

Commodity Revenue Shocks and Mortality*

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Abstract

We look at the relationship between crop revenues and mortality in the Midwest from 1980 to 2019. For identification, we combine an exposure design with a two-way (i.e., county and year) fixed effects estimator. On average, a decrease in soybean revenue is associated with an increase in mortality: A 10-percent decrease in soybean revenues is associated with a 0.1-percent increase in the age-adjusted all-cause death rate, or about 170 more deaths throughout the Midwest in 2024. Our findings are driven by individuals 65 and older, by women, and they appear mediated by cardiovascular disease and mental health-related issues.

Keywords: Agriculture, Agricultural Commodities, Commodities, Economic Shocks, Mortality

JEL Codes: I10, I31, Q11, Q12

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1 Introduction

What is the relationship between economic shocks and mortality? We examine the supply-side (i.e., production) channel by testing whether negative shocks to producer revenues for economically important commodities are associated with increased mortality by studying the relationship between producer revenues and age-adjusted all-cause mortality in the US Midwest, whose population of nearly 70 million represented over a fifth of the US population in 2024.¹ Because the US Midwest is heavily dependent on agriculture, and because the effects of shocks to the agricultural sector are more easily identifiable than those of shocks to either the industrial or services sectors, we focus on agricultural commodities – specifically, corn and soybeans, the dominant agricultural commodities in the Midwest ([United States Department of Agriculture, 2024](#)).

Agricultural producers are entrepreneurs whose livelihoods depend on their crop revenues, which are the product of two variables: (i) how much of each crop producers grow and sell, and (ii) at what price they do so. In the US Midwest, agricultural producers tend to produce exclusively for the market rather than for subsistence, and while they have some control over how much they produce (and thus over how much they can sell), all of them are price takers with no control over commodity prices.

Though there are a number of financial instruments and programs agricultural producers can use to hedge against revenue fluctuations (e.g., futures and options, crop insurance, trade adjustment assistance, market facilitation payments, and so on; see [Tack and Yu, 2021](#)), we take these instruments and programs as given in our analysis and focus here on the residual effects of agricultural commodity revenue shocks. That is, we focus on unanticipated commodity revenue shocks that are not covered by any such financial instruments or programs, if only because the data sources that do include information

¹In an earlier version of this paper, we used the same empirical setup but purported to look at the relationship between commodity *price* shocks and mortality. As it turns out, quantities cultivated seem to respond to prices (see Appendix Table A5) and so we cannot isolate the relationship between commodity price shocks and mortality – only the relationship between commodity *revenue* shocks and mortality.

on the use and availability of those instruments or programs (e.g., the USDA’s Agricultural Risk Management Survey) are not representative at the county level. These residual fluctuations are conceptually similar to basis risk in the insurance literature.

Unexpected negative shocks to commodity revenues cause unanticipated decreases in profits which, should they be severe enough, may lead to health issues, both mental (e.g., depression) and physical (e.g., heart attacks), which can ultimately lead to death. Because the effects of shocks to commodity revenues may also be felt by others who are not themselves agricultural producers but whose livelihoods also depend on how well the agricultural sector is doing, we look at the overall population instead of focusing more narrowly on agricultural producers.

Specifically, we study the relationship between commodity revenues and mortality at the county level for the period 1980-2019 in a sample of 644 rural counties (out of 1,055 total counties) across the 12 states of the US Midwest.² As outcome variable, we look at the age-adjusted all-cause death rate.³ As treatment, we rely on an exposure design by interacting (i) state-level prices for corn and soybeans with (ii) how much of each commodity is grown within a county. By interacting a plausibly exogenous price measure with county-level production (i.e., a measure of local exposure to commodity prices), our treatment variable thus captures revenues from each of corn and soybeans within a given county in a given year.^{4,5}

For identification, we further rely on a two-way (i.e., county and time) fixed effects estimator, and we also estimate specifications where the production of each commodity

²The counties we retain for analysis are those for which we have data on both our treatment and outcome variables for the period 1980 to 2019. The 12 states in the Midwest are Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, North Dakota, Ohio, South Dakota, and Wisconsin.

³The age-adjusted death rate is the death rate adjusted *ex ante* for the age distribution in the population of interest.

⁴While it is possible that commodity prices at the state level are not exogenous to county-level mortality, our results are robust to using global commodity prices to further exogenize our treatment variable.

⁵To assess the robustness of our findings as well as to avoid the bad control problem – each price being dependent on the other given complementarities between corn and soybeans – we look separately at the relationship between mortality and corn revenues and the relationship between mortality and soybean revenues. In an earlier version of this paper, we also combined corn and soybean revenues into a single measure of commodity revenues. Results are robust to doing so.

is lagged.⁶ This allows looking at how changes in commodity revenues — that is, unanticipated shocks to commodity revenue — are associated with age-adjusted all-cause mortality. Interacting commodity prices with how much of each commodity is grown in a given county allows focusing on the effects of those changes in the prices of those commodities *via the production channel*.⁷

We find a robust negative and statistically significant relationship between commodity revenues and mortality. Specifically, for the average county-year in our data, we find that a 10-percent decrease in soybean revenues is associated with an increase in the age-adjusted death rate of about 0.1 percent, or about 0.25 additional death in the average county (8.54 age-adjusted deaths per 1,000 persons \times 0.001 \times 28,900 persons = 0.246). Given that there are 690 rural counties in the Midwest, a back-of-the-envelope calculation combining our estimate for the period 1980-2019 with 2024 population figures would mean that a 10 percent decrease in soybean revenues would have been associated with over 170 more deaths throughout the Midwest in 2024. Depending on the specification, corn revenues are sometimes also negatively and significantly associated with mortality, but that finding is much less robust than that for soybean revenues.

For robustness, we also estimate specifications in which we instrument revenues from corn and soybeans or their total with a measure of drought occurrence and severity. Droughts — severe ones in particular — depress revenues from agricultural commodities (i.e., the instrument should be relevant) while presumably only affecting mortality through

⁶Some colleagues suggested interacting each commodity's price with the average or initial amount cultivated of that commodity in a county. Since state-level (global) prices do not vary across counties within a state (between states) in a given year, however, we cannot do as suggested as that would drastically reduce the amount of identifying variation.

⁷While some data sets allow looking directly at farm revenue, using those data sets would be second-best. The US Census of Agriculture has detailed longitudinal information on farms, but it is conducted only every five years, which would seriously reduce the statistical power of our analysis. Similarly, the US Department of Agriculture's Agricultural Risk Management Survey (ARMS) has detailed financial information on the farms it samples, but it is not a longitudinal data set. Moreover, neither the Census of Agriculture nor the ARMS are publicly available, which limits the transparency and replicability of any empirical work done using either source. Similarly, while the National Longitudinal Mortality Study has information on mortality and occupation from 1970 to 2010, the limitation of the public-use data is that those data can only identify residency at the state level, and not at the county level.

revenues from commodities (i.e., the exclusion restriction should hold). Instrument relevance is borne out in the data, and looking at local average treatment effect (LATE) estimates instead of average treatment effect (ATE) estimates, we find that for county-year observations where commodity revenues declined in response to drought conditions (i.e., the “compliers” in our two-stage least squares setup), a 10-percent decrease in corn or soybean revenues is associated with an increase in the age-adjusted death rate of about 0.5 percent, or about 1.2 additional deaths in the average county ($8.54 \text{ age-adjusted deaths per } 1,000 \text{ persons} \times 0.005 \times 28,900 \text{ persons} = 1.234$). Given that there are 690 rural counties in the Midwest, another back-of-the-envelope calculation combining our estimate for the period 1980-2019 with 2024 population figures would mean that a 10 percent decrease in soybean revenues would have been associated with over 850 more deaths throughout the Midwest in 2024. Our findings are driven by individuals aged 65 or older and by women.

Moreover, our findings are further supported by falsification tests in which we look at the subset of urban counties in the Midwest or at whether there is a relationship between unanticipated shocks to commodity revenues and certain conditions which have no *a priori* reason to respond to commodity revenue shocks (e.g., parasitic diseases, congenital malformations). Finally, our results appear mediated by deaths from cardiovascular disease (CVD) as well as by deaths from mental illness in the overall sample.

While our findings are *prima facie* consistent with the well-known “deaths of despair” narrative put forth by [Case and Deaton \(2020\)](#), looking at treatment effect heterogeneity paints a more nuanced picture. Indeed, negative shocks to soybean revenues are associated with more deaths from CVD and alcohol-related causes among women. But *positive* shocks to corn revenues are associated with more deaths from mental health- and drug-related causes among men. Taking these results at face value, it seems the deaths of despair narrative holds for women, whereas a more pro-cyclical story holds for men. That said, the size of our estimation sample decreases considerably for some causes of death

because of data reporting rules regarding mortality.

There is a well-known literature on the relationship between economic conditions and mortality. [Ruhm \(2000\)](#) finds that most sources of mortality are pro-cyclical, with suicide being an exception. More recently, [Ruhm \(2015\)](#) finds that mortality went from being pro-cyclical to being at best weakly related to economic conditions. He thus cautions researchers against using fewer than 15 years of data to study the association between economic conditions and mortality.⁸ Summarizing the literature on economic conditions and mortality, [Ruhm \(2016\)](#) concludes that national recessions translate into improved health conditions. More recently, [Hollingsworth et al. \(2017\)](#) have found a positive relationship between increases in the unemployment rate at the county level and deaths from opioid use, and [Schwandt \(2018\)](#) has found that wealth shocks, measured by the interaction of stock holdings and stock market changes, negatively affect health outcomes, both physical and mental. Similarly, [Pierce and Schott \(2020\)](#) look at the effect of trade shocks on mortality and find that areas more exposed to trade shocks are more likely to see a rise in mortality due to drug overdoses.⁹

Turning specifically to the agricultural sector, the literature on adverse shocks and mortality often focuses on farmer suicides and other self-inflicted deaths. [Carleton \(2017\)](#), for instance, establishes a causal link between high temperatures and farmer suicides in India, and [Christian et al. \(2019\)](#) establish a similar link between agricultural productivity changes and farmer suicides in Indonesia.¹⁰ More recently, [Proctor and Hopkins \(2024\)](#) have looked at the relationship between stress and alcohol use in a sample of US farmers and found that higher stress is associated with binge-drinking behavior, among other findings.

More broadly in terms of time, geography, or both, [Brueckner and Schwandt \(2015\)](#)

⁸In our analysis, we have more than twice as many years of data.

⁹A related strand of literature is the literature on how changes in international trade policy and technology have affected labor markets in the US ([Autor et al., 2003, 2013, 2014, 2019, 2020](#)).

¹⁰While [Carriere et al. \(2019\)](#) also look at farmer suicides, their analysis does not have a proper research design, which makes it more descriptive as it cannot establish a causal relationship.

find that rising incomes lead to growing populations via reductions in infant mortality. Using data on the Swedish agricultural revolution that took place between 1750 and 1860, [Dribe et al. \(2017\)](#) find that mortality responds to harvest fluctuations, especially to harvest failures, and to fluctuations in the prices of staple crops. [Fishback \(2017\)](#) concludes that the spending and lending policies adopted by Franklin D. Roosevelt's administration in the 1930s as part of the New Deal decreased the incidence of various types of mortality. Finally, in an analysis that is perhaps the closest in spirit to ours, [Singhal and Tarp \(2024\)](#) look at the impacts of coffee price volatility on the well-being of coffee producers in Vietnam and find that an increase in the volatility of the international price of coffee is associated with an increase in the psychological distress of coffee producers, a finding that appears mediated by increased alcohol consumption, a greater cognitive load, worsened expectations about the future, and a reduction in social capital.

We contribute to the literature on economic shocks and mortality by focusing on the relationship between shocks to commodity revenues and mortality in the US by focusing on shocks that affect the supply side of the economy, i.e., producers as well as others whose income is correlated with that of producers. To our knowledge, no other study has looked at the relationship between commodity revenue shocks and mortality via producer income *in the economy at large*. This matters because while the effects of commodity revenue shocks affect the producers of those commodities directly, they also affect those who depend on those commodities indirectly. In the context we study, while changes in revenues from corn and soybeans certainly affect the producers of those commodities, they also affect the livelihoods of others who depend on the financial well-being of agricultural producers, such as farm laborers, agricultural implement dealers, extension agents, and so on.

The remainder of this paper is organized as follows. We begin in section 2 by presenting our empirical framework and discussing the details of our estimation and identification strategies. Section 3 presents the data we use in our analysis and discusses some

summary statistics. In section 4, we start by presenting some ancillary results before moving on to our core results and the results of a number of robustness checks. Section 5 summarizes and offers some concluding remarks.

2 Empirical Framework

In this section, we first discuss our estimation strategy, and then discuss our identification strategy. In doing so, we also discuss the various robustness checks and falsification tests we conduct as well as the additional analyses we run to determine which cause of death appears to drive the relationship between commodity prices and mortality.

2.1 Estimation Strategy

We estimate the following equation using an unbalanced panel of 644 rural counties across 12 Midwestern states for the period 1980-2019 ($N = 18,500$ county-year observations) by ordinary least squares:

$$\ln y_{it} = \alpha_1 + \beta_1 \ln(p_{ct} \times q_{ict}) + \gamma_1 x_{ict} + \delta_{1i} + \tau_{1t} + \epsilon_{1ict} \quad (1)$$

where y is the age-adjusted death rate in county i in year t , p_{ct} is the price (either state-level or global, depending on the specification) of commodity c (corn or soybeans, depending on the specification) in year t , q_{ict} denotes how much of crop c is grown in county i in year t , δ is a vector of county fixed effects, τ is a vector of year fixed effects, and ϵ is an error term with mean zero. The vector x_{ict} of control variables includes the average commodity revenues in neighboring counties (to avoid bias from a potential violation of the stable unit treatment value assumption, wherein revenues in neighboring counties cause a change in mortality in a given county),¹¹ as well as lagged county-level employment (to

¹¹This allows ruling out between-county contemporaneous spillovers, or that changes to farm revenues in neighboring county j cause changes in the death rate in county i in year t , but it does not allow ruling

control for shocks to employment and for migration in and out of a county) and lagged county-level income. We use lagged values of those two variables because they are likely to be affected by the treatment, and so including their contemporaneous values would bias our estimate of the treatment variable of interest.

We also estimate an additional specification of Equation 1, which is such that

$$\ln y_{it} = \alpha_2 + \beta_2 \ln(p_{ct} \times q_{ic,t-1}) + \gamma_2 x_{ict} + \delta_{2i} + \tau_{2t} + \epsilon_{2ict}, \quad (2)$$

Equation 2 is nearly identical to Equation 1, except that in Equation 2, we construct our treatment variable using $q_{ic,t-1}$ instead of q_{ict} . We do so in an effort to exogenize our treatment variable by avoiding reverse causality issues due to the fact that at our level of aggregation (i.e., annual), the quantity cultivated for each crop in a given county in a given year might respond to a change in the price of that same commodity in the same year at the state and global levels.¹²

In our preferred specification, our main source of identification of a change in commodity revenue facing county i in year t is the variation in the interaction of the price of that commodity over time (prices do not vary between counties in a given state in a given year) and how much of that commodity is cultivated between counties in a given year and within a county over time. In other words, identification here comes from unexpected shocks to revenues from corn or soybeans between counties and over time.¹³

We estimate several variants of Equation 1. In addition to the two-way fixed effects within- or between-county spillovers over time.

¹²Some have suggested interacting p_{ct} with the average or initial value of q_{ict} in each county, but the fact that we rely on state-level and global prices for our analysis means that doing so would leave too little identifying variation. If we interacted initial or average quantities cultivated in each county with state- or global-level prices, the only variation within each county would stem from changes in state-level prices over time or in global-level prices over time.

¹³In a previous version of this paper, we also presented results for the estimators suggested or developed by Millimet and Bellemare (2024), finding our results to be robust to them. Given the many results in this paper and the fact that the estimators suggested by Millimet and Bellemare (2024) rely on differencing and we now make extensive use of lagged variables for identification, we omit those additional robustness checks from this version both for brevity and because it is not clear what differencing estimators identify when dealing with lagged variables.

(TWFE) specification in Equation 1, to properly account for the passage of time, we also estimate versions of Equation 1 with overall, state-, or county-specific trends linear or quadratic trends. Moreover, in an effort to further exogenize our treatment variable, we estimate specifications where we use global commodity prices instead of state-level prices. The latter, by virtue of not being dependent on local economic conditions, are less likely than the former to suffer from bias arising from reverse causality.

It is a well-known agronomic fact that when corn and soybeans are grown in rotation,¹⁴ soybeans replenish the soil nitrogen depleted by corn. Thus, since corn and soybeans are complements in production, we estimate separate versions of Equation 1 and Equation 2 for corn revenues and for soybean revenues. In preliminary work, we also estimated versions of Equations 1 and 2 where we combined corn and soybean revenues into a measure of total commodity revenues, which our results are robust to.

Finally, in an effort to further exogenize our treatment variable, we also estimate versions of Equation 1 where we instrument our treatment variable (i.e., $\ln(p_{ct} \times q_{ict})$) with a measure of recent drought severity in county i . We discuss the logic behind this instrumental variable in Section 2.2 below but briefly, by depressing the yields of corn and soybeans, the occurrence of drought and how severe it is will reduce corn and soybean revenues. Assuming that droughts only affect mortality through corn and soybean revenues, it is possible to estimate the local average treatment effect of commodity revenue shocks on mortality.

Given the observational nature of our data and our TWFE research design, we follow the recommendations in [Abadie et al. \(2023\)](#) and [MacKinnon et al. \(2023\)](#) and cluster standard errors at the county level throughout. For robustness, we also present population-weighted results for our core specifications.

Because we regress a logarithm on a logarithm, our coefficient of interest is an elasticity, which allows easily quantifying the economic significance of our results. For all

¹⁴Corn and soybeans can also be grown together, but this is less common.

estimates of β obtained from Equation 1 and the various specifications just discussed, we test the null hypothesis that $H_0: \beta = 0$ versus the alternative hypothesis that $H_A: \beta \neq 0$. Rejecting the null hypothesis in favor of the alternative hypothesis and finding that $\hat{\beta}$ is negative and statistically significant would thus lend support to the hypothesis that decreases in commodity prices are associated with increases in mortality.

2.2 Identification Strategy

Our research design consists of (i) an exposure design similar to that in [Dube and Vargas \(2013\)](#), who study the effect of commodity price shocks on conflict in Colombia, and (ii) a TWFE estimator.

An issue with the TWFE estimator is that when there is heterogeneity in the treatment effect of interest, the TWFE may not return an average of county-level estimated treatment effects unless some units are left untreated ([Sun and Shapiro, 2022](#)). In our data, no county-year observation has a value of corn or soybean revenues equal to zero, and so our TWFE results are presented under the caveat that they are only valid in the absence of treatment effect heterogeneity. In other words, we assume that treatment effects are homogeneous.

As we discussed in the previous section, we also present the results of two-stage least squares (2SLS) specifications in which we rely on measures of drought severity (i.e., dummies for whether a given county has experienced an exceptional drought, extreme drought, severe drought, or moderate drought in a given year) as instruments for corn and soybean revenues in a given county in a given year. Here, the relevance of the instrumental variables stems from the fact that a drought directly affects yields negatively, which translates into decreased revenues from the affected commodities.

While the relevance of our instrumental variables (IVs) is testable, whether those same variables meet the exclusion restriction—that is, whether the occurrence or duration of drought affects mortality only through commodity prices—is not. We argue that once

county-specific time-invariant heterogeneity and year-specific county-invariant heterogeneity are both accounted for, the only way drought affects mortality is through corn and soybean revenues. In other words, we assume that when both (i) county-specific time-invariant characteristics, and (ii) year-specific county-invariant characteristics are held constant, drought conditions do not affect mortality through, say, respiratory illnesses.¹⁵ While this is a strong assumption, we view our IV results as complementary to those of our preferred core TWFE specifications.

3 Data and Summary Statistics

The data we use for our analysis cover the period 1980-2019 and come from various sources. The US Centers for Disease Control and Prevention’s (CDC) National Center for Health Statistics (NCHS) provide mortality data at the county level, including the Compressed Mortality File (1980-1998) and the Multiple Cause of Death File (1999-2019).¹⁶ We use age-adjusted death rates for all ages and causes in our core analysis, but we look at specific causes of death (e.g., deaths from cardiovascular disease, deaths related to mental health) when assessing the mechanisms whereby our core results might be caused. We also use death from certain infections and parasitic diseases and from congenital malformations, deformations, and chromosomal abnormalities for the purpose of implementing a placebo outcome test (Eggers et al., 2024). An earlier version of this paper also used all-cause death rates in addition to all-cause age-adjusted death rates, with nearly identical findings.

Data on corn and soybeans (i.e., price and production) in the US Midwest are from the US Department of Agriculture’s National Agricultural Statistics Service. Annual commodity prices are only available at the state level, but annual commodity production is

¹⁵In an earlier version of this manuscript, we also ran the 2SLS specifications using death rates that omitted respiratory illnesses as our outcome of interest, and the results were robust.

¹⁶The mortality data from CDC consists of county-level mortality and population files. Deaths of nonresident aliens and fetal deaths are not included.

available at the county level. International primary commodity price data are from the International Monetary Fund's (IMF) Primary Commodity Price System. For our primary analysis, we use the commodity values for corn and soybeans by multiplying production data with state-level prices. We use the GDP deflator from the World Bank to express nominal prices in real (i.e., 2015 US dollar) prices.

For droughts, we use the monthly Palmer Drought Severity Index (PDSI) at the county level provided by the Cooperative Institute for Climate and Satellites-North Carolina. The PDSI is a standardized index that measures relative dryness, which is estimated via temperature and precipitation data. The PDSI ranges from -10 to $+10$, from dry to wet. We calculate the average monthly data to determine the annual drought. The drought classification is based on the US Drought Monitor.

To define rural versus urban counties, we use 1990, 2006, and 2013 data from the Urban-Rural Classification Scheme provided by the CDC's NCHS. We define urban counties as counties classified as urban in any of 1990, 2006, or 2013. Every other county in our data is defined as rural. Data on county-level annual employment is from the Quarterly Census of Employment and Wages (QCEW) by the US Bureau of Labor Statistics (BLS). Data on county-level annual personal income is from the US Bureau of Economic Analysis (BEA).

Table A1 presents descriptive statistics for the 644 counties we retain for analysis for the period 1980-2019 for our outcome of interest (i.e., age-adjusted death rates), for our variables of interest (i.e., commodity revenues for corn and soybeans), for our instrumental variables (i.e., drought severity), and for our control variables. Table A2 presents descriptive statistics for the variables we use for our mediation analyses as well as for our falsification tests (i.e., tests in which we use a "fake" outcome to test whether our core results are spurious). Tables A3 and A4 present detailed descriptions of the variables we use in our analysis.

Before presenting regression results, we present some visual representations of our

data. Figures I and II show the spatial distribution of within-county corn and soybeans average revenues over time. Unsurprisingly given that corn and soybeans are often complements in production, there appears to be a spatial correlation between corn and soybean revenues across counties.

Figures III and IV plot the relationship between mortality and commodity revenues, with the difference being that the variables in Figure IV are population-weighted but the variables in Figure III are not. In both figures, for both corn and soybeans, there seems to be an unconditional negative correlation between commodity revenues and age-adjusted death rates.

4 Results and Discussion

Turning to our empirical results, we first present and discuss our core empirical results and the results of robustness checks. Having established that our core results are robust, we then discuss the mechanisms whereby our results operate as well as the results of falsification tests.

4.1 Ancillary Results

Before discussing our core results, we briefly discuss the results of ancillary regressions that help put in context our main results.

Because the price and quantity of a commodity are likely to be related to each other, it is natural to ask what is the relationship between the quantity of corn or soybeans cultivated in a given county in a given year and the price of corn or soybeans in the same year for the state in which that county is located. Table A5 shows the relationship between the price and quantity of corn (column 1) and soybeans (column 2) conditional on county and year fixed effects. Because we look at the logarithm of both prices and quantities, the estimated coefficients are elasticities, and they suggest that a one-percent increase in the

state-level price of a given commodity in a given year is associated on average with a 2.5-percent (2.9-percent) decrease in the quantity of corn (soybeans) produced in the average county in the same year. In other words, conditional on county and year fixed effects, there appears to be an inverse relationship between the price and quantity cultivated for each commodity.

It is also natural to ask about the relationship between revenues from corn and soybeans in a given state in a given year and either income or farm income in a given county in the same year. Table A6 shows the relationship between farm income and revenues from corn (column 1) and soybeans (column 2) as well as the relationship between income and revenues from corn (column 3) and soybeans (column 4), conditional on county and year fixed effects. Unsurprisingly, the association between farm income and the revenues from each commodity is positive and statistically significant, although the magnitude of that association is almost five times as high for corn (column 1) as it is for soybeans (column 2). Here, too, the estimated coefficients are elasticities. What is perhaps more surprising is the fact that while corn revenues are not statistically significantly associated with income overall (column 3), the relationship between soybean revenues and income overall (column 4) is positive and statistically significant, and its magnitude exceeds that of the relationship between soybean revenues and farm income (column 2). Given that our research design is not aimed at causally identifying the relationships presented in this table, the coefficients in Table A6 may be biased.

Similarly, Table A7 looks at the relationship between commodity revenues and employment in agriculture and employment overall. While the estimation samples are not the same between the two measures of employment—the number of observations for employment in agriculture is smaller than for employment overall because the Bureau of Labor Statistics suppresses data to avoid identifying specific employers—it is notable that employment in agriculture does not seem to be significantly associated with either corn and soybean revenues conditional on county and year fixed effects, but that total employ-

ment is negatively and significantly associated with corn revenues (column 3) but positively and significantly associated with soybean revenues (column 4). Again, given our research design, these findings should be treated with caution, but this latter finding – the different signs in columns 3 and 4 of Table A7 – may help explain some of our findings below.

The results in Tables A6 and A7 help elucidate whether our results are driven by income effects for producers or labor-market spillovers for the population in general. The results in Table A6 show that commodity revenues are positively associated with both farm and overall income in a given county in a given year. The results in Table A7 show that shocks to either corn or soybean revenues are not significantly associated with employment in agriculture, but that corn revenue shocks are negatively associated with overall employment, while soybean revenues are positively associated with overall employment. So it seems that there are both income effects for producers *and* labor-market spillovers at play, with the latter exhibiting both pro- and countercyclical tendencies.

4.2 Core Results

Turning to our core results, Table I shows the results of a regression of the logarithm of the age-adjusted death rate on the logarithm of corn (columns 1 to 4) or soybean (columns 5 to 8) revenues based on state-level prices conditional on county and year fixed effects, on lagged employment and income, as well as on the contemporaneous average of the treatment variable in neighboring counties. In columns 1, 2, 5, and 6, we show the results of regressions that omit control variables (i.e., lagged employment in a given county in a given year and lagged income in the same county in the same year). In columns 2, 4, 6, and 8 we weight each county-year observation by the size of its population.

The results in Table I suggest that while there is no statistically significant relationship between corn revenues and mortality (columns 1 to 4), there is a persistent negative relationship between soybean revenues and mortality (columns 5 to 8) that is robust to

omitting or including control variables and to weighting observations by population or not. Specifically, for a 10-percent decrease in soybean revenues, there is an associated increase in mortality of 0.1 percent in the average rural county in the US Midwest for the period 1980-2019. The same cannot be said for the relationship between corn revenues and mortality. Although the sign of the coefficient of interest is the same in columns 1 to 4 as in columns 5 to 8, the magnitude of the estimated coefficients is roughly one order of magnitude smaller for corn than it is for soybeans. We speculate below about the reasons why that is.

The results in Table I are robust to using global commodity prices instead of state-level prices (Table A8), to using linear or quadratic trends that are either for the overall sample or state- or county-specific (Tables A9 and A10 respectively for corn and soybeans). Table A8 also shows commodity revenue based on state-level prices and lagged production, and our core results are also robust to doing so. Breaking down the results in Table I by decade by interacting the logarithm of revenues for soybeans with indicator variables for the 1990s, the 2000s, and the 2010s (i.e., leaving the 1980s as the reference category), the negative relationship between soybean revenues and mortality in Table I is present for every decade in Table A11 (column 2) as well as overall, and it seems that the negative relationship between commodity revenues and age-adjusted all-cause mortality increased monotonically in magnitude from the 1990s to the 2000s and from the 2000s to the 2010s for both corn and soybeans. Interestingly, there is a similar relationship in Table A11 between corn revenues and mortality (column 1), and the estimated coefficient for each of the 1990s, 2000s, and 2010s is larger in magnitude for corn revenues than it is for soybean revenues, but this does not translate into overall significance in Table I.

Table II shows the results of the specification in Table I broken down by age group (i.e., age 0-14, age 15-64, and age 65+). The sample size is smaller for the age 0-14 category, because the CDC suppresses low-count mortality data to prevent identification of individuals in that age category. While the association between corn or soybean revenues

and mortality in the age 0-14, and age 15-64 categories is not statistically significant, the associations between both corn revenues and mortality as well as soybean revenues and mortality in the age 65+ category are both negative and statistically significant. The results in Table II thus suggest that our core results are driven by the age 65+ category and that while this translates into a similar result for soybeans in the full sample, it does not for corn revenues.

Table III shows the results of the specification in Table I broken down by gender. While the association between corn revenues and mortality (columns 1 and 3) is not statistically significant for either gender, the association between soybean revenues and mortality is negative and statistically significant for women (column 2). The results in Table III thus suggest that our core results are driven by women.

Table IV shows results for our 2SLS specifications, where we instrument corn revenues with the occurrence of an extreme or exceptional drought (column 1) or with a moderate, severe, extreme, or exceptional drought (column 3). In both cases (columns 2 and 4), this causes the association between corn revenues and mortality to become negative and statistically significant. Similarly, we instrument soybean revenues with the occurrence of an extreme or exceptional drought (column 5) or with a moderate, severe, extreme, or exceptional drought (column 7). Only in the former case (column 6) does this cause the negative relationship between soybean revenues and mortality in Table I to increase in magnitude. While the results in previous tables were average treatment effects if one believes our research design, the results in Table IV are local average treatment effects if one believes that our IVs are valid. That is, they represent the effect of a change in commodity revenue on mortality in those counties where commodity revenues changed in response to a drought. The F-statistics for tests of weak instruments exceed the usual threshold of about 10 to 13 for all four specifications.

Table V conducts something akin to a mediation analysis by keeping the specification in Table I to look at whether our core results are driven by specific causes of death,

i.e., cardiovascular disease (columns 1 to 4) and from mental health issues (columns 5 to 8). The results in Table V suggest that the negative association between revenues from soybeans and mortality is driven by both cardiovascular disease (columns 3 and 4) and mental health issues (columns 7 and 8). It is noteworthy that while our core results suggest that there is no relationship between corn revenues and mortality, the results in Table V suggest a statistically significant negative relationship that is large in magnitude between corn revenues and deaths from mental health issues. Here, however, sample sizes are smaller than in our core analysis because the CDC suppresses low count mortality data to protect privacy.

While Table V looks at deaths from cardiovascular disease and mental health issues, Table A12 looks at deaths from self-harm (columns 1 and 2), alcohol (columns 3 and 4), and drugs (columns 5 and 6). While those causes of death do not seem related to commodity revenues at first glance, Tables A13 and A14 break down results for specific causes of death by gender. Table A13 shows that our core result for soybeans operates through cardiovascular disease among women (column 3), but Table A14 also suggests that corn revenues may also be related to mortality among women through alcohol-related deaths (column 3). Interestingly, both Tables A13 and A14 show that in some cases, an increase – not a decrease – in corn revenues is associated with an increase in mortality: In Table A13 through mental health-related deaths, and in Table A14, through drug-related deaths. We discuss these results below, when putting our results in the context of the “deaths of despair” narrative ([Case and Deaton, 2020](#)).

Finally, we conduct two falsification tests to support the notion that our results are not spurious and driven by unobserved confounders. In both Tables A15 and A16, the idea is to find a lack of statistical significance in an effort to ensure that our core results are not spurious. In Table A15, we look at the relationship between corn revenues (columns 1 and 2) and soybean revenues (columns 3 and 4) and all-cause age-adjusted mortality, both without (columns 1 and 3) and with controls (columns 2 and 4). The only signifi-

cant coefficient here (column 1) shows the opposite of what our core results show, as it suggests a positive relationship between corn revenues and mortality, but only in the absence of controls. In Table A16, we look at an outcome which should not *a priori* respond to changes in corn or soybean revenues, viz. deaths from certain infections and parasitic diseases and congenital malformations, deformations, as well as deaths from chromosomal abnormalities. Here, we see no significance anywhere, which is what we would expect.

In terms of economic significance, our core results suggest that for the average county-year in our data, a 10-percent decrease in soybean revenues is associated with an increase in the age-adjusted death rate of about 0.1 percent, or about 0.25 additional death in the average county ($8.54 \text{ age-adjusted deaths per } 1,000 \text{ persons} \times 0.001 \times 28,900 \text{ persons in the average rural county in } 2024 = 0.246$). Given that there were 690 counties classified as rural in the Midwest in 2024, this means that a 10-percent decrease in soybean revenues would have been associated with about 170 more deaths throughout the Midwest in 2024. Taking our 2SLS results for soybeans at face value suggest that the local average treatment effect is such that for a 10-percent decrease in soybean revenues in 2024, there would have been an additional 850 deaths throughout the Midwest in 2024.

To summarize, our results show a robust negative relationship between soybean revenues and mortality. While our results also occasionally show a negative relationship between corn revenues and mortality, that relationship is not robust.

If it is indeed the case that there is a negative relationship between soybean revenues and mortality but not between corn revenues and mortality, this begs the question: Why soybeans, but not corn? One possible answer may lie in Table A7, which shows that total employment in a county is positively associated with soybean revenues, but negatively associated with corn revenues. This suggests that negative shocks to soybean revenues may lead to increased mortality via job loss but that the opposite holds for corn revenues. Another possible answer is that soybean is a relatively new crop in the US Midwest—

farmers began planting soybeans only when the wheat frontier began moving north in response to a changing climate – and producers get to choose whether and how much insurance coverage to buy for each crop. If they are less familiar with soybeans, their soybean insurance purchase decisions may be sub-optimal relative to their corn insurance purchase decisions, which would lead to their being exposed more to fluctuations in soybean revenues than in corn revenues. Both of these explanations are speculative and thus deserving of further research.

Finally, there remains the question of whether mortality from fluctuations in commodity revenues is pro-cyclical, as in [Stevens et al. \(2015\)](#) and [Ruhm \(2015\)](#), or countercyclical, as in [Case and Deaton \(2020\)](#). If there is no relationship between corn revenues and mortality and there is only a negative relationship between soybean revenues and mortality, then our overall results contribute to the countercyclical “deaths of despair” narrative put forth by [Case and Deaton \(2020\)](#). But if there is indeed a relationship between corn revenues and mortality, then the results in Tables A13 and A14 suggest that the likely effect of fluctuations in commodity revenues on mortality are gendered and both pro-cyclical (via the positive relationship between corn revenues and deaths from drugs and mental health issues among men) *and* countercyclical (via the negative relationship between soybean revenues and deaths from CVD and alcohol among women), which paints a considerably more nuanced picture than the “deaths of despair” narrative.

5 Summary and Concluding Remarks

We have looked at the relationship between revenues from agricultural commodities and mortality in the rural Midwest for the period 1980-2019. To do so, we have relied on a combination of (i) an exposure design interacting state-level commodity prices with county-level quantities cultivated for each commodity, and (ii) a two-way (i.e., county and year) fixed effects estimator to look at the relationship between corn or soybean rev-

venues on the one hand and age-adjusted all-cause death rates on the other hand. Because the TWFE may be biased in the presence of treatment effect heterogeneity, we have also supplemented our core TWFE results with a number of robustness checks involving (i) global instead of state-level prices, (ii) lagged instead of contemporaneous production levels, (iii) full-sample, state-, or county-specific linear or quadratic trends, as well as on (iv) measures of drought severity as IVs. This is consistent with the hypothesis that economic shocks can cause mortality and, more specifically, with the findings in [Carleton \(2017\)](#), [Christian et al. \(2019\)](#), and [Singhal and Tarp \(2024\)](#).

We find a robust, statistically significant, and negative relationship between soybean revenues and mortality. That is, as soybean revenues decrease, mortality increases. While this relationship holds for all-cause age-adjusted mortality, we find that it is mediated by deaths from cardiovascular disease and mental health issues. Digging deeper, we also find that our finding is driven by individuals aged 65 or older and by women. And though we find a negative relationship between corn revenues and mortality, that relationship is not as robust as that for soybean revenues.

We speculate that this differential effect between corn and soybean revenues may be due to either (i) a pro-cyclical relationship between corn revenues and employment but a countercyclical relationship between soybean revenues and employment, or (ii) the different insurance purchases and coverage choices made by farmers when it comes to soybeans, a crop that is considerably newer to the US Midwest than corn. If it is indeed true that soybean revenues cause mortality but corn revenues do not, this warrants further research into the mechanisms behind this finding.

If both corn and soybean revenues cause mortality, then our findings become much more nuanced. Indeed, we find that while decreased soybean revenues seem to translate into increases in mortality for women via cardiovascular disease and alcohol use, increases in corn revenues seem to translate into increases in mortality for men via mental health and drug use. Thus, for the reader interested in knowing whether mortality

from agricultural commodity revenue fluctuations is pro-cyclical, as posited by [Stevens et al. \(2015\)](#) and [Ruhm \(2015\)](#), or countercyclical, as famously hypothesized by [Case and Deaton \(2020\)](#), the answer is that it depends on which source of mortality one chooses to look at—as well as on mortality for whom.

Our work is limited both in terms of internal validity and of external validity. On the internal validity front, while we do find a robust negative relationship between soybean prices and mortality, our work relies on observational data, and our results thus fall short of the gold standard of experimental evidence and should be treated as such. Moreover, an important recent literature has questioned the usefulness of TWFE designs in the presence of treatment effect heterogeneity. Against that, we present the results of a battery of robustness checks.¹⁷ On the external validity front, our results are only valid for corn and soybeans in the US Midwest for the period 1980 to 2019, and it is unclear whether they apply to other crops and other contexts.

The limitations above notwithstanding, if one were to grant internal validity to our findings, those findings would have clear implications for policy. Given our finding that soybean price decreases seem to translate into increased mortality from cardiovascular diseases and from mental health-related causes, one obvious policy implication would be to invest in better prevention, early detection, and treatment of those conditions in rural areas. Given the longer-than-average distances between individuals and their health care providers in rural areas, this may mean encouraging more rural health infrastructure or the deployment of mobile health care providers in rural areas.

It might also be possible to invest in additional income-support programs for farmers in the Midwest. While nothing in our findings suggests that the adverse effects of commodity revenue shocks are limited to farmers and, given data limitations, we cannot identify which groups of individuals are the ones more likely to suffer from increased mortality because of soybean revenue shocks, the presumed mechanism here is that de-

¹⁷An earlier version of this paper included many more robustness checks which are omitted for brevity.

pressed farm incomes lead to mortality, and so if those incomes were less likely to suffer unexpected decreases, there would likely be less mortality as a result. Less obviously, given that our results take into account the myriad of financial instruments and programs agricultural producers already have access to, our results may also offer a cautionary tale against curtailing access to those financial instruments or reducing income-support programs for agricultural producers.

The limitations above also have implications for future research. While it seems unlikely that one can improve on the internal validity of our results in the absence of data at a level below that of the county or of an experimental design, it is certainly possible to improve in terms of external validity by conducting similar studies in other contexts, for shocks to revenues from other commodities, or for shocks to the manufacturing and services sectors.

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Average Corn Revenues
Rural Counties in the Midwestern United States 1980–2019

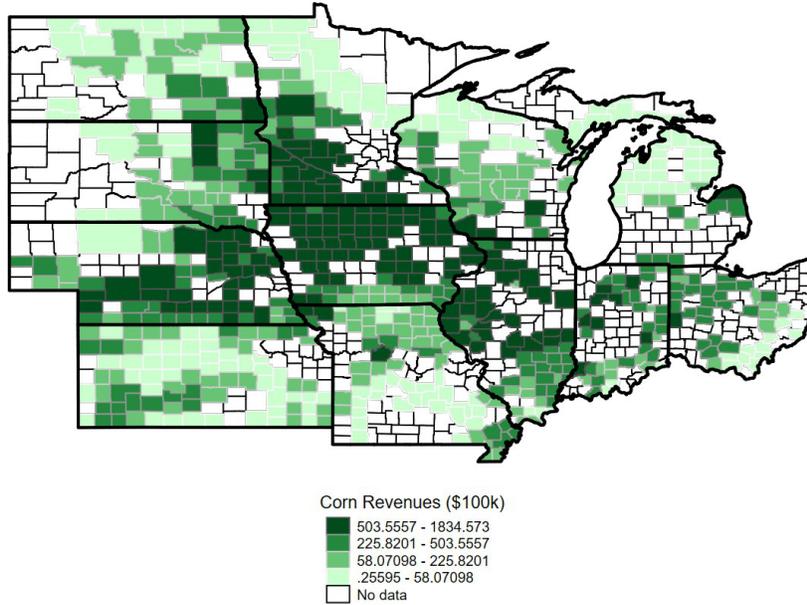


FIGURE I: County Corn Revenues, 1980–2019.
Alt Text: “Heat map of average county-level corn revenue in the Midwest, 1980-2019.”

Average Soybean Revenues
Rural Counties in the Midwestern United States 1980–2019

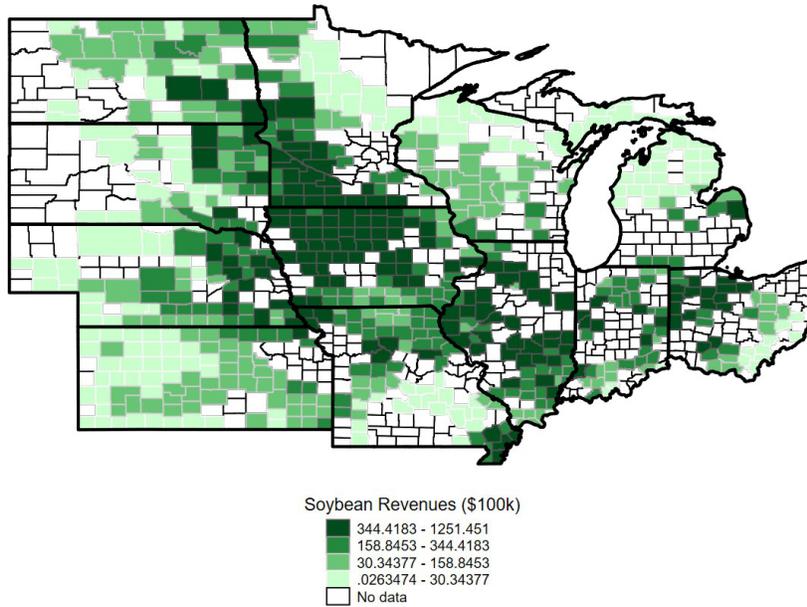


FIGURE II: County Soybean Revenues, 1980–2019.
Alt Text: “Heat map of average county-level corn revenue in the Midwest, 1980-2019.”

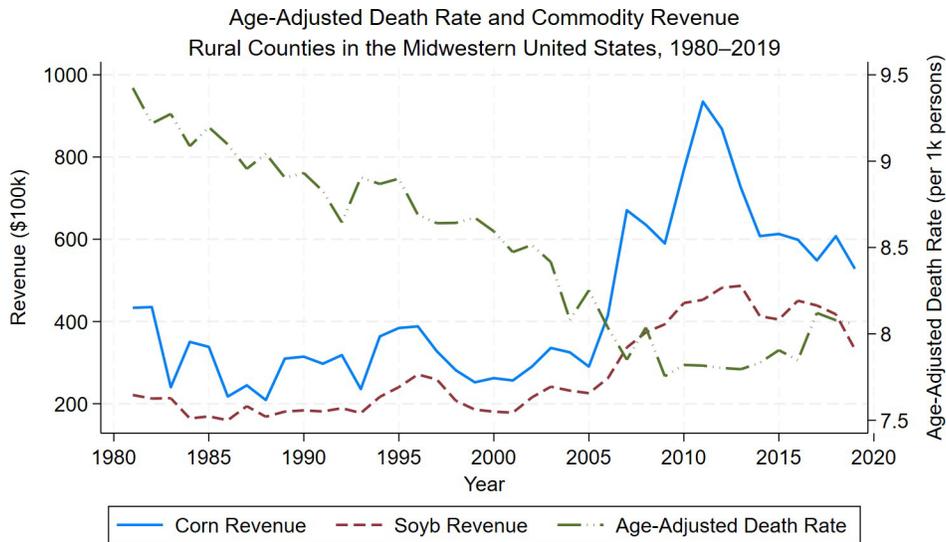


FIGURE III: Mortality Rate and Commodity Revenue Based on State Prices and County Production, 1980-2019.

Alt Text: "Time series of county averages of age-adjusted death rate, corn revenue, and soybean revenue, 1980-2019."

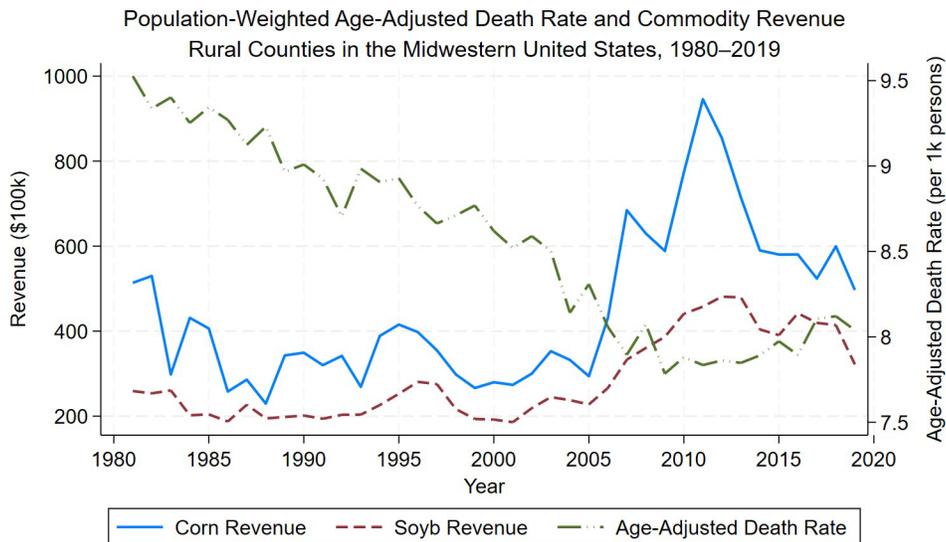


FIGURE IV: Population-Weighted Mortality Rate and Commodity Revenue Based on State Prices and County Production, 1980-2019.

Alt Text: "Time series of population-weighted county averages of age-adjusted death rate, corn revenue, and soybean revenue, 1980-2019."

TABLE I: TWFE estimates for correlation between rural mortality and commodity revenue, 1980 to 2019

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Corn				Soybeans			
	Dep Var: Log of age-adjusted death rates per 1k persons							
ln(Commodity revenue based on state prices)	-0.0002	-0.002	-0.003	-0.005	-0.010***	-0.010***	-0.010***	-0.010***
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.003)	(0.003)	(0.003)
ln(Neighbor commodity revenue based on state prices)	0.016**	0.015**	0.016***	0.016**	0.004	-0.003	0.006	-0.000
	(0.006)	(0.006)	(0.006)	(0.006)	(0.005)	(0.004)	(0.005)	(0.004)
County lag employment (1k persons)			-0.004***	-0.003***			-0.004***	-0.003***
			(0.001)	(0.001)			(0.001)	(0.001)
ln(County lag income)			-0.058***	-0.063***			-0.053***	-0.049***
			(0.014)	(0.015)			(0.015)	(0.015)
Constant	1.869***	1.920***	2.702***	2.854***	2.241***	2.367***	2.922***	3.005***
	(0.078)	(0.073)	(0.201)	(0.210)	(0.063)	(0.044)	(0.193)	(0.200)
Mean Outcome (level, per 1k)	8.543	8.582	8.543	8.582	8.543	8.582	8.543	8.582
Weighted Sample	No	Yes	No	Yes	No	Yes	No	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,500	18,500	18,500	18,500	18,500	18,500	18,500	18,500
R ²	0.629	0.726	0.633	0.729	0.629	0.727	0.632	0.730

Notes: Standard errors clustered at the county level in parentheses. Mean outcome reports the level of age-adjusted mortality rates per 1,000 persons. For the weighted sample, we use county population weights to compute both the coefficient estimates and the mean outcome. *** p < 0.01, ** p < 0.05, * p < 0.1

TABLE II: TWFE estimates of rural mortality and commodity revenue by age, 1980 to 2019

	(1)	(2)	(3)	(4)	(5)	(6)
	Age 0-14		Age 15-64		Age 65+	
	Corn	Soybeans	Corn	Soybeans	Corn	Soybeans
Dep Var: Log of age-adjusted death rates per 1k persons						
ln(Commodity revenue based on state prices)	0.010 (0.038)	-0.006 (0.029)	0.013 (0.008)	-0.004 (0.007)	-0.007* (0.004)	-0.011*** (0.004)
ln(Neighbor commodity revenue based on state prices)	0.028 (0.051)	-0.003 (0.039)	0.024** (0.011)	0.012 (0.009)	0.011* (0.006)	0.002 (0.005)
County lag employment (1k persons)	-0.043*** (0.009)	-0.045*** (0.009)	-0.013*** (0.002)	-0.014*** (0.002)	-0.001 (0.001)	-0.001 (0.001)
ln(County lag income)	0.196 (0.143)	0.191 (0.143)	-0.141*** (0.030)	-0.148*** (0.031)	-0.035** (0.014)	-0.024* (0.014)
Constant	-2.889 (1.983)	-2.042 (1.859)	2.432*** (0.394)	3.014*** (0.396)	4.302*** (0.199)	4.375*** (0.186)
Mean Outcome (level, per 1k)	1.064	1.064	3.104	3.104	50.187	50.187
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	4,336	4,336	18,500	18,500	18,500	18,500
R ²	0.267	0.267	0.471	0.470	0.540	0.542

Notes: There are fewer observations for ages 0–14 because the CDC suppresses low-count mortality data to prevent identification of individuals. Standard errors clustered at the county level in parentheses. Mean outcome reports the level of age-adjusted mortality rates per 1,000 persons. *** p < 0.01, ** p < 0.05, * p < 0.1

TABLE III: TWFE estimates of rural mortality and commodity revenue by gender, 1980 to 2019

	(1)	(2)	(3)	(4)
	Female		Male	
	Corn	Soybeans	Corn	Soybeans
Dep Var: Log of age-adjusted death rates per 1k persons				
ln(Commodity revenue based on state prices)	-0.001 (0.006)	-0.012*** (0.004)	-0.003 (0.005)	-0.005 (0.004)
ln(Neighbor commodity revenue based on state prices)	0.018** (0.008)	0.010 (0.006)	0.017** (0.007)	0.003 (0.005)
County lag employment (1k persons)	-0.005*** (0.001)	-0.005*** (0.001)	-0.004*** (0.001)	-0.004*** (0.001)
ln(County lag income)	-0.029 (0.018)	-0.024 (0.018)	-0.062*** (0.017)	-0.059*** (0.018)
Constant	2.061*** (0.268)	2.317*** (0.246)	2.976*** (0.231)	3.190*** (0.229)
Mean Outcome (level, per 1k)	6.901	6.901	10.734	10.734
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	18,500	18,500	18,500	18,500
R ²	0.434	0.434	0.581	0.580

Notes: Standard errors clustered at the county level in parentheses. Mean outcome reports the level of age-adjusted mortality rates per 1,000 persons.
 *** p < 0.01, ** p < 0.05, * p < 0.1

TABLE IV: Instrumental variables estimates for the impact of commodity revenue on rural mortality from 1980 to 2019 – using drought level as IV

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Corn				Soybeans			
	Commodity revenue based on State Prices & Prod.							
	ln(Corn revenue)	ln(Age-adj. death rates)	ln(Corn revenue)	ln(Age-adj. death rates)	ln(Soyb revenue)	ln(Age-adj. death rates)	ln(Soyb revenue)	ln(Age-adj. death rates)
ln(Commodity revenue)		-0.073** (0.030)		-0.029* (0.017)		-0.050* (0.026)		-0.013 (0.012)
D4 – exceptional drought	-0.534*** (0.062)		-0.608*** (0.062)		-0.257*** (0.072)		-0.383*** (0.072)	
D3 – extreme drought	-0.214*** (0.079)		-0.279*** (0.081)		-0.330*** (0.085)		-0.435*** (0.088)	
D2 – severe drought			-0.249*** (0.035)				-0.304*** (0.058)	
D1 – moderate drought			-0.101*** (0.019)				-0.235*** (0.029)	
County lag employment (1k persons)	-0.025*** (0.007)	-0.006*** (0.001)	-0.024*** (0.007)	-0.005*** (0.001)	0.001 (0.012)	-0.004*** (0.001)	0.001 (0.012)	-0.004*** (0.001)
ln(County lag income)	-0.178 (0.112)	-0.070*** (0.019)	-0.188* (0.111)	-0.062*** (0.016)	0.948*** (0.167)	-0.009 (0.030)	0.932*** (0.165)	-0.044** (0.018)
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,500	18,500	18,500	18,500	18,500	18,500	18,500	18,500
F-statistic	41.464		37.251		12.869		25.521	

Notes: Standard errors clustered at the county level in parentheses. D4 – exceptional drought is defined as an annual average PDSI of -5.0 or less, which may cause widespread crop losses. D3 – extreme drought is an annual average PDSI between -4.0 to -4.9, which may cause major crop losses. D2 – severe drought is an annual average PDSI between -3.0 to -3.9, which may likely cause crop losses. D1 – moderate drought is an annual average PDSI between -2.0 to -2.9, which may likely cause some damage to crop. *** p < 0.01, ** p < 0.05, * p < 0.1

TABLE V: TWFE estimates of rural mortality and commodity revenue by cause, 1980 to 2019

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Corn		Soybeans		Corn		Soybeans	
	Dep Var: Log of age-adjusted CVD death rates				Dep Var: Log of age-adjusted mental health death rates			
ln(Commodity revenue based on state prices)	-0.006	-0.007	-0.009*	-0.010**	-0.087***	-0.081**	-0.073***	-0.087***
	(0.006)	(0.007)	(0.005)	(0.005)	(0.032)	(0.038)	(0.022)	(0.026)
Mean Outcome (level, per 1k)	3.521	3.497	3.521	3.497	0.258	0.262	0.258	0.262
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weight	No	Yes	No	Yes	No	Yes	No	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,477	18,477	18,477	18,477	6,395	6,395	6,395	6,395
R ²	0.796	0.856	0.797	0.856	0.793	0.791	0.794	0.793

Notes: Standard errors clustered at the county level in parentheses. Mean outcome reports the level of age-adjusted mortality rates per 1,000 persons. For the weighted sample, we use county population weights to compute both the coefficient estimates and the mean outcome. The mediation analysis has fewer observations than the main results because the CDC suppresses low count mortality data to protect privacy. *** p < 0.01, ** p < 0.05, * p < 0.1

TABLE A1: Sample statistics of the selected variables

Variables	Mean	Std. Dev.
Outcomes of Interest		
Age-adjusted death rates (per 1k persons)	8.54	1.26
Commodity		
Corn revenue based on state-level prices (\$100k)	415.77	436.01
Soybean revenue based on state-level prices (\$100k)	264.81	246.64
Commodity in Neighboring Counties		
Neighbor corn revenue based on state-level prices (\$100k)	405.47	377.24
Neighbor soybean revenue based on state-level prices (\$100k)	258.51	207.77
County Characteristics		
Lag employment (1k persons)	8.40	7.68
Lag income (\$100k)	7.05	6.06
Local Disaster		
D4—exceptional drought (0/1)	0.001	0.03
D3—extreme drought (0/1)	0.01	0.10
D2—severe drought (0/1)	0.02	0.13
D1—moderate drought (0/1)	0.04	0.20
Observation (N*T)	18,500	

Notes: Revenue and income variables are adjusted to 2015 values.

TABLE A2: Sample statistics for mediation and falsification analysis

Variables	Mean	Std. Dev.
For Mediation Analysis		
Age-adjusted CVD death rates (per 1k persons)	3.52	1.08
Observation (N*I)	18,477	
Age-adjusted mental health death rates (per 1k persons)	0.26	0.19
Observation (N*I)	6,395	
Age-adjusted self-harm death rates (per 1k persons)	0.16	0.10
Observation (N*I)	3,973	
Age-adjusted alcohol-related death rates (per 1k persons)	0.12	0.09
Observation (N*I)	3,182	
Age-adjusted drug-related death rates (per 1k persons)	0.09	0.15
Observation (N*I)	790	
For Falsification Test		
Age-adjusted death rates due to infection or birth defect (per 1k persons)	0.17	0.10
Observation (N*I)	4,409	

Notes: We use county-level mortality data for the mediation analysis and the falsification test. Due to data privacy restrictions, specifying the cause of death at the county level results in a large loss of observations.

TABLE A3: Definition of variables

Variables	Description
Outcomes of Interest	
Age-adjusted death rates (per 1k persons)	The county-level weighted average number of age-specific deaths rates. The weights are retrieved from the number of population by age group. The age groups include less than 1 year, 1-4, 5-14, 15-24, 25-34, . . . ,85 years and over. Age-adjusted death rate = Sum of (Age Specific Death Rate * Standard Population weight) * 1,000.
Age-adjusted CVD death rates (per 1k persons)	The county-level weighted average number of age-specific deaths rates due to cardiovascular diseases.
Age-adjusted mental health death rates (per 1k persons)	The county-level weighted average number of age-specific deaths rates due to mental and behavioural disorders.
Age-adjusted alcohol-induced death rates (per 1k persons)	The county-level weighted average number of age-specific deaths rates due to alcohol.
Age-adjusted self-harm death rates (per 1k persons)	The county-level weighted average number of age-specific deaths rates due to intentional self-harm.
Age-adjusted death rates due to infection or birth defect (per 1k persons)	The county-level weighted average number of age-specific deaths rates due to certain infections and parasitic diseases and congenital malformations, deformations and chromosomal abnormalities.
Commodity	
Corn revenue based on state-level prices (\$100k)	County-level grain corn revenue based on state-level prices, measured in 2015 dollars. Corn revenue based on state-level prices = State-level corn prices (\$/bu) * Corn production (bu).
Soybean revenue based on state-level prices (\$100k)	County-level soybean revenue based on state-level prices, measured in 2015 dollars. Soybean revenue based on state-level prices = State-level soybean prices (\$/bu) * Soybean production (bu).

TABLE A3: Definition of variables

Variables	Description
Corn revenue based on IMF prices (\$100k)	County-level grain corn revenue based on IMF prices, measured in 2015 dollars. Corn revenue based on IMF prices = IMF corn prices (\$/bu) * Corn production (bu).
Soybean revenue based on IMF prices (\$100k)	County-level soybean revenue based on IMF prices, measured in 2015 dollars. Soybean revenue based on state-level prices = IMF soybean prices (\$/bu) * Soybean production (bu).
County Characteristics	
Rural (0/1)	County is defined as rural area if it belongs to nonmetropolitan in the 2013, 2006, and 2019 National Center for Health Statistics (NCHS) Urban-Rural Classification Scheme for Counties.
Lag income (\$100k)	County annual personal income for the previous year, in 2015 dollars.
Lag employment (1k persons)	County annual employment level for the previous year.
Local Disaster	
D4 – exceptional drought (0/1)	Dummy variable of D4 – exceptional drought which indicates that the county-level annual average of Palmer Drought Severity Index (PDSI) is -5.0 or less.
D3 – extreme drought (0/1)	Dummy variable of D3 – extreme drought which indicates that the county-level annual average of Palmer Drought Severity Index (PDSI) ranges between -4.0 and -4.9.
D2 – severe drought (0/1)	Dummy variable of D2 – severe drought which indicates that the county-level annual average of Palmer Drought Severity Index (PDSI) ranges between -3.0 and -3.9.
D1 – moderate drought (0/1)	Dummy variable of D1 – moderate drought which indicates that the county-level annual average of Palmer Drought Severity Index (PDSI) ranges between -2.0 and -2.9.

TABLE A4: Description for cause-specific mortality

Variables	Description
Deaths due to CVD	For sample from 1980 to 1998, deaths due to CVD includes ICD-9 Codes: 390-459 (Diseases of the circulatory system). For sample from 1980 to 1998, deaths due to CVD includes ICD-10 Codes: I00-I99 (Diseases of the circulatory system).
Death due to mental health	For sample from 1980 to 1998, deaths due mental and behavioural disorders includes ICD-9 Codes: 290-319 (Mental disorders). For sample from 1999 to 2019, deaths due to mental health issues includes ICD-10 Codes: F01-F99 (Mental and behavioural disorders).
Death due to self-harm	For sample from 1980 to 1998, deaths due to intentional self-harm includes ICD-9 Codes: E950-E959 (Suicide and self-inflicted injury). For sample from 1999 to 2019, deaths due to mental health issues includes ICD-10 Codes: X60-X84 (Intentional self-harm).
Death due to alcohol	For sample from 1980 to 1998, deaths due to alcohol includes ICD-9 Codes: 291.0 (Alcohol withdrawal delirium); 303 (Alcohol dependence syndrome); 305.0 (Alcohol abuse); 425.5 (Alcoholic cardiomyopathy); 535.3 (Alcoholic gastritis); 571.0 (Alcoholic fatty liver); 790.3 (Excessive blood level of alcohol); E860.0 (Alcoholic beverages); E947.3 (Alcohol deterrents). For the sample from 1999 to 2019, deaths due to alcohol includes ICD-10 Codes: F10 (Mental and behavioural disorders due to use of alcohol); I42.6 (Alcoholic cardiomyopathy); K29.2 (Alcoholic gastritis); K70 (Alcoholic liver disease); R78.0 (Finding of alcohol in blood); X45 (Accidental poisoning by and exposure to alcohol); X65 (Intentional self-poisoning by and exposure to alcohol); Y15 (Poisoning by and exposure to alcohol, undetermined intent).

TABLE A4: Description for cause-specific mortality

Variables	Description
Death due to drug	<p>For sample from 1980 to 1998, deaths due to alcohol includes ICD-9 Codes: 292 (Drug psychoses); 304 (Drug dependence); 648.3 (Drug dependence); E850–E858 (Accidental poisoning by drugs, medicinal substances, and biologicals); E950.4 (Other specified drugs and medicinal substances); E950.5 (Unspecified drug or medicinal substance); E962.0 (Drugs and medicinal substances); E980.4 (Other specified drugs and medicinal substances); E980.5 (Unspecified drug or medicinal substance). For the sample from 1999 to 2019, deaths due to alcohol includes ICD-10 Codes: F11 (Mental and behavioural disorders due to use of opioids); F12 (Mental and behavioural disorders due to use of cannabinoids); F13 (Mental and behavioural disorders due to use of sedatives or hypnotics); F14 (Mental and behavioural disorders due to use of cocaine); F15 (Mental and behavioural disorders due to use of other stimulants, including caffeine); F16 (Mental and behavioural disorders due to use of hallucinogens); F19 (Mental and behavioural disorders due to multiple drug use and other psychoactive substances); O99.3 (Mental disorders and diseases of the nervous system complicating pregnancy, childbirth and the puerperium); X40–X44 (Accidental poisoning by drugs, medicaments and biological substances); X60–X64 (Intentional self-poisoning by drugs, medicaments and biological substances); X85 (Assault by drugs, medicaments and biological substances); Y10–Y14 (Poisoning by drugs, medicaments and biological substances, undetermined intent).</p>
Deaths due to infection or birth defect	<p>For sample from 1980 to 1998, deaths due to infection or birth defect includes ICD-9 Codes: 001-139 (Infectious and parasitic diseases); 740-759 (Congenital anomalies) For sample from 1999 to 2019, deaths due to infection or birth defect includes ICD-10 Codes: A00-B99 (Certain infectious and parasitic diseases); Q00-Q99 (Congenital malformations, deformations and chromosomal abnormalities).</p>

TABLE A5: TWFE estimates for correlation between commodity prices and quantities, 1980 to 2019

	(1) Corn	(2) Soybeans
	Dep Var: log(Commodity production)	
ln(Commodity state-level prices)	-2.539*** (0.163)	-2.889*** (0.313)
Constant	18.848*** (0.218)	20.554*** (0.708)
County FE	Yes	Yes
Year FE	Yes	Yes
Observations	18,500	18,500
R ²	0.932	0.900

Notes: Standard errors clustered at the county level in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1

TABLE A6: TWFE estimates for correlation between income and commodity revenue, 1980 to 2019

	(1) Corn	(2) Soybeans	(3) Corn	(4) Soybeans
	Dep Var: Log of Farm Income		Dep Var: Log of Income	
ln(Commodity revenue based on state prices)	0.048*** (0.005)	0.009** (0.004)	-0.002 (0.005)	0.028*** (0.004)
Constant	10.594*** (0.085)	11.259*** (0.064)	12.875*** (0.087)	12.401*** (0.061)
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	18,500	18,500	18,500	18,500
R ²	0.382	0.370	0.833	0.838

Notes: Standard errors clustered at the county level in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1

TABLE A7: TWFE estimates for correlation between employment and commodity revenue, 1980 to 2019

	(1) Corn	(2) Soybeans	(3) Corn	(4) Soybeans
	Dep Var: Log of Employment in Agriculture		Dep Var: Log of Employment (1k persons)	
ln(Commodity revenue based on state prices)	0.023	0.028	-0.013**	0.018***
	(0.035)	(0.028)	(0.006)	(0.005)
Constant	3.573***	3.521***	1.785***	1.285***
	(0.598)	(0.444)	(0.093)	(0.072)
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	6,675	6,675	18,500	18,500
R ²	0.276	0.276	0.489	0.493

Notes: The number of observations for Employment in Agriculture is smaller than in the main results because the Bureau of Labor Statistics suppresses data to avoid identifying specific employers. Standard errors clustered at the county level in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1

TABLE A8: TWFE estimates for correlation between rural mortality and commodity revenue based on different measure, 1980 to 2019

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Corn				Soybeans			
	Dep Var: Log of age-adjusted death rates per 1k persons							
ln(Commodity revenue based on IMF prices)	-0.004 (0.004)	-0.005 (0.004)			-0.010*** (0.003)	-0.010*** (0.003)		
ln(Commodity revenue based on state prices and lag prod.)			-0.004 (0.004)	-0.005 (0.004)			-0.007* (0.004)	-0.008** (0.003)
Mean Outcome (level, per 1k)	8.543	8.582	8.543	8.581	8.543	8.582	8.537	8.581
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weighted Sample	No	Yes	No	Yes	No	Yes	No	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	18,500	18,500	18,212	18,212	18,500	18,500	18,038	18,038
R ²	0.633	0.729	0.635	0.731	0.632	0.730	0.635	0.730

Notes: Standard errors clustered at the county level in parentheses. Mean outcome reports the level of age-adjusted mortality rates per 1,000 persons. Controls include neighboring-county commodity revenue and county-level lagged employment and income. For the weighted sample, we use county population weights to compute both the coefficient estimates and the mean outcome. Fewer observations for lagged-production revenue reflect missing lagged production data in some counties. *** p < 0.01, ** p < 0.05, * p < 0.1

TABLE A9: Robustness checks for correlation between rural mortality and corn revenue, 1980 to 2019

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Corn						
	Dep Var: Age-adjusted death rates (per 1k persons)						
ln(Commodity revenue based on state-level prices)	-0.003 (0.004)	-0.003 (0.004)	-0.003 (0.004)	-0.004 (0.004)	-0.002 (0.004)	-0.007* (0.004)	-0.008* (0.004)
ln(Neighbor commodity revenue based on state-level prices)	0.016*** (0.006)	-0.002 (0.005)	-0.004 (0.006)	-0.016*** (0.005)	-0.026*** (0.005)	-0.005 (0.005)	-0.011** (0.005)
County lag employment (1k persons)	-0.004*** (0.001)	-0.003*** (0.001)	-0.002*** (0.001)	-0.003*** (0.001)	0.005*** (0.001)	-0.002*** (0.001)	-0.001 (0.001)
ln(County lag income)	-0.058*** (0.014)	-0.075*** (0.014)	-0.076*** (0.014)	-0.038*** (0.014)	-0.043*** (0.015)	-0.052*** (0.014)	-0.059*** (0.014)
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	No	No	No	No
Linear time trend	No	Yes	No	No	No	No	No
Quadratic time trend	No	No	Yes	No	No	No	No
County specific linear time trend	No	No	No	Yes	No	No	No
County specific quadratic trend	No	No	No	No	Yes	No	No
State specific linear trend	No	No	No	No	No	Yes	No
State specific quadratic trend	No	No	No	No	No	No	Yes
Observations	18,500	18,500	18,500	18,500	18,500	18,500	18,500
R ²	0.313	0.284	0.285	0.386	0.431	0.300	0.306

Notes: Standard errors clustered at the county level in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1

TABLE A10: Robustness checks for correlation between rural mortality and soybean revenue, 1980 to 2019

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Soybeans						
	Dep Var: Age-adjusted death rates (per 1k persons)						
ln(Commodity revenue based on state-level prices)	-0.010*** (0.003)	-0.010*** (0.003)	-0.010*** (0.003)	-0.009*** (0.003)	-0.009** (0.004)	-0.009*** (0.003)	-0.008*** (0.003)
ln(Neighbor commodity revenue based on state-level prices)	0.006 (0.005)	0.001 (0.004)	-0.001 (0.004)	-0.009** (0.004)	-0.014*** (0.005)	-0.001 (0.004)	-0.004 (0.004)
County lag employment (1k persons)	-0.004*** (0.001)	-0.003*** (0.001)	-0.002*** (0.001)	-0.002** (0.001)	0.005*** (0.001)	-0.002*** (0.001)	-0.001 (0.001)
ln(County lag income)	-0.053*** (0.015)	-0.065*** (0.014)	-0.065*** (0.014)	-0.034** (0.014)	-0.036** (0.015)	-0.046*** (0.013)	-0.052*** (0.013)
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	No	No	No	No
Linear time trend	No	Yes	No	No	No	No	No
Quadratic time trend	No	No	Yes	No	No	No	No
County specific linear time trend	No	No	No	Yes	No	No	No
County specific quadratic trend	No	No	No	No	Yes	No	No
State specific linear trend	No	No	No	No	No	Yes	No
State specific quadratic trend	No	No	No	No	No	No	Yes
Observations	18,500	18,500	18,500	18,500	18,500	18,500	18,500
R ²	0.313	0.286	0.287	0.385	0.428	0.300	0.304

Notes: Standard errors clustered at the county level in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1

TABLE A11: TWFE estimates of rural mortality and commodity revenue by decade, 1980 to 2019

	(1) Corn	(2) Soybeans
	Dep Var: Log of age-adjusted death rates per 1k persons	
ln(Commodity revenue based on state prices)	0.005 (0.004)	-0.007** (0.004)
1990s × ln(Commodity revenue based on state prices)	-0.008*** (0.002)	-0.005*** (0.002)
2000s × ln(Commodity revenue based on state prices)	-0.014*** (0.002)	-0.011*** (0.002)
2010s × ln(Commodity revenue based on state prices)	-0.016*** (0.003)	-0.012*** (0.003)
ln(Neighbor commodity revenue based on state prices)	0.009 (0.006)	0.002 (0.005)
County lag employment (1k persons)	-0.003*** (0.001)	-0.004*** (0.001)
ln(County lag income)	-0.074*** (0.014)	-0.065*** (0.015)
Constant	3.043*** (0.200)	3.212*** (0.215)
Mean Outcome (level, per 1k)	8.543	8.543
County FE	Yes	Yes
Year FE	Yes	Yes
Observations	18,500	18,500
R ²	0.636	0.634

Notes: Standard errors clustered at the county level in parentheses. The 1980s serve as the baseline period, and the interaction terms capture changes in the effect of log commodity revenue in subsequent decades relative to this baseline. Mean outcome reports the level of age-adjusted mortality rates per 1,000 persons.

*** p < 0.01, ** p < 0.05, * p < 0.1

TABLE A12: TWFE estimates of rural mortality and commodity revenue by causes due to self-harm, alcohol-related, or drug-related, 1980 to 2019.

	(1) Corn	(2) Soybeans	(3) Corn	(4) Soybeans	(5) Corn	(6) Soybeans
	Dep Var: Log of age-adjusted self-harm death rates		Dep Var: Log of age-adjusted alcohol-related death rates		Dep Var: Log of age-adjusted drug-related death rates	
ln(Commodity revenue based on state prices)	0.045 (0.041)	0.006 (0.033)	-0.027 (0.056)	-0.009 (0.037)	0.015 (0.088)	-0.041 (0.051)
Mean Outcome (level, per 1k)	0.159	0.159	0.120	0.120	0.091	0.091
Controls	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,973	3,973	3,182	3,182	790	790
R ²	0.372	0.372	0.401	0.402	0.892	0.892

Notes: Standard errors clustered at the county level in parentheses. Mean outcome reports the level of age-adjusted mortality rates per 1,000 persons. Controls include neighboring-county commodity revenue and county-level lagged employment and income. The mediation analysis has fewer observations than the main results because the CDC suppresses low count mortality data to protect privacy. *** p < 0.01, ** p < 0.05, * p < 0.1

TABLE A13: TWFE estimates of rural mortality and commodity revenue by gender and by cause of death (CVD or mental health-related), 1980 to 2019.

	(1) Female	(2) Male	(3) Female	(4) Male	(5) Female	(6) Male	(7) Female	(8) Male
	Corn		Soybeans		Corn		Soybeans	
	Dep Var: Log of age-adjusted CVD death rates				Dep Var: Log of age-adjusted mental health death rates			
ln(Commodity revenue based on state prices)	-0.010	-0.002	-0.014**	-0.005	-0.064	0.169*	0.023	-0.001
	(0.008)	(0.008)	(0.006)	(0.006)	(0.108)	(0.087)	(0.053)	(0.055)
Mean Outcome (level, per 1k)	2.948	4.624	2.948	4.624	0.144	0.209	0.144	0.209
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,115	16,115	16,115	16,115	1,236	1,236	1,236	1,236
R ²	0.683	0.742	0.683	0.742	0.661	0.656	0.661	0.655

Notes: Standard errors clustered at the county level in parentheses. Mean outcome reports the level of age-adjusted mortality rates per 1,000 persons. The mediation analysis has fewer observations than the main results because the CDC suppresses low count mortality data to protect privacy. *** p < 0.01, ** p < 0.05, * p < 0.1

TABLE A14: TWFE estimates of rural mortality and commodity revenue by gender and by cause of death (self-harm, alcohol-related, or drug-related), 1980 to 2019.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male
	Corn		Soybeans		Corn		Soybeans		Corn		Soybeans	
	Dep Var: Log of age-adjusted self-harm death rates				Dep Var: Log of age-adjusted alcohol-related death rates				Dep Var: Log of age-adjusted drug-related death rates			
ln(Commodity revenue based on state prices)	-0.007	0.035	0.071	0.067	-0.197**	-0.069	-0.104	0.067	0.469	0.993**	0.379	0.425
	(0.087)	(0.095)	(0.062)	(0.079)	(0.096)	(0.125)	(0.066)	(0.079)	(0.416)	(0.394)	(0.593)	(0.644)
Mean Outcome	0.105	0.240	0.105	0.240	0.097	0.179	0.097	0.179	0.099	0.128	0.099	0.128
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,080	1,080	1,080	1,080	1,078	1,078	1,078	1,078	46	46	46	46
R ²	0.600	0.393	0.601	0.393	0.467	0.385	0.466	0.386	0.934	0.943	0.949	0.928

Notes: Standard errors clustered at the county level in parentheses. Mean outcome reports the level of age-adjusted mortality rates per 1,000 persons. The mediation analysis has fewer observations than the main results because the CDC suppresses low count mortality data to protect privacy. *** p < 0.01, ** p < 0.05, * p < 0.1

TABLE A15: Falsification analysis – TWFE estimates for correlation between urban mortality and commodity revenue, 1980 to 2019

	(1)	(2)	(3)	(4)
		Corn		Soybeans
	Dep Var: Log of age-adjusted death rates per 1k persons			
ln(Commodity revenue based on state prices)	0.021*** (0.006)	0.007 (0.007)	0.004 (0.006)	-0.002 (0.005)
ln(Neighbor commodity revenue based on state prices)	-0.006 (0.007)	0.008 (0.007)	-0.012 (0.008)	-0.003 (0.008)
County lag employment (1k persons)		-0.000*** (0.000)		-0.000*** (0.000)
ln(County lag income)		-0.128*** (0.012)		-0.127*** (0.012)
Constant	1.889*** (0.085)	3.771*** (0.174)	2.260*** (0.087)	4.084*** (0.172)
Mean Outcome (level, per 1k)	8.510	8.510	8.510	8.510
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	11,220	11,220	11,220	11,220
R ²	0.767	0.784	0.766	0.783

Notes: Standard errors clustered at the county level in parentheses. Mean outcome reports the level of age-adjusted mortality rates per 1,000 persons.
 *** p < 0.01, ** p < 0.05, * p < 0.1

TABLE A16: Falsification analysis – TWFE estimates for correlation between unrelated cause-specific rural mortality and commodity revenue, 1980 to 2019

	(1)	(2)	(3)	(4)
	Corn		Soybeans	
	Dep Var: Log of age-adjusted death rates due to infection or birth defect per 1k persons			
ln(Commodity revenue based on state prices)	0.053 (0.041)	0.047 (0.041)	0.010 (0.028)	0.014 (0.028)
ln(Neighbor commodity revenue based on state prices)	-0.032 (0.052)	-0.044 (0.052)	-0.061 (0.037)	-0.061* (0.037)
County lag employment (1k persons)		-0.038*** (0.009)		-0.038*** (0.008)
ln(County lag income)		0.208 (0.155)		0.224 (0.155)
Constant	-2.256*** (0.636)	-4.337** (2.096)	-1.092** (0.489)	-3.715* (2.017)
Mean Outcome (level, per 1k)	9.217	9.217	9.217	9.217
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	4,409	4,409	4,409	4,409
R ²	0.372	0.375	0.372	0.375

Notes: For the falsification test, we use death due to certain infections and parasitic diseases and congenital malformations, deformations, and chromosomal abnormalities, which should not be correlated with commodity prices. Standard errors clustered at the county level in parentheses. Mean outcome reports the level of age-adjusted mortality rates per 1,000 persons. The falsification analysis has fewer observations than the main results because the CDC suppresses low count mortality data to protect privacy. *** p < 0.01, ** p < 0.05, * p < 0.1