, C. (2010). Logistic regression: Why we cannot do what we think we can do, and what we can do about it. *European Sociological Review*, *26*(1), 67–82.
- National Research Council & Committee on Population. (2013). US health in international perspective: Shorter lives, poorer health. National Academies Press.
- Piketty, T., Saez, E., & Zucman, G. (2018). Distributional national accounts: Methods and estimates for the United States. *Quarterly Journal of Economics*, 133(2), 553–609.
- Reeves, A., McKee, M., Mackenbach, J., Whitehead, M., & Stuckler, D. (2017). Introduction of a national minimum wage reduced depressive symptoms in lowwage workers: A quasi-natural experiment in the UK. *Health Economics*, 26(5), 639–655.
- Rudd, R. A., Seth, P., David, F., & Scholl, L. (2016). Increases in drug and opioid-involved overdose deaths—United States, 2010–2015. *Morbidity and Mortality Weekly Report*, 65(50 & 51), 1445–1452.
- Shanahan, L., Hill, S. N., Gaydosh, L. M., Steinhoff, A., Costello, E. J., Dodge, K. A., Harris, K. M., & Copeland, W. E. (2019). Does despair really kill? A roadmap for an evidence-based answer. *American Journal of Public Health*, 109(6), 854–858.
- Stone, D. M., Simon, T. R., Fowler, K. A., Kegler, S. R., Yuan, K., Holland, K. M., Ivey-Stephenson, A. Z., & Crosby, A. E. (2018). Vital signs: Trends in state suicide rates—United States, 1999–2016 and circumstances contributing to suicide—27 states, 2015. *Morbidity and Mortality Weekly Report*, 67(22), 617.
- Thoits, P. A. (2010). Stress and health: Major findings and policy implications. *Journal of Health and Social Behavior, 51*(1_suppl), S41–S53.
- Wehby, G. L., Dave, D. M., & Kaestner, R. (2020). Effects of the minimum wage on infant health. Journal of Policy Analysis and Management, 39(2), 411–443.
- Wood, A. M., Kaptoge, S., Butterworth, A. S., Willeit, P., Warnakula, S., Bolton, T., Paige, E., Paul, D. S., Sweeting, M., & Burgess, S. (2018). Risk thresholds for alcohol consumption: Combined analysis of individual-participant data for 599 912 current drinkers in 83 prospective studies. *The Lancet*, 391(10129), 1513–1523.
- Xu, J., Murphy, S. L., Kochanek, K. D., & Arias, E. (2020). Mortality in the United States, 2018. National Center for Health Statistics.