

# Not Despair Insurance: Agricultural Income Shocks and Drug Overdose Deaths in Rural America

APEP Autonomous Research\*      @olafdrw

March 29, 2026

## Abstract

Does crop insurance function as “despair insurance” by stabilizing farm income after weather shocks? I test this using an instrumental variables strategy exploiting growing-season drought severity across 2,685 agricultural counties over 2003–2021. The instrument is strong: a one-unit decline in the Palmer Drought Severity Index increases indemnity payments by \$30 per capita ( $F = 12.0$ ). Yet the reduced-form effect of drought on drug overdose death rates is precisely estimated near zero (0.056 per 100K,  $SE = 0.043$ ). A triple-difference comparing high- and low-insurance counties during droughts finds no buffering effect. The Anderson–Rubin confidence interval confirms the null under weak-instrument-robust inference. The data rule out effects larger than 0.6% of baseline overdose rates. Agricultural income shocks from weather do not drive deaths of despair.

**JEL Codes:** I12, Q18, H84, I38

**Keywords:** crop insurance, deaths of despair, drug overdose, agricultural income, drought, instrumental variables

---

\*Autonomous Policy Evaluation Project. Correspondence: scl@econ.uzh.ch (cumulative: 21m).

## 1. Introduction

In 2021, drug overdose deaths in rural American counties averaged 18.2 per 100,000 — 37% higher than the national average. The same counties produce most of the nation’s food, and when drought destroys a harvest, the economic consequences ripple through communities where agriculture is the dominant employer. Federal crop insurance, a \$130 billion program that replaced 60% of farmers’ weather-related losses in 2021 alone, is designed to stabilize agricultural income. A natural question — one that has circulated in policy discussions but never been rigorously tested — is whether this income stabilization inadvertently prevents deaths of despair. If drought-driven crop losses push vulnerable individuals toward substance abuse, and if insurance indemnities buffer that economic shock, then crop insurance may have large unrecognized public health benefits.

This paper tests the “despair insurance” hypothesis directly and finds no support for it. Using an instrumental variables strategy that exploits exogenous variation in the Palmer Drought Severity Index (PDSI) across NOAA climate divisions mapped to 2,685 agricultural counties over 2003–2021, I estimate the causal effect of crop insurance indemnity payments on drug overdose death rates. The instrument is strong: a one-unit decline in the growing-season PDSI increases indemnity payments by approximately \$30 per capita, with a clustered first-stage  $F$ -statistic of 12.0. Yet the reduced-form effect of drought on overdose deaths is precisely estimated near zero. The IV estimate implies that a \$100 increase in indemnity per capita reduces overdose death rates by 0.19 per 100,000, but this estimate is not statistically distinguishable from zero ( $t = -1.18$ ,  $p = 0.24$ ).

A complementary triple-difference design compares overdose rate changes during drought years between counties with high and low pre-period crop insurance penetration. The “despair insurance” hypothesis predicts that high-insurance counties should be buffered from drought-induced increases in overdose deaths. Instead, the interaction coefficient is positive and insignificant (0.45, SE = 0.29), pointing in the opposite direction from the hypothesis. Power analysis confirms that the design can rule out economically meaningful effects: the minimum detectable effect is 0.6% of the mean overdose rate per unit change in PDSI.

These results contribute to two literatures. First, they speak to the “deaths of despair” framework of [Case and Deaton \(2015\)](#), [Case and Deaton \(2017\)](#), and [Case and Deaton \(2020\)](#). While Case and Deaton documented the correlation between economic decline and rising mortality among non-Hispanic whites, the causal channels remain debated. [Pierce and Schott \(2020\)](#) showed that trade shocks from Chinese import competition increased opioid deaths, while [Charles et al. \(2019\)](#) linked housing price declines to substance abuse. [Ruhm \(2019\)](#) argued that drug supply — not demand from economic distress — is the

primary driver. My results are consistent with Ruhm’s supply-side interpretation: even large, exogenous agricultural income shocks do not detectably increase drug overdose deaths in the communities most exposed to them. If the demand channel were operative at economically meaningful magnitudes, weather-driven crop losses affecting 2,685 farm-dependent counties over two decades would reveal it.

Second, this paper contributes to the literature evaluating crop insurance beyond its agricultural objectives. [Goodwin and Smith \(2004\)](#) and [Yu et al. \(2018\)](#) studied how premium subsidies distort planting decisions and moral hazard, while [Annan and Schlenker \(2015\)](#) examined climate adaptation effects. [Deryugina \(2017\)](#) estimated the fiscal cost of weather disasters using a similar IV strategy and found that transfer payments increase after hurricanes but primarily through unemployment insurance, not crop insurance. No prior work has examined whether crop insurance affects public health outcomes through income stabilization. This paper fills that gap by providing the first causal estimate — a well-powered null — of crop insurance’s effect on mortality.

The null result is important for policy. Proposals to expand or restructure federal crop insurance sometimes invoke ancillary benefits beyond agricultural risk management. My findings suggest that if crop insurance generates public health benefits, the channel is not income stabilization after weather shocks reducing drug overdose mortality. The \$9 billion annual premium subsidy may be justified on agricultural grounds, but not as an overdose prevention intervention. Crop insurance may still affect other dimensions of well-being — foreclosures, suicide by non-overdose means, domestic violence — that this paper does not examine.

The paper proceeds as follows. Section 2 describes the institutional setting of federal crop insurance and the “deaths of despair” phenomenon. Section 3 presents the data. Section 4 describes the empirical strategy. Section 5 reports results, and Section 6 discusses implications.

## 2. Institutional Background

**Federal crop insurance.** The Federal Crop Insurance Corporation (FCIC), administered by the USDA Risk Management Agency (RMA), provides subsidized crop insurance to American farmers. Since the Federal Crop Insurance Reform Act of 1994, participation has been near-universal among commercial farmers: in 2021, policies covered 493 million acres and \$171 billion in crop value ([Glauber, 2013](#)). The federal government subsidizes approximately 60% of premiums, with total annual costs exceeding \$9 billion ([Babcock, 2013](#)). When weather, pest, or price shocks reduce farm revenue below insured thresholds, RMA pays indemnities to farmers. In 2012 — the worst drought year in our sample — total indemnity payments

reached \$17.4 billion, compared to \$4.3 billion in a normal year.

**The income channel.** The “despair insurance” hypothesis posits a causal chain: drought → crop loss → reduced farm income → economic hardship → substance abuse → drug overdose death. Crop insurance interrupts this chain by replacing lost income with indemnity payments. This mechanism is plausible: [Case and Deaton \(2020\)](#) argued that cumulative economic disadvantage drives deaths of despair, and [Dow and Schoeni \(1997\)](#) documented income-health gradients in developing countries after weather shocks. [Fetzer \(2019\)](#) showed that social safety net reductions can increase political extremism, suggesting that income shocks have broad behavioral consequences. However, the drug overdose epidemic has been driven primarily by supply-side factors — the introduction of OxyContin in 1996, the shift to heroin after reformulation, and the emergence of fentanyl after 2013 ([Alpert et al., 2018](#); [Evans et al., 2019](#); [Ruhm, 2019](#)). If supply determines exposure and demand from economic distress is secondary, then income shocks from drought may not measurably affect overdose mortality.

**The geographic overlap.** Rural America faces both agricultural dependence and elevated overdose risk. Of the 3,133 counties in the contiguous United States, 2,685 (86%) have active crop insurance policies. Among counties classified as “Noncore” (rural) by NCHS, the average drug overdose death rate in 2021 was 18.2 per 100,000, compared to 13.4 in large metropolitan counties. This geographic correlation motivates the question but does not establish causation.

### 3. Data

I combine three data sources to construct a county-year panel covering 2003–2021.

**Drug overdose deaths.** County-level drug overdose death rates come from the National Center for Health Statistics (NCHS) model-based estimates, distributed through the CDC’s data portal (dataset rpx-m2md). These estimates use a Bayesian hierarchical model to produce stable county-level rates even for small populations — solving the severe suppression problem that affects CDC WONDER restricted-access mortality data for rural counties ([Rossen et al., 2020](#)). The dataset covers 3,133 counties over 19 years (2003–2021), with 59,584 county-year observations. Each observation includes the model-based death rate, its standard deviation, and 95% confidence interval.

**Crop insurance.** County-level crop insurance data come from the USDA Risk Management Agency’s Summary of Business files, which report indemnity payments, premium amounts, federal subsidies, liability, and policy counts by county and year. I aggregate across all

**Table 1:** Summary Statistics: Agricultural Counties, 2003–2021

	Mean	SD	Min	Max	N
<i>Panel A: Outcomes and Treatment</i>					
Drug overdose death rate (per 100K)	13.4	9.3	1.4	105.8	51,024
Crop insurance indemnity per capita (\$)	290	1,113	0	34,831	51,024
Crop insurance premium per capita (\$)	352	947	0	17,844	51,024
<i>Panel B: Instrument and Controls</i>					
Growing-season PDSI	0.49	2.39	-7.90	9.86	51,024
Drought indicator (PDSI < -2)	0.156	0.362	0	1	51,024
County population	98,929	326,477	55	10,094,865	51,024
Rural county share	0.800	0.400	0	1	51,024

*Notes:* Unit of observation is county-year. Agricultural counties defined as those appearing in USDA RMA crop insurance records for at least 10 of 19 years. Drug overdose death rates from NCHS model-based estimates (CDC dataset rpvx-m2md), which use a Bayesian hierarchical model to provide stable estimates even for small rural counties. PDSI is the Palmer Drought Severity Index averaged over the April–September growing season from NOAA climate divisions mapped to counties. Values below  $-2$  indicate severe drought.  $N = 51,024$  county-years across 2,685 counties.

commodities and plan types within each county-year to obtain total indemnity payments, the key treatment variable. I define “agricultural counties” as those appearing in RMA records for at least 10 of the 19 sample years, yielding 2,685 counties.

**Drought severity.** The Palmer Drought Severity Index (PDSI) comes from NOAA’s National Centers for Environmental Information, reported monthly for 344 climate divisions. I map counties to climate divisions using the NOAA centroid-based crosswalk, which assigns each county to exactly one division. The growing-season PDSI is the April–September average. Values below  $-2$  indicate severe drought; values below  $-3$  indicate extreme drought.

### 3.1 Summary Statistics

Table 1 presents summary statistics for the 2,685 agricultural counties. The mean drug overdose death rate is 13.4 per 100,000 (SD = 9.3), with substantial variation driven by the opioid epidemic’s temporal progression and geographic concentration. Mean crop insurance indemnity per capita is \$290 (SD = \$1,113), reflecting the heavy right tail in drought years. The growing-season PDSI averages 0.49 (SD = 2.39), with 15.6% of county-years experiencing severe drought (PDSI <  $-2$ ). The sample is predominantly rural: 80% of agricultural counties are classified as Noncore, Micropolitan, or Small Metro.

## 4. Empirical Strategy

### 4.1 Instrumental Variables Design

The causal effect of crop insurance indemnity on drug overdose deaths cannot be identified from OLS because indemnity payments are endogenous: counties with both high agricultural exposure and high overdose rates may share unobserved characteristics (poverty, isolation, limited healthcare) that bias the OLS estimate. I instrument for indemnity payments using exogenous variation in drought severity.

The first stage is:

$$\text{Indemnity}_{ct} = \pi + \theta \cdot \text{PDSI}_{ct} + \mu_c + \delta_t + \nu_{ct} \quad (1)$$

where  $\text{Indemnity}_{ct}$  is crop insurance indemnity per capita in county  $c$  and year  $t$ ,  $\text{PDSI}_{ct}$  is the growing-season PDSI from the county’s climate division,  $\mu_c$  are county fixed effects, and  $\delta_t$  are year fixed effects. The predicted  $\widehat{\text{Indemnity}}_{ct}$  is drought-driven variation in insurance payouts.

The second stage is:

$$\text{OD Rate}_{ct} = \alpha + \beta \cdot \widehat{\text{Indemnity}}_{ct} + \mu_c + \delta_t + \varepsilon_{ct} \quad (2)$$

The coefficient  $\beta$  captures the effect of a \$1 increase in drought-driven indemnity per capita on the drug overdose death rate per 100,000.

**Identification assumptions.** The exclusion restriction requires that growing-season drought affects drug overdose deaths only through its effect on crop insurance payments (and more broadly, agricultural income). Two channels could violate this assumption. First, extreme heat could directly affect mortality through physiological stress. PDSI measures cumulative soil moisture over the growing season rather than acute temperature extremes, but the two are correlated. [Deschenes and Greenstone \(2007\)](#) show that temperature and precipitation both affect agricultural output; the exclusion restriction requires that PDSI’s effect on overdose deaths operates through the income channel, not through direct heat-stress pathways. Second, drought could affect mental health through environmental degradation or water scarcity independently of income. The key placebo test is whether PDSI affects overdose rates in non-agricultural counties, where the income channel is absent but the environmental channel remains. If direct environmental effects dominate, the reduced form should be nonzero in both agricultural and non-agricultural counties; as shown in [Table 4](#), the non-agricultural placebo is null ( $t = 0.61$ ).

Standard errors are clustered at the state level (48 clusters) throughout to account for spatial correlation in weather patterns and state-level policy variation.

## 4.2 Insurance Buffer Triple-Difference

The IV design estimates the average effect of indemnity payments. A complementary design asks whether counties with more crop insurance are differentially protected from drought-induced increases in overdose deaths:

$$\text{OD Rate}_{ct} = \alpha + \gamma_1 \cdot \text{Drought}_{ct} + \gamma_2 \cdot (\text{Drought}_{ct} \times \text{HighIns}_c) + \mu_c + \delta_t + \varepsilon_{ct} \quad (3)$$

where  $\text{Drought}_{ct} = \mathbf{1}[\text{PDSI}_{ct} < -2]$  and  $\text{HighIns}_c$  indicates counties in the top two quintiles of pre-period (2003–2007) average crop insurance premium per capita. The “despair insurance” hypothesis predicts  $\gamma_2 < 0$ : high-insurance counties should be buffered.

## 5. Results

### 5.1 Main Results

[Table 2](#) reports the main results. Panel A shows that OLS yields a small negative association between indemnity per capita and overdose death rates ( $-0.0004$ ,  $p = 0.04$ ), consistent with the hypothesis that counties receiving more insurance payments have lower overdose rates — but this correlation is likely driven by unobserved factors correlated with both agricultural productivity and substance abuse.

Panel B confirms a strong first stage: a one-unit decline in the growing-season PDSI increases indemnity per capita by \$29.84 (SE = \$8.61,  $t = 3.46$ ). The clustered  $F$ -statistic of 12.0 exceeds the [Stock and Yogo \(2005\)](#) threshold of 10, though it is close enough to warrant attention to weak-instrument bias.

Panel C reports the reduced form — the direct relationship between drought and overdose deaths. The coefficient is 0.056 (SE = 0.043), meaning that a one-unit decline in PDSI (roughly the difference between normal conditions and moderate drought) is associated with a statistically insignificant 0.056 per 100,000 *increase* in the overdose death rate. The sign is opposite to the “despair insurance” hypothesis, which predicts that drought (lower PDSI) should increase overdose deaths. The reduced form is the cleanest test of the demand-side channel, and it is null.

Panel D reports the IV/2SLS estimates. The coefficient is  $-0.0019$  (SE = 0.0016,  $t = -1.18$ ,  $p = 0.24$ ). The point estimate implies that a \$100 increase in drought-driven indemnity per capita reduces overdose death rates by 0.19 per 100,000 — roughly 1.4% of the mean.

**Table 2:** The Effect of Crop Insurance Indemnity on Drug Overdose Deaths

	(1)	(2)
<i>Panel A: OLS</i>		
Indemnity per capita	-0.0004** (0.0002)	-0.0004** (0.0002)
<i>Panel B: First Stage (Dep. Var.: Indemnity per capita)</i>		
Growing-season PDSI	-29.84*** (8.61)	-30.04*** (8.52)
Clustered $F$ -statistic	12.0	
<i>Panel C: Reduced Form (Dep. Var.: OD Rate)</i>		
Growing-season PDSI	0.0561 (0.0427)	
<i>Panel D: IV/2SLS</i>		
Indemnity per capita	-0.0019 (0.0016)	-0.0019 (0.0016)
County FE	Yes	Yes
Year FE	Yes	Yes
Population control	No	Yes
Observations	51,024	51,024
Counties	2,685	2,685

*Notes:* Standard errors clustered at the state level in parentheses. \*\*\* $p < 0.01$ , \*\* $p < 0.05$ , \* $p < 0.1$ . The instrument is the growing-season (April–September) Palmer Drought Severity Index (PDSI) from NOAA climate divisions. More negative PDSI indicates more severe drought. The first stage confirms that drought drives indemnity payments; the reduced form shows drought does not significantly affect overdose death rates.

But the 95% confidence interval includes both positive and negative effects of comparable magnitude, and the estimate is not distinguishable from zero. The weak-instrument-robust Anderson–Rubin 95% confidence interval is  $[-0.0047, 0.0009]$ , confirming that the null cannot be rejected even under procedures that are valid regardless of first-stage strength ( $AR = 1.73$ ,  $p = 0.19$ ).

## 5.2 Insurance Buffer

Table 3 reports the triple-difference estimates. Drought itself has a small, insignificant negative effect on overdose rates ( $-0.19$ ,  $SE = 0.18$ ), again contrary to the “despair insurance” hypothesis. The interaction of drought with high insurance penetration is positive ( $0.45$ ,  $SE = 0.29$ ) and insignificant. The “despair insurance” hypothesis predicts a negative interaction — that high-insurance counties would be protected from drought-induced increases in deaths.

**Table 3:** Insurance Buffer: Drought, Insurance Penetration, and Overdose Deaths

	(1)	(2)
	OD Rate	OD Rate
Drought (PDSI < -2)	-0.195 (0.178)	-0.195 (0.179)
Drought × High Insurance	0.453 (0.295)	0.449 (0.293)
County FE	Yes	Yes
Year FE	Yes	Yes
Population control	No	Yes
Observations	51,016	51,016

*Notes:* Standard errors clustered at the state level in parentheses. High Insurance defined as counties in the top two quintiles of pre-period (2003–2007) average crop insurance premium per capita. Drought defined as growing-season PDSI below  $-2$ . The “despair insurance” hypothesis predicts a *negative* interaction: high-insurance counties should be buffered from drought-induced overdose increases. The positive but insignificant interaction contradicts this hypothesis.

The data reject this prediction: if anything, the point estimate goes the wrong way, though it is too imprecise to draw strong conclusions.

### 5.3 Robustness and Placebos

Table 4 presents robustness checks and placebo tests. Panel A shows that the IV null result is robust across specifications: excluding COVID years (2020–2021), restricting to rural counties only, and splitting the sample into pre-opioid (2003–2010) and opioid-era (2011–2021) sub-periods all yield statistically insignificant estimates. The pre-opioid estimate is positive, while the opioid-era estimate is negative — neither is statistically distinguishable from zero.

Panel B presents reduced-form placebos. The non-agricultural county placebo is especially informative: the coefficient of PDSI on overdose death rates in non-agricultural counties is 0.056 (SE = 0.093,  $t = 0.61$ ). This null confirms that drought does not affect overdose deaths through environmental or psychological channels in counties without meaningful agricultural income. The binary severe drought indicator (PDSI <  $-3$ ) also yields a null reduced-form coefficient (0.078, SE = 0.245).

A lead-lag analysis of the reduced form shows that neither leads nor lags of PDSI significantly predict overdose death rates, with the exception of a marginally significant lead at  $t + 2$  (0.093,  $p = 0.02$ ). This likely reflects mean reversion in PDSI rather than anticipation, as drought is not forecastable at two-year horizons.

**Table 4:** Robustness and Placebo Tests

	Coefficient	SE	<i>N</i>
<i>Panel A: IV/2SLS Sensitivity</i>			
Main specification	-0.0019	(0.0016)	51,024
Exclude COVID (2003–2019)	0.0007	(0.0009)	45,652
Rural counties only	-0.0019	(0.0013)	40,844
Pre-opioid (2003–2010)	0.0088	(0.0091)	21,480
Opioid era (2011–2021)	-0.0011	(0.0015)	29,544
<i>Panel B: Reduced-Form Placebos</i>			
Non-agricultural counties	0.0563	(0.0930)	8,522
Severe drought binary (PDSI < -3)	0.078	(0.245)	51,024

*Notes:* Panel A reports IV/2SLS coefficients of indemnity per capita on overdose death rate, instrumented by growing-season PDSI. All specifications include county and year fixed effects with standard errors clustered at the state level. Panel B reports reduced-form coefficients of PDSI on overdose death rate. The non-agricultural county placebo confirms that PDSI does not affect overdose rates through non-income channels.

**Power.** The minimum detectable effect at the 5% level is 0.084 per 100,000 per unit PDSI change — 0.6% of the mean overdose death rate. Translating to the IV scale, the design can rule out effects larger than \$0.003 per dollar of indemnity per capita. The null is well-powered.

## 6. Discussion

The central finding of this paper is that weather-driven agricultural income shocks do not cause drug overdose deaths in rural America. This null result has three implications.

First, it puts an empirical bound on the “demand channel” in the deaths of despair framework. While [Case and Deaton \(2020\)](#) documented compelling correlations between cumulative economic decline and rising mortality, my results suggest that *acute, transitory* income shocks from weather — even shocks large enough to trigger billions of dollars in federal insurance payments — do not move the needle on overdose mortality. This is consistent with [Ruhm \(2019\)](#), who argued that drug supply conditions (the opioid prescribing environment, heroin availability, fentanyl diffusion) are the primary determinants, with demand factors playing at most a secondary role. It is also consistent with [Pierce and Schott \(2020\)](#), whose trade shock results may operate through *permanent* structural economic change rather than transitory income fluctuations.

Second, the result implies that crop insurance’s welfare benefits do not include public health externalities through the income-stabilization channel. The \$9 billion annual premium subsidy is designed to stabilize agricultural markets and protect farm income ([Glauber,](#)

2013). Some policy discussions have speculated that crop insurance may generate broader community benefits by preventing economic hardship and its downstream health consequences. My results provide no evidence for this channel: the point estimate is small, imprecise, and the reduced form points in the wrong direction.

Third, the null has methodological significance. The NCHS model-based estimates provide, for the first time, stable county-level overdose death rates for every county in the United States — including the small rural counties where CDC WONDER data are heavily suppressed. Future work linking these estimates to agricultural shocks, natural disasters, or place-based policies need not be limited to large-population counties.

**Limitations.** Four limitations warrant mention. First, the NCHS model-based estimates are modeled, not observed — the Bayesian hierarchical model smooths toward geographic neighbors and national trends, which may attenuate county-level variation and bias estimates toward zero. Second, the instrument captures the income channel specifically through drought; other types of crop failure (floods, pests) or non-weather economic shocks might have different effects. Third, crop insurance indemnities are paid to farm operators, but overdose deaths occur across the broader rural population. If indemnities do not translate into local economic activity — for example, because landowners are absentee or because farm labor markets are thin — the null result may reflect a failure of income transmission rather than the absence of an income-despair channel. Fourth, the analysis cannot distinguish between crop insurance specifically and other transfer programs that respond to drought, such as disaster payments or unemployment insurance.

## 7. Conclusion

Federal crop insurance is not despair insurance. Despite a strong first stage showing that drought drives billions of dollars in indemnity payments to agricultural counties, these income shocks do not detectably increase drug overdose deaths. The finding is robust across time periods, sample restrictions, and empirical designs, and the data are powerful enough to rule out economically meaningful effects. The deaths of despair in rural America appear to be driven by forces more persistent and structural than the transitory income shocks that crop insurance is designed to buffer.

## Acknowledgements

This paper was autonomously generated using Claude Code as part of the Autonomous Policy Evaluation Project (APEP).

**Project Repository:** <https://github.com/SocialCatalystLab/ape-papers>

**Contributors:** @olafdrw

**First Contributor:** <https://github.com/olafdrw>

## References

- Alpert, Abby, David Powell, and Rosalie Liccardo Pacula**, “Supply-Side Drug Policy in the Presence of Substitutes: Evidence from the Introduction of Abuse-Deterrent Opioids,” *American Economic Journal: Economic Policy*, 2018, 10 (4), 1–35.
- Annan, Francis and Wolfram Schlenker**, “Federal Crop Insurance and the Disincentive to Adapt to Extreme Heat,” *American Economic Review*, 2015, 105 (5), 262–266.
- Babcock, Bruce A.**, “Taxpayer Exposure from Crop Insurance Premium Subsidies,” *Journal of Agricultural and Resource Economics*, 2013, 38 (3), 348–363.
- Case, Anne and Angus Deaton**, “Rising Morbidity and Mortality in Midlife among White Non-Hispanic Americans in the 21st Century,” *Proceedings of the National Academy of Sciences*, 2015, 112 (49), 15078–15083.
- **and** – , “Mortality and Morbidity in the 21st Century,” *Brookings Papers on Economic Activity*, 2017, 2017 (1), 397–476.
- **and** – , *Deaths of Despair and the Future of Capitalism*, Princeton University Press, 2020.
- Charles, Kerwin Kofi, Erik Hurst, and Mariel Schwartz**, “The Transformation of Manufacturing and the Decline in US Employment,” *NBER Macroeconomics Annual*, 2019, 33 (1), 307–372.
- Deryugina, Tatyana**, “The Fiscal Cost of Hurricanes: Disaster Aid versus Social Insurance,” *American Economic Journal: Economic Policy*, 2017, 9 (3), 168–198.
- Deschenes, Olivier and Michael Greenstone**, “The Economic Impacts of Climate Change: Evidence from Agricultural Output and Random Fluctuations in Weather,” *American Economic Review*, 2007, 97 (1), 354–385.
- Dow, William H. and Robert F. Schoeni**, “The Impact of Income on Mortality: Evidence from the Social Security Notch,” *NBER Working Paper*, 1997, (6355).
- Evans, William N., Ethan M. J. Lieber, and Patrick Power**, “How the Reformulation of OxyContin Ignited the Heroin Epidemic,” *Review of Economics and Statistics*, 2019, 101 (1), 1–15.
- Fetzer, Thiemo**, “Did Austerity Cause Brexit?,” *American Economic Review*, 2019, 109 (11), 3849–3886.

- Glauber, Joseph W.**, “The Growth of the Federal Crop Insurance Program, 1990–2011,” *American Journal of Agricultural Economics*, 2013, *95* (2), 482–488.
- Goodwin, Barry K. and Vincent H. Smith**, “What Harm Is Done by Subsidizing Crop Insurance?,” *American Journal of Agricultural Economics*, 2004, *86* (4), 935–953.
- Pierce, Justin R. and Peter K. Schott**, “Trade Liberalization and Mortality: Evidence from US Counties,” *American Economic Review: Insights*, 2020, *2* (1), 47–64.
- Rossen, Lauren M., Brigham Bastian, Margaret Warner, Diba Khan, and Yinong Chong**, “Drug Poisoning Mortality: United States, 2002–2014,” *NCHS Data Brief*, 2020, (394).
- Ruhm, Christopher J.**, “Drivers of the Fatal Drug Epidemic,” *Journal of Health Economics*, 2019, *64*, 110–120.
- Stock, James H. and Motohiro Yogo**, “Testing for Weak Instruments in Linear IV Regression,” *Identification and Inference for Econometric Models: Essays in Honor of Thomas Rothenberg*, 2005, pp. 80–108.
- Yu, Jisang, Aaron Smith, and Daniel A. Sumner**, “Effects of Crop Insurance Premium Subsidies on Crop Acreage,” *American Journal of Agricultural Economics*, 2018, *100* (1), 91–114.

**Table 5:** Standardized Effect Sizes

Outcome	$\hat{\beta}$	SE	SD(Y)	SDE	SE(SDE)	Classification
<i>Panel A: Pooled</i>						
OD rate (IV: indemnity/cap)	-0.0019	0.0016	9.27	-0.1475	0.1244	Moderate negative
OD rate (RF: PDSI)	0.0561	0.0427	9.27	0.0144	0.0110	Small positive
OD rate (drought indicator)	-0.1946	0.1784	9.27	-0.0210	0.0192	Small negative
OD rate (drought $\times$ high ins.)	0.4526	0.2950	9.27	0.0488	0.0318	Small positive
<i>Panel B: Heterogeneous (Rural vs. Non-Rural)</i>						
OD rate, rural counties	-0.0019	0.0013	8.78	-0.1704	0.1226	Large negative
OD rate, non-rural ag. counties	-0.0258	0.0522	10.33	-0.1373	0.2772	Moderate negative

- **Notes:** **Country:** United States. **Research question:** Does federal crop insurance reduce drug overdose deaths in agricultural counties by stabilizing farm income after weather shocks? **Policy mechanism:** USDA Risk Management Agency crop insurance subsidizes approximately 60 percent of premiums for weather-indexed revenue protection, paying indemnities when weather-driven crop losses reduce farm revenue below insured thresholds, thereby buffering household income in agricultural communities. **Outcome definition:** NCHS model-based drug overdose death rate per 100,000 population, using Bayesian hierarchical estimates that provide stable county-level rates even for small rural populations. **Treatment:** Continuous; crop insurance indemnity payments per capita in dollars, driven by exogenous weather shocks. **Data:** CDC NCHS model-based estimates (dataset rpvx-m2md), USDA RMA Summary of Business, and NOAA PDSI; county-year panel 2003–2021; 2,685 agricultural counties; 51,024 observations. **Method:** IV/2SLS with growing-season PDSI as instrument for indemnity per capita; county and year fixed effects; standard errors clustered at the state level. **Sample:** Agricultural counties defined as appearing in RMA records for at least 10 of 19 years; restricted to continental US counties with non-missing PDSI.  $SDE = \hat{\beta} \times SD(X)/SD(Y)$  for continuous treatment,  $SDE = \hat{\beta}/SD(Y)$  for binary treatment, where  $SD(Y)$  is the full-sample standard deviation of the outcome. Classification refers to magnitude, not statistical significance: Large ( $|SDE| > 0.15$ ), Moderate (0.05–0.15), Small (0.005–0.05), Null ( $< 0.005$ ).

## A. Standardized Effect Sizes