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ADAPTATION TO ENVIRONMENTAL CHANGE: AGRICULTURE AND THE UNEXPECTED INCIDENCE OF THE ACID RAIN PROGRAM

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ABSTRACT

The Acid Rain Program (ARP) cut sulfur dioxide (SO2) emissions from power plants in the United States, with considerable benefits. We show this also reduced ambient sulfate levels, which lowered agriculture productivity through decreased soil sulfur. Using plant-level SO2 emissions and an atmospheric transport model, we estimate the relationship between airborne sulfate levels and yields for corn and soybean. We estimate crop revenue losses for these two crops around $1-1.5 billion per year, with accompanying decreases in land value. Back of the envelope calculations of the costs to replace lost sulfur suggest producer responses were limited and suboptimal.

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> "[...] changes in sulfur emission management, primarily due to the Federal Clean Air Act, have significantly reduced the amount of sulfur released into the atmosphere. While a good thing for the environment in general, these stricter laws have created some severe shortages of sulfur for farmers already struggling to grow crops on marginal lands."
>
> ("Sulfur deficiency cutting yields in sandy Southeast soils, 2012")

In 1995, the Acid Rain Program (ARP) regulated sulfur dioxide (SO2) emissions from coal power plants across the Midwest and Eastern United States (US). Environmental Protection Agency (EPA) reports credit the ARP and associated reductions in "acid rain" with protecting forests, lakes, and rivers from dangerously high soil and water acidity (Clean Air Markets Division, 2006), and reduced mortality (Barreca, Neidell and Sanders, 2017). A recent hypothesis among the agricultural science community suggests the ARP fundamentally altered a decades-old contribution to agricultural inputs, reducing beneficial regional sulfur deposition. Burning coal increases atmospheric sulfur flows, and sulfur is a key nutrient in the cultivation of modern high-yield crops. We present evidence that reducing sulfur pollution from power plants removed a source of nutrients for crops, presenting a rare case where pollution removal itself imposed a negative externality on a sector of the economy. The worldwide magnitude of coal-fired plants and the importance of agriculture for societal welfare make this an important finding.

Our study makes two contributions to the environmental policy and agricultural literature at large. First, we test the causal link between ambient sulfur pollution and agricultural output in a large-scale, real world application using a quasi-experimental framework. While prior randomized experiments tested the importance of sulfur as a nutrient in controlled settings, various factors make it difficult to use results from these experiments to infer a priori effects of SO2 emissions and the ARP across the U.S. For example, soil drainage and rainfall rates both alter the returns to ambient sulfur. Simple cross-sectional or time series correlations between ambient sulfur pollution and agricultural output in the real world could be biased by confounders, like climatic conditions or business cycles. The end effect of an atmospheric change is also uncertain unless one can predict the responses of producers — research shows agricultural producers do not always optimally adapt to changes in sulfur needs (Weil and Mughogho, 2000; Harou et al., 2019). Our empirical approach exploits the installation of sulfur control technologies at ARP-regulated plants, with treatment intensity determined by an atmospheric transport model, to test for changes in county agricultural yields over time.

Second, we examine the adaptability of agriculture in the face of a structural shift in environmental conditions. Agents can adjust in response to a changing environment leading to smaller long-run costs.[1] Economic concerns over climate change makes forecasting the scope for adaptation in different settings a critical direction for research (Schlenker and Roberts, 2009; Feng, Oppenheimer and Schlenker, 2012; Fisher et al., 2012; Deschenes and Greenstone, 2007), but applied studies using structural shocks remain limited. Some examples include Hornbeck (2012) showing farmers were slow to adapt to new soil conditions after the 1930's Dust Bowl, and Burke and Emerick (2016) examining gradual temperature shifts over 20 years. The sulfur-agriculture link is an important case in adaptation since soil sulfur levels are costly to monitor at the individual farm level and agricultural yields vary significantly from year to year, making it difficult to identify sulfur deficiencies.

Our empirical approach uses a continuous difference-in-differences strategy comparing within-county changes in agricultural yields based on exposure to changes in ARP-regulated plants. The height of coal plant smoke stacks means SO2 pollution travels large distances. We construct treatment intensity based on an atmospheric transport model, power plant SO2 output, and ARP-driven technological upgrades to coal plants intended to reduce sulfur emissions. To quantify impacts on crop agriculture, we examine annual yields for corn and soybean, the two largest crops in the US by acreage and revenues and the crops with the most

[1]For example, Barreca et al. (2013) show long-run technological innovation greatly reduced the health costs of extreme temperatures.

widely-available longitudinal data. As a measure of financial losses net of crop substitution or other such unobservable adjustment, we investigate impacts on farm income, crop revenues, and land value directly, as well as collections on crop insurance as a potential offsets to losses.

Our regression results indicate ARP-associated air improvements decreased receipts for corn and soybean by \$1-1.5 billion a year, and decreased agricultural land values by an average of 7%, or approximately \$1.4 billion. These additional social welfare costs are small compare to the \$120 billion in estimated annual benefits of the program, most of which accrue to human health (Chestnut and Mills, 2005), and the ARP remains a large social net positive. But these costs represent a substantial share of overall program costs, which the EPA had formerly estimated at approximately \$3 billion per year.[2] This shows SO2-abatement policies have unusual and previously undocumented distributional impacts on agriculture. Anecdotal evidence suggests this spillover is not unique to US agriculture. SO2 levels in China decreased by 75% from 2007 to 2017 (Li et al., 2017). At the same time, sulfur deficiencies in China became more of a concern within the industry.[3] Future policy programs designed to reduce ambient sulfur should consider these additional spillovers into the agricultural sector.

We provide evidence yield decreases and financial losses from sulfur shortages persist almost 20 years after the ARP. We cannot rule out that our results are net of some adaptation; but back-of-the-envelope calculations suggest producers are adapting at a suboptimal level. Based on sulfur usage by crop type and average fertilizer prices, we estimate the cost to fully replace lost sulfur via fertilizer would be \$40-60 million for corn and soybean, a relatively small adaptation cost compared to the losses in yields. Using literature from agricultural

[2] *Acid Rain Program Benefits Exceed Expectations*, www.epa.gov/capandtrade/documents/benefits.pdf.

[3] Taken from The Sulfur Institute (TSI) report for the Fertilizer Industry Round Table (FIRT), *Agricultural Demand for Sulphur — The Challenges, The Future*, downloaded from http://www.firt.org/sites/default/files/TFI\%20FIRT\%20Outlook\%20-\%20Agricultural\%20Demand\%20for\%20Sulphur\%20-\%20TSI.pdf and accessed on May 4, 2018.

extension centers and field publications, we show suggestive evidence that the industry remained unaware of the ARP's impact on yields for a decade.[4] The slow pace of adaptation was likely driven by complications in sulfur testing at individual producer level. Aggregated information available to regional extension centers helped the industry better understand the proper response. This case highlights the important role of centralized institutions in consolidating information when signals of productivity are noisy.

1 The Acid Rain Program

Acid rain concerns in the 1970s spurred the Acid Deposition Act of 1980, a 10-year program to monitor ambient SO2, precipitation acidity, and sulfur deposition. Lessons from the Acid Deposition Act led to the Acid Rain Program, a provision of the Clean Air Act Amendments of 1990. The ARP had two phases. Phase I began in 1995, regulating the 110 US power plants with the highest SO2 emissions. In 2000, Phase II further constrained emissions and added over 900 additional plants to the program. Both phases used an SO2-emission cap and trade system, and all plants were subject to regulation regardless of age. We focus on Phase I in our analysis since firms could bank permits from year to year and smooth emissions across Phase II, but not Phase I. As a result, there is relatively little change in SO2 emissions at the start of Phase II (Siikamäki et al., 2012; Ellerman et al., 2000).

The EPA distributed SO2 allowances to 263 power generation units at the 110 plants based on baseline (1985-1987) "heat input" (Stavins, 1998).[5] "Heat input" is the heat used to produce a given amount of electricity, expressed in British Thermal Units (BTUs), and the EPA calculates the value by multiplying the quantity of fuel burned by the heat rate of the fuel. The generation units chosen all corresponded to an average annual emissions rate of over 2.5 pounds of SO2 per million BTUs, and permits granted were designed to get plants

[4]David, Gentry and Mitchell (2016) notes decreased sulfate levels in samples taken from agricultural watersheds from lowered sulfur deposition potentially from the ARP, which also supports this finding.

[5]Additional allowances were available under special provisions. See Stavins (1998) and Joskow and Schmalensee (1998) for details on the political economy of the SO2 trading program.

to reduce average emissions to 2.5 pounds of SO2 per million BTUs (Carlson et al., 2000). Regulated plants report emissions to the EPA each year, ideally holding permits for each ton of SO2 produced. Plants can bank unused permits, and sell or transfer permits across years. For plants polluting in excess of held permits, the EPA assigns a fine adjusted for inflation (initially $2,000) per ton of overage and, in addition, requires eventual accounting for overages by purchasing sufficient permits at market price.[6] The EPA reports the ARP achieved close to full compliance, with large decreases in wet sulfate deposition (sulfates transferred through rain, snow, and fog) and ambient sulfur dioxide. Much of the reduction came from a transition to sulfur scrubbers, shutting off older and less efficient boilers, and adoption of low-sulfur coal (Siikamäki et al., 2012).

We primarily consider the role of the ARP in SO2 emissions in this paper, but the ARP-induced changes in other pollutants that could also shift crop yields. The ARP regulated nitrogen oxides (NOx) to a lesser degree, and despite no specific ozone (O3) controls, NOx reductions may alter the O3 formation process. NOx can alter soil acidity and nitrogen levels (EPA, 1999). O3 can negatively affect yields by directly damaging plants: two recent papers directly consider the role of ground level O3 is damage to corn and soybean yields, Boone, Schlenker and Siikamäki (2013) and McGrath et al. (2015). The ARP had smaller effects on these other correlated pollutants — the majority of NOx emissions in the United States are from transportation, so the relative effect of the ARP on NOx (and subsequent O3) levels is smaller than the effect on SO2. Regardless, in later analysis we control for such alternate pollutants, and show that the weight of the change in crop yields falls on shifts in ambient sulfur. The following section presents the scientific baseline for this finding.

[6]The EPA gave plants a 60-day grace period to buy additional permits from other firms needed to avoid the fines. Over much of the program, the nominal cost of an SO2 permit fluctuated between $100 and $200 per ton. Costs increased in 2004, with price peaking over $1,200 per ton, as firms began banking additional permits in anticipation of the Clean Air Interstate Rule, which took effect in 2005. A series of lawsuits threatening the Clean Air Interstate Rule and additional policies caused prices to fall rapidly in 2006, with prices below $1 in 2012. See Schmalensee and Stavins (2013) for in-depth discussion of SO2 markets.

2 Airborne SO2, Sulfates, and Agriculture

Sulfur pollution reductions from the ARP could affect agricultural output through pure sulfur (S) and three sulfur compounds: SO2, sulfuric acid (H2SO4), and sulfate (SO4). SO2 is a byproduct of fossil fuel combustion emitted from power plant smokestacks. Sulfuric acid, sometimes called hydrogen sulfate (H2SO4), is the main determinant of "acid rain," forming when SO2 combines with oxygen (forming SO3) and water (H2O) in the troposphere. Sulfate (SO4) is a residual from dilution of H2SO4 in water, and a common byproduct of H2SO4 deposition. Sulfur (S) is the base chemical element.

These all have potentially disparate impacts on crop output, making the *a priori* effect of airborne SO2 reduction ambiguous.[7] SO2 and H2SO4 may damage leaves, and H2SO4 may raise soil acidity. However, soil acidity in itself is less of a concern with field crops than in forest areas, given regular fertilizer use helps "buffer" the detrimental effects.[8] Conversely, ground-level S and SO4 plays a fundamental role in crop growth. Field crops consume soil sulfur as part of the germination process, and extreme cases of insufficient soil sulfur levels at key points in the growth process cause yield reductions up to 75%.[9]

[7]For an extensive review of the agricultural science literature on the role of sulfur, see EPA (2008). Experimental research under controlled field conditions found direct exposure to H2SO4 on field crops caused little damage. Irving and Miller (1981) tested differential effects from sulfur deposition via exposure to H2SO4 versus exposure to airborne gaseous SO2. When administered alone, gaseous SO2 accelerated aging and increased leaf fall in soybean. Exposure to acid rain alone did not significantly impact soybean yields, but did improve seed growth, which the authors hypothesized was due to the beneficial effect of additional sulfur and nitrogen absorption. Exposure to gaseous SO2 and acid rain simultaneously had no net effect.

[8]`articles.chicagotribune.com/1987-12-28/news/8704060486_1_acid-rain-soybeans-crops`. See also the EPA discussion of acid rain and soil damages, available online at `http://www3.epa.gov/acidrain/effects/forests.html`, accessed February 18, 2016.

[9]From an article published in the Southeast Farm Press in August of 2012 ("Sulfur deficiency cutting yields in sandy Southeast soils"), "Yield losses from sulfur deficiency, especially in corn, can be catastrophic, if the problem isn't addressed quickly. Research has shown that for each day sulfur is deficient, past the first 21 days after corn emerges from the soil, there is a loss of 1-2 bushels per day. If sulfur is deficient when corn is in the silking stage, yields could be reduced by as much as 75 percent."

3 Data

Our crop data are from two sources: crop data are from the United States Department of Agriculture (USDA), and land value and expenditure data are from the bi-decadal Census of Agriculture (COA), taken in years ending in 2 and 7. With our primary sample, we include three COAs before the ARP (1982, 1987, and 1992) and three after (1997, 2002, and 2007). We end our primary sample in 2007 to minimize confounding from the Clean Air Interstate Rule, which took effect in 2006, and biofuel subsidies, which began in 2007.[10] Crop data include all years between 1982 and 2007, not just COA years. Following Schlenker and Roberts (2009), we focus on counties east of the 100-degree meridian since this area covers almost all corn- and soybean-growing counties, and Phase I did not regulate plants west of the 100th degree. We only include counties for which we have a non-missing county/year observation for 1982 and 2007. In cases with missing data between those years, we use linear imputation, and include a regression where we add a fixed effect indicator for imputed years. As a further robustness check, we also consider the persistence of effects through 2017.

There are several years with droughts that had drastically different effects across regions. As these shocks could correlate with geography and thus potentially with treatment exposure (see Appendix B), we run several robustness checks where we (1) include more flexible region-by-time fixed effects and (2) split the sample years into drought and non-drought years. We also explore standard errors that allow for various degrees of geographic correlation to address potential for regionally common shocks.

Crop yield data: Crop data come from surveys conducted by the U.S. Department of Agriculture (USDA) National Agricultural Statistical Service (NASS). We construct log county-level yields per acre using yield in bushels divided by planted acres.[11] Given the

[10]The Clean Air Interstate Rule introduced additional regulator consideration to address downwind states, which may shift the importance of general plant proximity. Biofuels subsidies could incentivize farmers to expand corn and soybean planting to more marginal lands, which could pull down mean yield per acre — if regions near treated plants have different acreage availability, this could correlate with ARP treatment.

[11]We have also run results using yield per acre as reported in the data, which is yield per harvested acre.

NASS survey is voluntary, some county/year cells have missing data. Conversations with NASS data specialists at the USDA indicate they mask some yearly data when there are too few farmers reporting, causing privacy concerns, or when neighboring counties have privacy concerns.

Weather: In the chance local weather fluctuations correlate with both the timing of the ARP and location of regulated plants, we control for temperature and rainfall using data from the PRISM climate group.[12] As in Schlenker and Roberts (2009), we focus on weather during the optimal growing season (March-August). We control for the number of days the maximum temperature falls in 3 degree Celsius bins and the number of days the minimum temperature falls in 3 degree bins.[13] We also control for a quadratic in cumulative rainfall over the growing season.

Coal plant data: We obtain a list of all ARP power plants from EPA Air Markets Program Data. Prior to the ARP, plant-level SO2 emissions are available every 5 years, in years ending in 0 or 5 (1980, 1985, 1990). These data include boiler-level information on SO2 output, which we use to construct our atmospheric concentration measures. The data also list the specific year of installation for any sulfur reduction technology.[14] It is this final piece of information that we use to construct our measure for ARP-related ambient airborne sulfate levels.[15]

Pollution data: We use two sources of pollution data. Our primary method uses EPA daily monitor-level pollution data to test effects on SO2, O3, and NO2, reported in ppb or ppm (parts per million) depending on the pollutant. We construct county-year measures

The two could differ due to crop losses that alter harvestable acres, but sign and magnitudes of all results are robust to using either measure.

[12]The ARP could have an impact on weather due to changes in atmospheric pollution. Controlling for weather affects the interpretation of the reduced-form parameter.

[13]We group all temperatures below 0 degrees Celsius into a single bin, and use the temperature range of 27-30 degrees Celsius as the omitted group for each.

[14]The data list the year of installation even if it is not the reporting year. For example, the 1995 data will list installations that occur in 1994, noting the relevant date.

[15]See `http://ampd.epa.gov/ampd/`.

of pollution by calculating the distance between each monitor and each county centroid, then collapsing monitor data to the county-by-year level using inverse distance weights for distances up to 50 miles. As with crop output, we use data from counties in which we have at minimum observations in 1982 and 2007, and impute missing years. As an alternate source that expands the number of counties, we use a Land-Use Regression model provided by the Center for AIR, Climate, & Energy Solutions (CACES)[16]. This model uses information on monitor emissions, combined with known pollution sources and local conditions, to generate an annual airborne concentration estimate for all three pollutants. Because these are modeled results, data are available in all years and for all counties. This allows us to expand our sample at the cost of using largely imputed data for many counties with no true pollution monitors.

We build anticipated annual county-level airborne sulfates using data on ARP-plant SO2 emissions and the second iteration of the Air Pollution Emission Experiment and Policy Analysis (APEEP) model (Muller, 2014). This model takes as input SO2 emissions in a given county and, by taking into account local factors such as topography, wind direction, and dispersion patterns, estimates how that SO2 results in changing airborne sulfate levels in all other counties in the United States. Here, airborne sulfates refers to both basic "sulfate" (SO4) and ammonium sulfate ((NH4)2SO4) combined. Ideally, we would examine direct changes in soil deposition as an additional test of the policy mechanism. However, deposition data are limited. Data are available from the EPA Clean Air Markets Division, Clean Air Status and Trends Network (CASTNET) Total Deposition data, but at only 130 monitor points and not across all years.[17] Using these limited data, we show changes in airborne sulfates line up very well with changes in H2SO4 deposition. When matching predicted county-level sulfur levels to county-matched deposition monitors, our sulfate measure and

[16]https://www.caces.us/data.

[17]Deposition data are available at `www.epa.gov/castnet`. Date accessed: January 11, 2016.

H2SO4 deposition have a correlation coefficient of approximately 0.90; Appendix Figure A-1 illustrates this relationship visually.[18]

Other variables: We use a number of county-level economic variables from the Bureau of Economic Analysis (BEA) Regional Economic Accounts Local Area Personal Income dataset. Using these data, we calculate employment rate (total wage employment divided by total population), farm and nonfarm income per capita, and fertilizer expenditures per acre of cropland. Fertilizer expenditure data are based on questions from the COA. The BEA interpolates fertilizer usage data at the county level between non-COA years by incorporating year-to-year variation in available state-level data.[19] We calculate average fertilizer expenses per acre by dividing by each county's total acreage for crops.[20] For variables involving dollar values we adjusted to 2017 dollars using annual Consumer Price Index data from the Bureau of Labor Statistics.

An additional confounder is the expansion of crop insurance in the United States. A policy change increased the fraction of crops covered by crop insurance in 1995, the same time as the first enforcement of the ARP. We use data from the USDA Risk Management Agency (RMA) to examine the number of insurance policies claimed by crop and total dollar value of insurance collections by crop.

Summary statistics: Appendix Figure A-2 shows all counties in our analysis with data available for SO2 (1,215 counties), sulfates (2,490 counties), corn (1,614 counties), and soybean (1,344 counties) — pollution and crop data are not available for a fully matching set of counties, and as such the number of counties used to derive estimates varies by outcome. Panel A of Table 1 shows means for county-level airborne SO2, sulfate particulates, soybean, and corn yields per acre, as well as soybean and corn acreage. Columns 1 and 2 split means

[18] The figure shows sulfur deposition (in kilograms per hectare) versus ambient sulfates (in $\mu g/m^3$).

[19] See *Local Area Personal Income Methodology*, available online at `http://www.bea.gov/regional/pdf/lapi2016.pdf`, (accessed January 14, 2016) .

[20] We linearly interpolate total acreage at the county level in the non-COA years.

into the 1982-1994 and 1995-2007 periods, or pre- and post-ARP. Average contemporaneous SO2 levels across the period are 7.8 ppb before the ARP, down to 4.4 ppb after. Airborne sulfates move similarly, starting at 7.1 $\mu g/m^3$ and dropping to 4.6 $\mu g/m^3$ in the later period. Both average corn and average soybean bushels per acre are increasing over time. Average corn yield is 80.5 bushels per acre prior to the ARP, and 101.0 after. Country acreage dedicated to corn also increases across the period, from an average of 42,062 acres pre-ARP to 44,101 acres post-ARP. Average soybean yield is 29.4 bushels per acre prior to the ARP, and 34.6 after. Growth in soybean acreage was more drastic, rising from an average of 44,029 acres per county to 51,152.[21]

4 Method

The ARP was split into two phases: Phase I and Phase II.[22] Phase I began in 1995, with additional power plants added in Phase II in 2000. Much of the reductions in SO2 occurred after Phase I, which we make the focus of our analysis. We employ a pollution transport model that predicts county sulfate levels based on SO2 emissions throughout the United States. We first obtain a list of all ARP plants and their associated boilers from the EPA Air Markets Program Data, which includes the location of each plant. We use data on SO2 emissions at the plant level as inputs into the APEEP atmospheric transport model to predict sulfate concentrations for each county throughout the region. The APEEP model takes SO2 emissions from a given county, and, after accounting for factors such as topography, wind direction, and average source type, predicts how this SO2 converts into airborne sulfates for all other counties (as well as the emitting county).

For example, a Phase I power plant exists in the county of Franklin County, MO (FIPS code 29071). According to the atmospheric transport matrix, the conversion rate between a

[21] In calculation of our yield per acre here, we do not weight by county-level crop-specific acreage as we do in regressions.

[22] We follow an identification strategy very similar to Barreca, Neidell and Sanders (2017). As a result, much of this section mirrors text from that work.

ton of SO2 produced in Franklin County, MO and a microgram per cubic meter of sulfates in the same county is 0.0000209. The conversion for nearby St. Louis, MO county (FIPS 29189) is 0.00000125, and for further away Wayne County, MI (FIPS 26163) is 0.000000665. Thus, 100,000 tons of SO2 produced in Franklin County, MO would predict an additional 2.09 micrograms per cubic meter of PM2.5 in Franklin County, MO, 0.125 additional units in St. Louis County, MO, and 0.0665 units in Wayne County, MI.

Our model premise is that, in response to the ARP, coal power plants reduced SO2 emissions from pre-ARP levels, which then led to reductions in ambient sulfates across not only the county in which the plant resides but also, to varying degrees, all other counties. Our measure of sulfates does not describe the total levels in a given county, but rather the contribution to levels in a given county from ARP-associated power plants. EPA data on plant-level emissions are available annually beginning in 1995. Prior to that, measures are provided every 5 years: 1980, 1985, and 1990. To estimate boiler-level emissions for the years with missing data, we assume constant emissions from the last year of available data (e.g., we assign 1980 levels to 1981-1984, 1985 levels to 1986-1989, and 1990 levels to 1991-1994). Based on the limited changes in SO2 emissions between 1980 and 1985, and 1985 and 1990, we view this as an appropriate approximation. If plants lower emissions in 1994 in anticipation of the ARP, this may inflate the change in predicted emissions between 1994 and 1995. Other data sources, such as monitor-level data for county-level SO2 concentrations, supports the assumption that the most substantial change in emissions occurred in 1995.

Our empirical approach exploits plant-level timing of the installation of sulfur-control technologies, such as Flue Gas Desulfurization, that collect SO2 before being released out of stacks.[23] We define our treatment variable, new sulfur controls (SC), as the exposure to

[23]Installation of sulfur control technology results in rapid and lasting reductions in plant-level SO2 emissions, with reductions from 50% to 98%, obtained from "Air Pollution Control Technology Fact Sheet" EPA document EPA-452/F-03-034.

sulfur control installations that accounts for the transport of emissions from these boilers:

$$SC_{c,t} = f(\text{Phase I Sulfur Controls}_{i,t}) * 100,000, \tag{1}$$

where $SC_{c,t}$ is the measure of exposure to boiler sulfur control installations, $f()$ is the atmospheric transport model, and sulfur controls addresses the sum of all Phase I boilers with sulfur-controlling technology installed in the specified year in a given county. We multiply this by 100,000 for ease of reading coefficients.

Returning to our prior example, we now illustrate the treatment intensity Franklin County, MO would receive from the top three outside county contributors with upgrades present by 1995: Gibson, IN (FIPS 18051), Carroll, KY (FIPS 21041), and Warrick, IN (FIPS 18173). In practice, emissions from multiple counties contribute, but we focus on these for illustrative purposes. The conversion matrix assigns the following receiving weights: 0.000000395 for Gibson, IN; 0.000000312 for Carroll, KY; and 0.000000303 for Warrick, IN. Gibson, IN and Carroll, KY each had one Phase 1 sulfur control in 1995, while Warrick, IN had two. If we based $SC_{c,t}$ on only these three outside counties, Franklin County would receive a value of:

$$100,000 * (1 * 0.000000395 + 1 * 0.000000312 + 2 * 0.000000303) = 0.1313.$$

Figure 1 illustrates how the policy affected plant behavior, and how we operationalize this to address data limitations. Panel A shows the running tally of installed controls on Phase I boilers, by month and year. The majority of Phase I control installs occurred either just before, during, or shortly after 1995, and remain largely stable after that. This supports our assumption of assigning 1990 emissions to the years 1991-4, and shows the sharp impact of the ARP on these plants response to the policy.

To understand the impact of these sulfur control installations on emissions, Panel B shows an event study of boiler-level emissions, where the relevant treatment year (0) is the year in which plants install sulfur control technology. We control for boiler and year fixed effects, and assign all power plants that do not install control technology in our period a period of 0. The model shows that a Phase I boiler with such technology installed saw reductions of an average of around 40,000 tons of SO2 annually (we cluster standard errors at the boiler level). This suggests installation of sulfur-controls is a strong predictor of plant-level emissions changes. While Phase II control installations also reduce boiler-level emissions, the effects are much smaller.

Panel C shows the trends in total boiler emissions by year and plant Phase, which also illustrates that (1) the majority of reductions appear in 1995, and (2) all reductions are due to Phase I plant behavior. On net, Phase I plants reduced SO2 output by around 50 million tons in 1995, while Phase II plants saw largely no change, and even small increases early on. Our model approach assumes each sulfur control installation reduces pollution by the same amount. We favor this approach from further weighting by baseline boiler emission level for simplicity of exposition. We also explore models in which we further weight installed sulfur controls by baseline emissions, and show results are consistent.

Appendix Figure A-3 illustrates the county-level values of our upgrade exposure in the first year in our sample (1982), the first year of the ARP (1995), and the last year in our primary sample (2007). The figure highlights several important factors. First, the exposure to upgraded Phase I plants is zero in the beginning of our sample, with substantially higher levels across the country in 1995. Second, from 1995 to 2007, there is little change in county-level exposure to upgraded plants, as most of the large upgrades occurred in the first year of the ARP. Finally, if upgrades reduce emissions, we expect the majority of the pollution benefits from the ARP to play out in the Midwest and Northeast, which projects the largest treatment effects due to location of Phase I ARP plants and atmospheric dispersion patterns. Figure 2 illustrates that predicted sulfate changes line up with our measure of treatment intensity. Graphs show the ARP-associated sulfate predicted by the APEEP model in 1982, 1995, and 2007. As with our measure of upgrade exposure intensity, we see large changes in predicted sulfate in the Midwest and Northeast between 1985 and 1995, but little additional change by 2007.

Our reduced form regression model is:

$$outcome_{c,t} = \beta SC_{c,t} X Post_t + \omega_{c,t} + \lambda_t + \gamma_c + \phi_c * year + \eta_{c,t} \ , \tag{2}$$

where $outcome_{c,t}$ is our outcome in county c in year t, $SC_{c,t}$ is each counties weighted sum of exposure to Phase I plant upgrades in a given year, and $Post$ is an indicator for years t greater than or equal to 1995. We include a vector of weather controls for temperature and rainfall, ω, and year and county fixed effects (λ and γ, respectively) — see Section 3 for a detailed description of weather variables. We also control for county-specific time trends to address potential confounders such as increasing agricultural yields over time. For corn and soybean, we weight regressions using annual county crop-specific acreage, and for all COA-based variables we weight by annual county total crop acreage. In robustness checks, we weight each observation by the county's average pre-ARP acreage values as a check on the concern that total acreage is endogenous to the policy. We do not weight pollution regressions. We cluster all standard errors at the level of crop reporting district (CRD). CRDs are made up of multiple contiguous counties, divided into areas of approximate similar size, with similar soil types and growing conditions. This allows for common errors within contiguous counties classified as similar in agricultural makeup. We also explore clustering by state, using spatially-correlated Conley standard errors, and bootstrapped errors cluster-sampled by year.

This model compares the change in outcomes for counties by relative exposure to upgraded Phase I plants, after controlling for general differences in geography, weather, and production trends. Our treatment measure, $SC_{c,t}$, captures that while boiler upgrades universally decreased SO2 emissions, the impact of those reductions varied across space due to wind patterns, topography, and geography.

To help explore the mechanism of the ARP's effects, we also use (2) as a first stage regression in estimating the marginal impact of airborne sulfates on our relevant outcomes. Our ordinary least squares (OLS) and second stage IV model is:

$$outcome_{c,t} = \beta sulfates + \omega_{c,t} + \lambda_t + \gamma_c + \phi_c * year + \eta_{c,t} \ , \tag{3}$$

where all other controls are as above. This estimates the marginal effect of an additional unit of airborne sulfates. Interpretation of marginal changes in ambient sulfates is in some ways less complex than the reduced form marginal change of weighted atmospheric transport values, and allows for a direct calculation of replacement costs of lost atmospheric sulfates.

5 Results

As a demonstration of our reduced form model, we split counties by "high" and "low" upgrade plant exposure as of 1995, the first year of the ARP and the year with the largest number of single plant controls installed. We define "high exposure" counties as those above the median of our $SC_{c,t}$ measure as of 1995, and "low exposure as those at or below the median measure of $SC_{c,t}$ in 1995.

The first graph of Figure 3 shows annual average ambient SO2 across these two groups. Both experienced declining pollution levels prior to the ARP's implementation, potentially due to deregulation of railroads in the early 1980s and related reductions in the cost of transporting and adopting low-sulfur coal (Ellerman and Montero, 1998). "High exposure" counties experienced a sharp decline in SO2 in the first year of the ARP of almost 2 parts per billion (ppb). There is a much smaller decline in SO2 in "low exposure" counties.

The second graph shows a similar pattern for projected airborne sulfates. Counties with greater exposure to sulfur controls saw airborne sulfate drops of almost 4 $\mu g/m^3$, while counties with lower exposure saw effectively no change. Effects are more drastic for sulfates than SO2, likely due to determining our sulfate measure using only ARP-related power plants, while SO2 data are from air monitors and cover all possible SO2 sources.

The third and fourth graphs of Figure 3 show log yield per acre for corn and soybean in the period of our analysis.[24] Yields just before the ARP were particularly variable — Appendix B provides background on changes in the agricultural sector around this time as well as discussion of relevant regional weather shocks. Our identification strategy mitigates the noise and potential biases from these general trends by focusing on changes in yields by level of exposure to sulfur control upgrades, while also controlling for area-specific time trends. The graphs suggest high treatment counties saw relative decreases in average yields, with a timing that corresponds to the beginning of the ARP.

The final graph in Figure 3 shows trends in log of crop receipts per acre. These data cover all crops, and thus represent changes in receipts beyond the corn and soybean outputs we consider. They also allow for prices to change across time, so in that sense represent a greater overall impact on producers. In this case, low exposure counties appear to be gaining crop receipts across time, while high exposure counties remain largely flat after the ARP.

5.1 Event Study Analysis

To explore different pre-trends by treatment exposure while controlling for weather, county, and year fixed effects, we next show basic event studies. This provides a visual test for time differences correlated with treatment exposure. Given our empirical model relies on continuous treatment intensity, we show the marginal effects across time rather than differences across binary treatment and control groups.

[24]We show the average of log yields for each group for consistency with our main regressions. The log of the average for each group has the same basic pattern.

Figure 4 shows annual estimates for marginal effects, with 95% confidence intervals. To approximate a standard event study with a singular change in treatment, we interact each year with the level of treatment each county receives in 1995. Figure 1 shows that the majority of airborne sulfate changes happened in 1995 alone. We treat 1994 as the baseline year, so each coefficient represents the marginal effect as compared to 1994. For example, a negative coefficient in 2002 indicates the regression-adjusted impact of our $SC_{c,t}$ measure was more negative in 2002 than it was in 1994.[25] Results for SO2 indicate no clear pre-trend across treatment exposure. There is a stark decline in SO2 in 1995. Sulfate levels follow a similar pattern but with a more drastic transition.

Crop yield results are noisier given substantial variation in annual yields. In a study of distribution of crop yields, Just and Weninger (1999) note, “Farm-specific randomness may be caused by errors in management, farm-specific resource constraints, and farm-specific weather and pest conditions. For example, the impact of floods depends on elevation, slope, and soil density while drought effects depend on soil depth and quality”. This makes year-by-year inference difficult. However, there is a downward shift in average yields after 1995 for both crops. For both corn and soybean, not a single estimate from 1995 onward is above 1994 levels. Crop receipts follow a similar pattern, with a decrease after 1995.

1993 is an outlier due to a confluence of bad events, including freezes, unusual rainfall, a Midwestern flood, a drought, and insects (see Appendix B). The large positive coefficient suggests that areas with that saw higher levels of our $SC_{c,t}$ measure by 1995 were comparatively less harmed by the confluence of these shocks. Given treatment is spatially correlated and the bad events are spatially correlated, it raises the possibility that random deviations are correlated with levels of treatment. We address the potential for spatial correlation in a series of robustness checks. Another possibility is that sulfur can buffer against negative shocks and that the treatment area had a higher baseline level of sulfur in the soil.[26] In later

[25] With all graphs we weight in the same manner as done in our regressions (see Section 4).

[26] “Sulfur (S) is an important secondary macronutrient that interacts with several stress metabolites to

regressions, we explore the interactive effects of drought and sulfates, and show that drought damages are more extreme in areas that also face reduced ambient sulfates.

To better quantify the ARP's impact, we next use our regression model in (2). Table 2 presents main specification results for ambient sulfate levels, corn yield per acre, and soybean yield per acre, with different sets of controls. Our model has variation across two dimensions: time and intensity: time allows the effect to vary across years, particularly before and after the ARP, and intensity allows for the post-1995 effects of the ARP to vary by exposure to ARP-related sulfur controls.

The estimated effect of the ARP is negative for all three outcomes, and in each case is economically significant and statistically significant at 1 or 5%. In our most basic specification (Column 1) controlling for only year and county fixed effects, we find exposure to an additional weighted unit of sulfur control (approximately 86% of a post-ARP standard deviation) correlates with a reduction in airborne sulfates of 1.6 $\mu g/m^3$, a reduction in corn yield of 3.6%, and soybean yield by 1.7% . Controlling for weather (Column 2) does little to change the results.

The addition of county trends (Column 3) does little to change the estimate for sulfates, but does increases the magnitude of the effects for both corn and soy. In our full model, an additional unit of treatment exposure correlates with a reduction sulfates of 1.2 $\mu g/m^3$, with an associated decrease in corn and soybean yields of 5.8% and 4.8%, respectively. Given the long-run general trend in increased agricultural output across this period, controlling for regional background trends matters for proper identification.

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improve performance of food crops under various environmental stresses including drought. Increased S supply influences uptake and distribution of essential nutrients to confer nutritional homeostasis in plants exposed to limited water conditions. (Usmani et al., 2020)

6 Estimates per Unit of SO2 and Sulfates

Thus far our focus has been the reduced form effect of the installation of sulfate control technology. To better investigate the role of sulfur, we next consider the effects of airborne sulfates directly. We begin with an OLS analysis, and then expand to an IV setting, using our reduced form measure of treatment exposure as an instrument airborne sulfate levels — our first stage F-statistics are always greater than 10.

Table 3 Panel A shows OLS results for corn yields. We find a statistically and economically significant increase in yields of 2.4-5.5% per $\mu g/m^3$ of sulfates. Panel B shows sulfate estimates are largely unchanged, ranging from 2.6-6.3%. Results for soybean follow a similar pattern. After controlling for county trends, the sulfate estimates are significant at 1% and range from 1.6-4.3%. In the IV, sulfate estimates are largely unchanged, ranging from 1.7-6.5% and remain significant at 1%.

7 Robustness Checks and Extensions

Table 4 explores sensitivity of our IV results to different control variables and samples. Appendix Table A-1 repeats this using our reduced form results.[27] Column 1 adds an indicator equal to 1 for each imputed observation. Columns 2-4 alter the choice of time controls. Column 2 expands county trends to quadratic. Column 3 replaces county trends with Crop Reporting District trends. Column 4 adds state-by-year fixed effects to adjust for state-level policy changes and regional changes in farming technologies. For example, genetically modified (GMO) strains for various crops first appeared in 1996, and state-by-year effects adjust for policies that either encourage or discourage adoption of GMOs. State-by-year fixed effects cause the largest change by reducing estimate magnitudes, particularly

[27] We also examined models with varied weighting assumptions. One model, omitting weights, ignores relative county crop magnitudes but is less sensitive to shifts in planting behavior. Another, weighting by the average crop acreage of the pre-ARP period, avoids post-policy endogeneity from planting behavior. Both caused effectively no change to our main results.

in the reduced form, which is also expected given treatment has a geographically correlated component. In all three cases the sign remains negative and statistically and economically significant. In Column 5, we drop all counties with Phase I or Phase II plants located within their borders. If economic effects of regulation, or effects of changes in copollutants, are largely local effects, what remains with our estimate is the isolated effect of transmitted sulfur.

Column 6 adds additional controls for O3. Prior research (Boone, Schlenker and Siikamäki, 2013; McGrath et al., 2015) suggests O3 can damage both corn and soybean. While the ARP did not regulate O3, it did generate the potential to change local O3 levels through two primary channels. First, SO2 can serve as a source of light refraction, and its removal via the ARP could increase O3 formation due to increased ground-level light. Second, the ARP had some impacts on NO2, a precursor pollutant to O3. The findings in Boone, Schlenker and Siikamäki (2013) suggests nonlinearities in O3, with particular sensitivity once hourly values exceed 77 ppm. As a control, we approximate this using the number of days in a year where county O3 average 8-hour readings exceed 77 ppm (which is more extreme). This reduces our coefficients somewhat, but effects remain statistically and economically significant.

Columns 7 and 8 separately consider effects for drought and non-drought years.[28] Our results support the idea of sulfur buffering stressful crop conditions; effects in drought years are 2-3 times as large for the reduced form and 4-10 times larger in the IV.

We also investigate the robustness of our results to alternative measures of treatment intensity. Similar to our main specification, in each of these tests we interact a measure of upgrades to ARP plants with an indicator for *Post*, though we now add additional weighting metrics. Appendix Table A-2 shows our results. Column 1 replicates our main results, while Column 2 adds an additional instrument that allows for Phase II plant upgrades interacted

[28]Drought years in our main sample include 1983, 1988, 1993, 1999, 2002, and 2005.

with a *Post* indicator as well. Columns 3 and 4 mirror 1 and 2, but weight results by the amount of SO2 each boiler released in 1985, the period used for calculation of initial permit allocations. Columns 5 and 6 mirror 3 and 4, but replace 1985 SO2 with 1985 heat output. In each case, our IV results are effectively unchanged. Given the robustness to different measures of exposure, we focus on our original model for ease of discussion.

As a further consideration, we explore various modeling assumptions for our standard errors. Our main analysis clusters by crop reporting district, an area made up of multiple contiguous counties. In Appendix Table A-3, we try alternate models. Column 1 replicates our main result. Column 2 omits weights as a comparison baseline, as we omit weights in the Conley and bootstrapped errors for computational simplicity. Weighting does little to change our main results. The following columns explore clustering at the state level, using geospatial (Conley) standard errors with a radius of 200 miles[29], and bootstrapped standard errors (stratified on years with replacement) with 10,000 replications. In all models results remain significant at 1-5%.

7.1 Pollutant Expansions

We test for alternative pollution mechanisms, but analysis by specific pollutant carries two challenges. First, data are limited by the availability of air monitor data. Second, many pollutants correlate with each other, and each could play a role in crop yields, which means considering independent pollution effects could induce bias. Appendix Figure A-4 shows raw trends and event studies for NO2 and O3, two other pollutants that could also impact crop yields. While transitions across the ARP are less drastic, there is suggestive movement, particularly with NO2, that may correlate with the ARP.

In Appendix Table A-4, we attempt to address both these concerns. To deal with limited monitor data, we expand pollution data to include the Land Use Regression (LUR) data,

[29]This process uses the Stata ado file "ols_spatial_HAC" from Hsiang (2010).

provided by the Center for Air, Climate and Energy Solutions (CACES). To address the issue of multiple pollutants, we run several separate OLS models (given our single instrument, we do not use the IV in multi-pollutant models). Using LUR data, we first show that controlling for LUR-estimated SO2, NO2, and O3 does little to change the coefficient on sulfates. We then repeat the exercise using a much more restricted data set on monitor-based measures. Restricting to a sample of counties with nonmissing data for all three pollutants cuts our sample to approximately 1/10th the size. This sample change decreases the magnitude of our sulfate estimate and, in the case of soybean, removes statistical significance. However, conditional on this lower estimate, adding the other pollutants does not change the estimate on sulfates. This evidence jointly suggests that the mechanism for our effect is airborne sulfates, which also aligns with the agricultural science.

8 Testing for Industry Adjustment

Given the observed reductions in yields, one consideration is whether this outcome is net of adjustment behavior on behalf of producers. Based on our investigation of the agricultural science literature, we do not find references to Clean Air Act-related sulfur loses until 10 or so years into the program. Further, we found several articles (see Appendix B that suggests that early on, producers confused sulfur shortages for nitrogen issues or were otherwise unaware of the link between air pollution, ambient sulfates, and ground sulfur levels. We test for industry-level responses to the ARP by examining a variety of additional outcomes. For ease of discussion, we compare our IV models, but results are similar in net effect when using the reduced form.

We first use planted acres as an outcome — farms may shift land to more productive uses as the ARP reduced yields. In Table 5, we show no economically significant change in reported acreage differences for corn or soybean. We also construct a measure of total crop acreage based on information from the agricultural census, interpolated for all non-ag census years, and see no economically or statistically significant changes. We next consider changes in the probability of reporting *any* harvested acres for corn or soybean to test for more drastic reductions in acreage. We find no change in the difference in the probability of a county reporting corn or soybean by treatment exposure.

We estimate reported spending on fertilizer expenditures per acre, using data from the REIS. In Appendix B we provide anecdotal evidence agriculture extension groups eventually proposed changes in baseline sulfur flows as a cause of recent increases in crop deficiencies, so to the extent producers already adapted by using more sulfur-based fertilizer (e.g., elemental sulfur and sulfate compounds such as calcium sulfate and ammonium sulfate), our welfare calculations underestimate the costs of the ARP. For example, a report from the "Corn and Soybean Digest" in 2009, shortly after our initial sample ends, notes adding sulfur was giving higher yields in some parts of Iowa, and suggested sulfur sales had jumped 30%[30]. The sulfur scrubbing process generates synthetic gypsum (calcium sulfate), which private companies sell as an additive marketed to improve soil drainage. If producers increased use of synthetic gypsum after the ARP, this might partially offset productivity losses. We find no statistically or economically significant effect on fertilizer expenditure per acre. This is a rough measure of fertilizer usage with imputed acreage for non-COA years, and it includes within it changes in prices, particular fertilizer mix choices, and quantities, so this result alone cannot verify there was no change in fertilizer mix or behavior.

In sum, we observe little behavioral response by producers in the first decade or so following the ARP. The structural shifts in productivity may have been hard to observe from the perspective of producers, especially in the context of the time trends. Agricultural yields were increasing over time, so any simple comparison between before and after the ARP's implementation would falsely suggest the ARP helped yields. Even if producers did

[30] "Does Sulfur Pay?", *Corn and Soybean Digest*, Feb 1 2009, available online at `http://cornandsoybeandigest.com/does-sulfur-pay`.

identify the shift in productivity, singling out sulfur deficiency as the causal mechanism would have been difficult. Sulfur deficiencies are often confused with nitrogen deficiencies (and vice versa), and soil tests for sulfur are more complex and less precise than tests for other minerals.[31] This highlights a role for institutions as disseminators of information in situations where subtle environmental shifts are difficult to detect on an individual level.

8.1 Expansion of Crop Insurance

The expansion of crop insurance in the United States is a potential confounder in identifying a link between sulfur reductions and losses in yields. As a result of the 1994 Federal Crop Insurance Reform Act, participation in crop insurance increased substantially around the same time as the passage of the ARP. If changes in the take-up of crop insurance: (1) result in changes in yields, (2) correlate with proximate intensity of SO2 emissions from Phase I plants, and (3) potentially alter producer responses to production shocks (Annan and Schlenker, 2015), this could be a source of bias in our results. To test for such effects, we examined data on crop insurance indemnities collected by county/year/crop cell. These data are available from the USDA Risk Management Agency (RMA), which the government created in 1996 to help with crop risk and insurance in US agriculture.[32] We consider two primary outcome variables: a binary indicator for any insurance indemnity claim in a given county/year/crop cell, and the log of crop-specific indemnity claims per acre, in 2017 dollars, (plus 1, to address the issue of zeros) in a county/year/crop cell. Given crop insurance had

[31] An article on sulfur deficiency in Northeast Iowa notes, "The soil test for S (measures sulfate-S) is not an effective means to determine S needs for crops. The estimated available S in a 6 to 8-inch soil core sample does not correlate to crop yield responses relative to S fertilizer applications. This is because the subsoil can also provide various amounts of S to crops, S mineralization can quickly change plant-available sulfate in the soil, potential S mineralization is not measured by the test, and that plant available sulfate-S can leach from the surface sample depth." (Dealing with Sulfur Deficiency in Northeast Iowa Alfalfa Production, presented at the 2006 Integrated Crop Management Conference. November 29-30, 2006, p. 225-235. Iowa State University, Ames, IA.)

[32] Timing information for this section comes from the "History of the Crop Insurance Program" information section of the USDA website (`https://www.rma.usda.gov/aboutrma/what/history.html`, accessed April, 2018).

major reforms in 1988, we begin our sample there.

Table 6 and Appendix Figure A-5 both show insurance take-up shifts around the ARP in ways that correlate with changes in ambient sulfates. Our results suggest that for every additional unit of airborne sulfates, the probability of filing an indemnity claim decreases by 8.4 percentage points for corn and 6.0 percentage points for soy. However, pure dollar value changes are small on average. An additional unit of sulfates means a decrease in indemnity claims of \$1.23 per acre for corn and \$1.76 per acre for soy. Collections are not evenly distributed: for example, in 1995 the median county collected \$10.40 per acre, while the 90th percentile was approximately \$20 per acre. However, given the price of corn in 1994 was approximately \$140 (adjusted to 2017\$) per ton, there was an estimated 39.4 bushels per ton, and the pre-ARP average yield was approximately 80 bushels per acre, our estimated 6.3% reduction in corn yields would be a loss of around \$18 per acre. It appears indemnity payments were not nearly large enough to shield producers from losses.

8.2 Estimated Economic Effects

Our yield results, combined with the crop insurance results, suggest producers should have seen substantial economic losses as a result of reduced ambient sulfates. In Table 7, we test for changes in a variety of outcomes to see if yield losses translated into other economic effects. Our main outcome is atmospheric sulfate, so positive coefficients indicate the ARP had a negative effect, as it lowered atmospheric sulfate levels. Columns 1 and 2 look at log of farm and nonfarm income. We see that each additional unit of ambient sulfates raises farm income by 4.5%, a result that is statistically significant at 10%. We also see a smaller 1% increase in nonfarm income, which could be a spillover effect into other parts of the economy. There is a 0.2% increase wage employment over population, suggesting small employment effects. While overall farm costs per acre are unaffected by sulfate levels, farm labor expenses increase by 1.4% per $\mu g/m^3$, and crop receipts increase by 5.7%. Not surprisingly, there is a decrease in government payments per acre of 3.1%, suggesting regions with higher ambient sulfates receive less government farm assistance, all else held constant. Farm assistance in this case includes disaster payments, conservation payments, price supports, and other such programs. In dollar terms, this is a reduction of $0.98 per acre for each unit of ambient sulfates, making it similar in value to our prior crop indemnity payments estimate and still a very small share of overall losses.

Given the visible economic effects, a natural question is whether or not the shift in ambient sulfates changed agricultural land values. Theory suggests the value of agricultural land should be a function of its expected return, which it itself a function of profitability. Whether or not producers knew why yields were dropping, we would expect the reduction in revenues to translate to a loss in land values, all else held constant. Assuming producers base land values somewhat on expectations, this also informs whether or not the market viewed these revenue reductions as transitory or permanent. Using data from every 5 years in the agricultural census, we test for changes in the log of land values. We find that each unit of ambient sulfates raises land values by 7%. Assuming 1992 land values and agricultural crop acreage, this works out to a decrease of approximately $1.4 billion after the ARP.

8.3 Longer-term Results

As an expansion, we consider effects further into the future, up through the most recent COA in 2017. Three main confounders exist with the 2007-2017 period. First, major changes in SO2 regulation with the Clean Air Interstate Rule caused substantial price fluctuations in sulfur permits, which may weaken the link between our measure of initial treatment and current emissions levels. Second, expansions of ethanol subsidies were a potential source of bias in terms of expanded acreage for corn. Finally, like 1993, 2012 was a very unusual year for crop yields due to regional droughts.

We illustrate longer-term trends visually in Appendix Figure A-6 by extending our event studies to 2017. The first and second panels show results for corn and soybean yields, respectively. Even extending into 2017, both corn and soybean yields appear lower than prior to the ARP. Crop receipts follow a similar pattern (panel 3). Panel 4 shows that sulfate levels dropped even more in the later 2000/2010s, suggesting some adaptation by producers at this point: while sulfate levels dropped substantially, yields largely plateaued at lower post-ARP levels.

8.4 Counterfactual Losses and Costs of Sulfur Replacement

Our evidence suggests no statistically discernable adaptation response in the years immediately following the ARP, but we cannot rule out some level of adaptation. To infer the size of the adaptation response, we conduct a back-of-the-envelope estimate of the expected yield losses assuming no adaptation and extrapolating from experiments on the effects of sulfur on crop yields. Our estimates suggest the average county lost 0.91 $\mu g/m^3$ of ambient sulfates due to the ARP. Using data from ground monitors, we estimate this translates to 0.55 pounds of sulfate deposition per acre.[33] Based on data from the agricultural extension and professional literature, corn extracts 0.5 lbs of sulfur per 10 bushels/acre. Soybean is more intensive at 1.7 lbs per 10 bushels/acre. This suggests the sulfate losses should reduce corn yields by 11 bushels per acre, and soybean by 3.3 bushels per acre, each of which is around 10% of 1994 yields. We observe that the average county saw losses closer to 5%, which suggests producers may have employed some form of mitigation, and our estimates are net of such effects.

With this information we can also ask how expensive it would be to fully "replace" the lost sulfates. Using fertilizer price data from the USDA, we estimate the replacement cost purchasing ammonium sulfate. Since ammonium sulfate is approximately 24% sulfur, one ton of ammonium sulfate yields 480 lbs. of sulfur. Based on ammonium sulfate prices, which

[33] We regress ground SO4 on our measure of estimated ambient sulfates, controlling for county and year fixed effects as well as county linear trends.

range from $\$237-622$ (in \$2017), crop acreage, and our estimated sulfur loses, it would cost a total of around \$40-60 million in 2017 dollars per year to replace all ARP-driven sulfate losses. This is small compared to the substantial losses from corn and soybean. Using our estimates on bushels lost, price data from the IMF, and regional crop acreage, we estimated revenue losses ranging up to \$1-1.5 billion a year for corn and soybean nationwide. While our back of the envelope calculations suggest producers offset reductions somewhat, the level of adaptation was suboptimal. We provide an in-depth description of our calculations, as well as relevant data sources for all values, in Appendix C.

9 Conclusion

The Acid Rain Program produced large reductions in ambient SO2 levels, which improved human health and reduced environmental harm to old growth forests, rivers, and lakes. Agricultural science suggests it also imposed unexpected costs on agricultural producers by altering atmospheric sulfate levels, fundamentally changing the transfer of production inputs for high-yield crops like corn and soybean. We test this hypothesis and consider, more broadly, the adaptability of the agricultural sector to shifting environmental conditions. Our results present an unusual case where pollution can generate a positive externality.

We find annual crop revenue losses for corn and soybean total \$1-1.5 billion, and associated losses in all agricultural land value of \$1.4 billion. We observe little evidence of adjustment to the crop losses in the decade following the ARP, suggesting individuals and industries can be slow to adapt to environmental shifts. The delayed adjustment could be explained by difficulty with testing ground-level sulfur levels, while annual fluctuations in yields confound the ability of any one producer to draw inference about changing conditions. The "signal vs. noise" issue is not be unique to agriculture: research shows environmental factors have subtle impacts on human health and labor productivity, both difficult to detect at the level of the individual firm (Graff Zivin and Neidell, 2012; Chang et al., 2015). This highlights a continuing role for institutions, in our case extension centers, in collecting and disseminating information regarding changing environmental conditions.

Using back of the envelope calculations based on plant-specific sulfur take-up, we estimate the observed crop reductions are below those predicted given the observable reduction in sulfates. We take this as some indication of producer adjustment behavior, though the level of adaptation is suboptimal. We estimate the total cost of replacing lost sulfur at $40-60 million a year. This is less than 1/10th of the estimated crop revenue losses we calculate for corn and soybeans.

While the reduction in yields is a previously unaccounted cost of the Acid Rain Program, it hardly affects the net social benefits of coal regulation — previously estimated benefits of the ARP dwarf costs, largely due to avoided mortality. But it raises important distributional impacts of coal regulation. Various European countries and China are pursuing SO2 controls. Countries with larger agricultural sectors may incur larger costs of regulation, and countries with high levels of subsistence farming or extreme poverty might experience greater inequities. Providing fertilizer subsidies, alleviating credit constraints, supporting shifts to less sulfur-intensive crops, and increasing information networks to help identify and detect sulfur shortages are all potential policy tools to help offset the agricultural costs of coal regulation.

There remain important related issues for future research. Our analysis focuses on corn and soybean, but other crops could experience different outcomes depending on their sensitivity to soil acidification, leaf damage, and changes in ground-level sulfur. Further, our results are in the context of the United States, where pollution levels are modest by historical and cross-country comparison. In countries with greater levels of pollution, reductions may have different impacts on even the same crops. Present efforts to reduce greenhouse gas emissions around the world and move away from coal-generated power motivate a need to study the pollution-agricultural relationship in other settings.

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Table 1
Summary Statistics

	1982-1994	1995-2007
Panel A: Pollution and Crop Outcomes		
Airborne SO2 (ppb)	7.48	4.33
Airborne Sulfates ($\mu g/m^3$)	7.07	4.54
Corn (Bushels per Acre)	80.45	101.03
Corn Acres	42,062.14	44,101.73
Soybean (Bushels per Acre)	29.44	34.55
Soybean Acres	44,028.99	51,152.35
Weighted Sulfur Controls	0.05	0.84

Note: We base SO2 measures on monitor-level readings aggregated to county. Airborne sulfate is predicted by the APEEP atmospheric transport model using ARP-regulated power plant-level SO2 emissions as inputs. Crop yield per acre is total yield per acre divided by planted acres in that county-year. Weighted Sulfur Controls is a measure of county-level exposure to plant upgrades, which is determined by the APEEP atmospheric transport model (see Section 4).

Table 2
Relationship Between Phase 1 Plant Upgrades, Atmospheric Sulfates, and Crop Outcomes

	(1)	(2)	(3)
Panel A: First Stage for Sulfates			
SC X Post	-1.580	-1.577	-1.234
	(0.244)	(0.248)	(0.262)
Clusters	235	235	235
Observations	64,740	63,622	63,622
Panel B: Reduced Form for Corn			
SC X Post	-0.036	-0.032	-0.050
	(0.011)	(0.010)	(0.014)
Clusters	211	211	211
Observations	41,964	41,964	41,964
Panel C: Reduced Form for Soybean			
SC X Post	-0.017	-0.019	-0.048
	(0.007)	(0.008)	(0.016)
Clusters	175	175	175
Observations	34,944	34,944	34,944
County FE	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Weather	No	Yes	Yes
Linear County Trends	No	No	Yes

Note: We cluster standard errors at the crop reporting district level. We weight crop regressions by annual county-level acreage, and do not weight pollution regressions. Outcome for corn and soybean is log of crop yield per planted acre. We derive airborne sulfate measures from the APEEP atmospheric transport model using ARP-regulated power plant-level SO2 emissions as inputs. Crop yield per acre is total yield per acre divided by planted acres. *SC X Post* refers to an indicator for all years 1995 onward interacted with the count of ARP-regulated boilers with installed sulfur controls, weighted by the APEEP model to calculate a county-level measure (see Section 4).

Table 3
OLS and IV Estimate of Airborne Sulfate on Crop Yields

	(1)	(2)
Panel A: OLS for Corn		
Sulfates ($\mu g/m^3$)	0.025	0.055
	(0.003)	(0.007)
Clusters	211	211
Observations	41,964	41,964
Panel B: IV for Corn		
Sulfates ($\mu g/m^3$)	0.026	0.063
	(0.004)	(0.008)
First Stage F	24.570	16.784
Clusters	211	211
Observations	41,964	41,964
Panel C: OLS for Soybean		
Sulfates ($\mu g/m^3$)	0.016	0.043
	(0.002)	(0.007)
Clusters	175	175
Observations	34,944	34,944
Panel D: IV for Soybean		
Sulfates ($\mu g/m^3$)	0.017	0.065
	(0.003)	(0.008)
First Stage F	18.994	14.741
Clusters	175	175
Observations	34,944	34,944
County FE	Yes	Yes
Year FE	Yes	Yes
Weather	Yes	Yes
Linear County Trends	No	Yes

Note: We cluster standard errors at the crop reporting district level. We weight crop regressions by annual county-level acreage. Outcome for corn and soybean is log of crop yield per planted acre. We derive airborne sulfate measures from the APEEP atmospheric transport model using ARP-regulated power plant-level SO2 emissions as inputs. Crop yield per acre is total yield per acre divided by planted acres. The first stage of IV regressions corresponds to the model in Panel A of Figure 2 — different samples and crop weights explain variation in F-statistics.

Table 4
Robustness of IV Estimates to Alternate Model Choices

	(1) Imputed Indicator	(2) Quad Trends	(3) CRR Trends	(4) State Year FE	(5) Drop Plant Counties	(6) O3 Control	(7) Omit Droughts	(8) Just Droughts
Panel A: Corn								
Sulfates ($\mu g/m^3$)	0.063	0.062	0.047	0.045	0.069	0.041	0.020	0.201
	(0.008)	(0.008)	(0.009)	(0.010)	(0.008)	(0.007)	(0.006)	(0.028)
Damaging O3 Days						-0.011		
						(0.003)		
F Statistic	16.783	15.440	13.705	11.021	25.996	14.942	16.757	10.645
Clusters	211	211	211	211	208	201	211	211
Observations	41,964	41,964	41,964	41,964	35,620	29,743	32,280	9,684
Panel B: Soybean								
Sulfates ($\mu g/m^3$)	0.065	0.063	0.045	0.035	0.074	0.041	0.035	0.138
	(0.008)	(0.008)	(0.008)	(0.010)	(0.009)	(0.006)	(0.008)	(0.023)
Damaging O3 Days						-0.008		
						(0.004)		
F Statistic	14.741	13.220	12.153	13.291	20.893	14.399	14.589	9.093
Clusters	175	175	175	175	173	168	175	175
Observations	34,944	34,944	34,944	34,944	29,952	24,417	26,880	8,064

Note: We cluster standard errors at the crop reporting district level. We weight crop regressions by annual county-level acreage. Outcome for corn and soybean is log of crop yield per planted acre. We derive airborne sulfate measures from the APEEP atmospheric transport model using ARP-regulated power plant-level SO2 emissions as inputs. Crop yield per acre is total yield per acre divided by planted acres. The first stage of IV regressions corresponds to the model in Panel A of Figure 2 — different samples and crop weights explain variation in F-statistics. Column headers describe variation in models, and Section 7 describes each model modification in detail.

Table 5
IV Estimate of Adaptive Responses

	(1) Corn Acres	(2) Soybean Acres	(3) Total Acres	(4) Grow Corn	(5) Grow Soybean	(6) Fertilizer Expenses
Sulfates ($\mu g/m^3$)	0.001	0.008	-0.001	-0.005	-0.011	0.001
	(0.005)	(0.010)	(0.002)	(0.008)	(0.009)	(0.004)
First Stage F	17.768	13.387	22.030	37.210	38.307	19.278
Clusters	211	175	235	148	164	214
Observations	42,250	34,944	62,764	26,962	32,318	43,966

Note: We cluster standard errors at the crop reporting district level. We weight crop regressions by annual county-level acreage. The first stage of IV regressions corresponds to the model in Panel A of Figure 2 — different samples and crop weights explain variation in F-statistics. Column headers describe variation in outcomes, which Section 8 describes in detail.

Table 6
IV Estimate of Payouts and Collection of Crop Insurance (Per Acre)

	(1) Corn Prob.	(2) Soybean Prob.	(3) Log Soybean Claim (Dollars)	(4) Log Corn Claim (Dollars)
Sulfates ($\mu g/m^3$)	-0.084	-0.061	-1.240	-1.775
	(0.029)	(0.019)	(0.716)	(0.448)
First Stage F	14.763	14.461	14.763	14.461
Clusters	208	187	208	187
Observations	29,659	25,965	29,659	25,965

Note: We cluster standard errors at the crop reporting district level. We weight crop regressions by annual county-level acreage. The first stage of IV regressions corresponds to the model in Panel A of Figure 2 — different samples and crop weights explain variation in F-statistics. Outcomes are probability of any crop insurance collection and average dollar value per acre of crop insurance collection. Section 8.1 describes outcomes in detail.

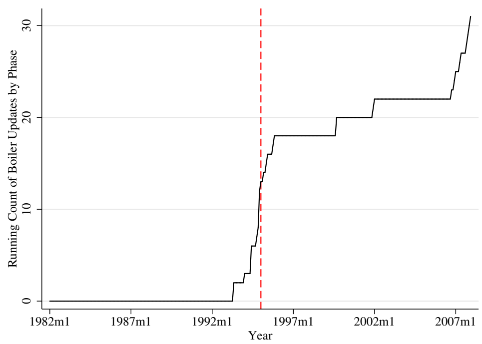
Table 7
IV Estimate of Economic Effects

	(1) Log Farm Income	(2) Log Non-Farm Income	(3) Wage Emp. Over Pop.	(4) Log Costs Per Acre	(5) Log Labor Expenses	(6) Log Crop Rcpt. Per Acre	(7) Log Gov't Pmt. Per Acre	(8) Log Land Value
Sulfates ($\mu g/m^3$)	0.048	0.010	0.002	0.000	0.014	0.058	-0.031	0.070
	(0.024)	(0.003)	(0.001)	(0.004)	(0.005)	(0.011)	(0.011)	(0.018)
First Stage F	20.601	20.601	19.286	19.278	19.278	18.510	18.800	13.210
Clusters	214	214	214	214	214	211	210	235
Observations	42,962	42,962	44,045	43,966	43,966	40,352	40,274	14,520

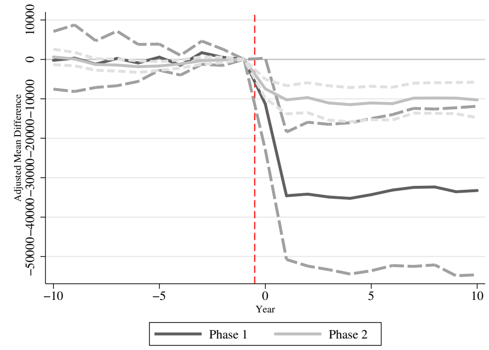
Note: We cluster standard errors at the crop reporting district level. We weight crop regressions by annual county-level acreage. The first stage of IV regressions corresponds to the model in Panel A of Figure 2 — different samples and crop weights explain variation in F-statistics. Column headers describe variation in outcomes, which Section 8.2 describes in detail.

Figure 1
Installation of Sulfur Controls and Boiler Emissions

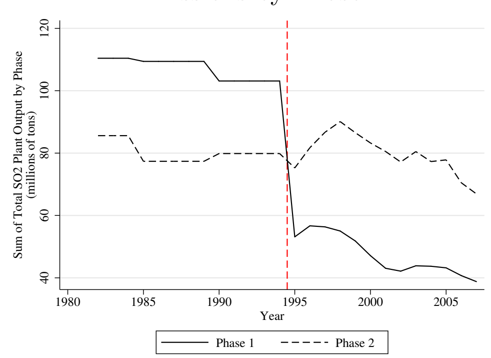
Panel A: Monthly Running Count of Phase I Boilers with Sulfur Control Technology Installs



Panel B: Boiler-Level Sulfur Controls and SO2 Emissions

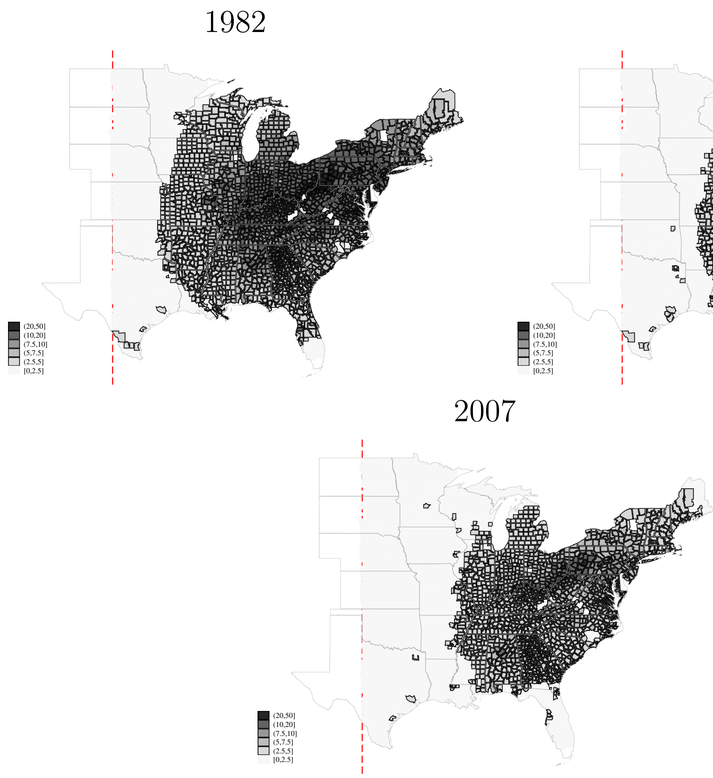


Panel C: Total Annual ARP SO2 Emissions by Phase



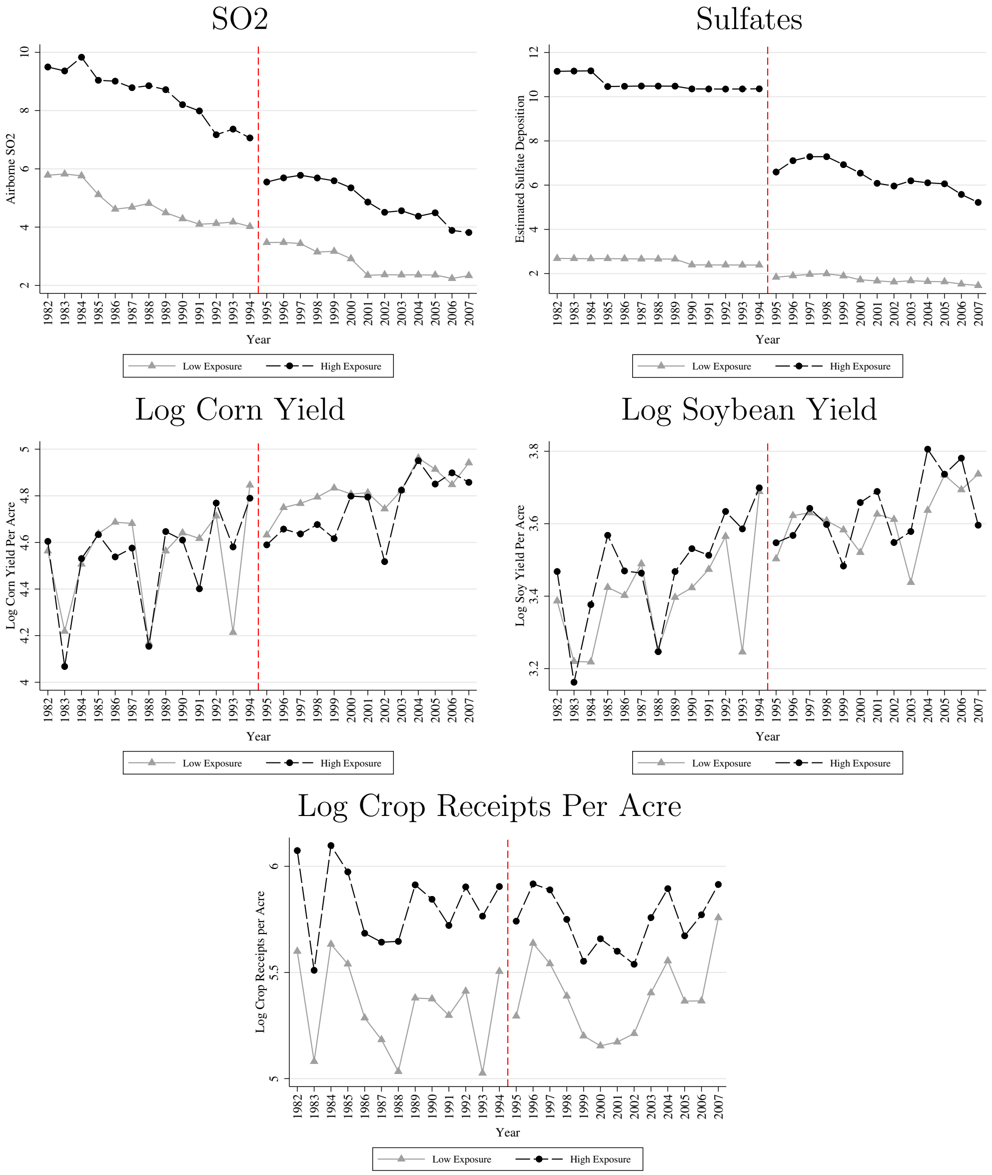
Note: All figures based on data from the EPA Clean Air Markets Acid Rain power plant data set. Panel A shows the running total of upgraded Phase I boilers by month. Panel B shows the change in boiler-level SO2 emissions leading up to and following a sulfur control update, by phase category, and includes any plants without installed sulfur upgrades as controls set to relative time zero. Panel C shows the sum total of all SO2 emissions from Phase 1 and Phase 2 plants, by year. Dashed vertical line indicates the beginning of enforcement of the Acid Rain Program. Thick dashed lines indicate 95% confidence intervals.

Figure 2
County-Level Variation in Sulfates from ARP Plant Sources



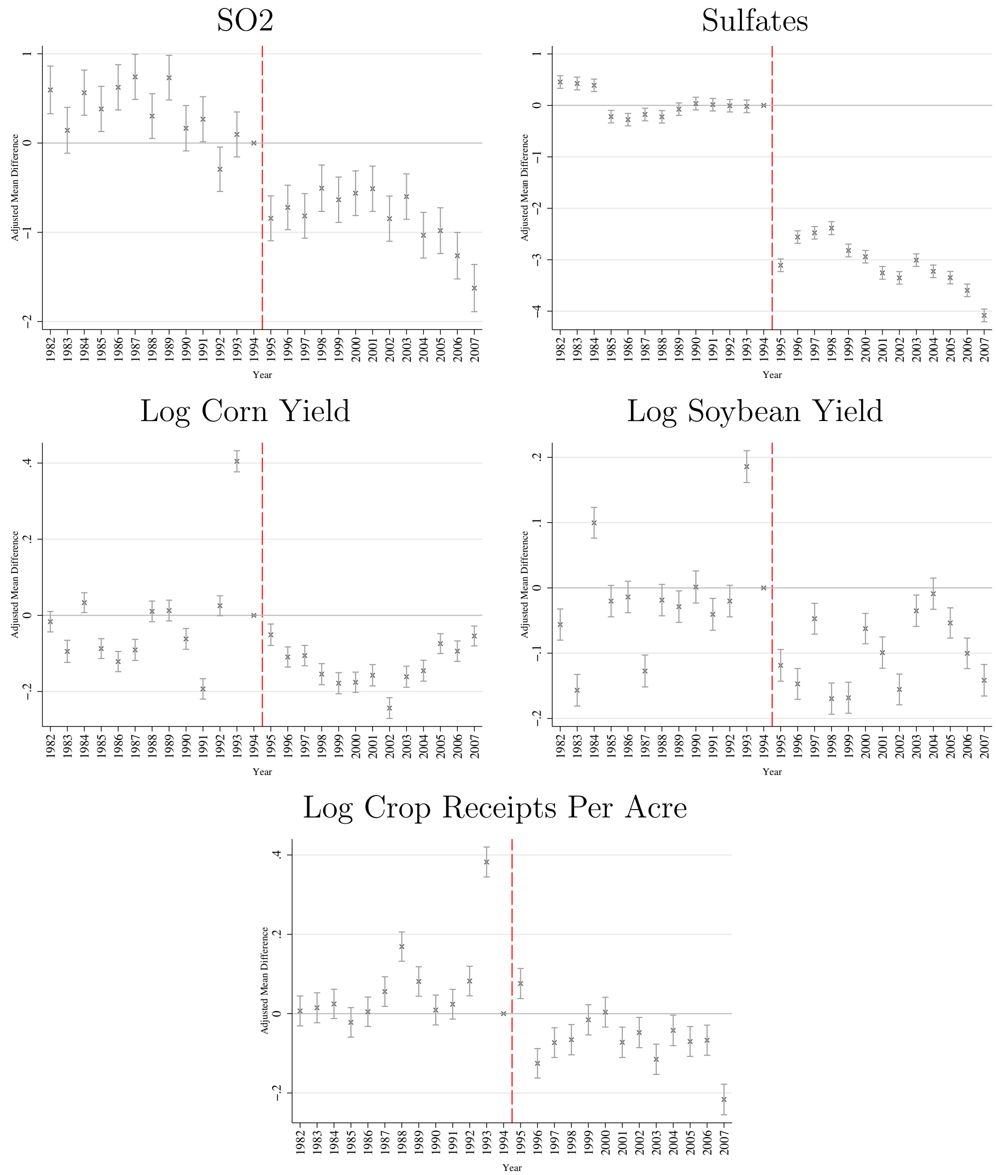
Note: We generate predicted sulfate levels using the APEEP atmospheric conversion matrix which uses boiler-level SO2 emissions to estimate sulfates, which include sulfate and ammonium sulfate. See Section 4 for details.

Figure 3
Trending Effects by Treatment Intensity



Note: Each figure shows outcome trends split by above vs. below the median level of treatment intensity in 1995 for all available counties east of the 100th degree meridian. SO2 data are from EPA air quality monitors, which we aggregate to the county level. We derive atmospheric sulfate projections using the APEEP transport model. Corn and soybean outcomes are log of yield per planted acre from the USDA NASS. Crop receipts are from BEA data and are divided by total crop acreage from the Census of Agriculture. We linearly impute crop acreage at the county-level between COA years.

Figure 4
Event Studies by Treatment Intensity



Note: Event studies show the annual marginal effect of an additional unit of our treatment measure as we describe in Section 4. We use 1994, the year prior to the enforcement of the ARP, as baseline for comparison, and assign 1995 upgrade counts to 1995 and all following years. All estimates include 95% confidence intervals, where we cluster standard errors by crop reporting district. SO2 data are from EPA air quality monitors, which we aggregate to the county level. We derive atmospheric sulfate projections using the APEEP transport model. Corn and soybean outcomes are log of yield per planted acre from the USDA NASS. Crop receipts are from BEA data and are divided by total crop acreage from the Census of Agriculture. We linearly impute between-COA crop acreage at the county-level.

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Appendix Material

Table A-1
Robustness of Reduced Form Estimates to Alternate Model Choices

	(1) Imputed Indicator	(2) Quad Trends	(3) CRR Trends	(4) State Year FE	(5) Drop Plant Counties	(6) O3 Control	(7) Omit Droughts	(8) Just Droughts
Panel A: Corn								
SC X Post	-0.050	-0.051	-0.030	-0.017	-0.068	-0.027	-0.016	-0.050
	(0.014)	(0.014)	(0.009)	(0.005)	(0.015)	(0.007)	(0.006)	(0.014)
Damaging O3 Days						-0.012		
						(0.003)		
Clusters	211	211	211	211	208	201	211	211
Observations	41,964	41,964	41,964	41,964	35,620	29,743	32,280	41,964
Panel B: Soybean								
SC X Post	-0.048	-0.049	-0.026	-0.011	-0.072	-0.025	-0.025	-0.048
	(0.016)	(0.016)	(0.010)	(0.005)	(0.019)	(0.007)	(0.011)	(0.016)
Damaging O3 Days						-0.009		
						(0.004)		
Clusters	175	175	175	175	173	168	175	175
Observations	34,944	34,944	34,944	34,944	29,952	24,417	26,880	34,944

Note: We cluster standard errors at the crop reporting district level. We weight crop regressions by annual county-level acreage. Outcome for corn and soybean is log of crop yield per planted acre. We derive airborne sulfate measures from the APEEP atmospheric transport model using ARP-regulated power plant-level SO2 emissions as inputs. Crop yield per acre is total yield per acre divided by planted acres. refers to an indicator for all years 1995 onward interacted with the count of ARP-regulated boilers with installed sulfur controls, weighted by the APEEP model to calculate a county-level measure (see Section 4). Column headers describe variation in models, and Section 7 describes each model modification in detail.

Table A-2

Alternate Instrument Choices for Sulfate

	(1)	(2)	(3)	(4)	(5)	(6)
	Basic Update		1985 Sulfur Weighted		1985 Heat Weighted	
	Phase 1	Phase 1 & 2	Phase 1	Phase 1 & 2	Phase 1	Phase 1 & 2
Panel A: Corn						
Sulfates ($\mu g/m^3$)	0.063	0.062	0.040	0.040	0.040	0.040
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
F Stat	16.784	11.588	50.572	29.126	39.560	27.432
Observations	41,964	41,964	41,964	41,964	41,964	41,964
Panel B: Soybean						
Sulfates ($\mu g/m^3$)	0.065	0.066	0.062	0.060	0.064	0.064
	(0.008)	(0.009)	(0.010)	(0.010)	(0.011)	(0.011)
F Stat	14.741	10.162	18.192	10.807	19.086	15.633
Observations	34,944	34,944	34,944	34,944	34,944	34,944

Note: We cluster standard errors at the crop reporting district level. We weight crop regressions by annual county-level acreage. Outcome for corn and soybean is log of crop yield per planted acre. We derive airborne sulfate measures from the APEEP atmospheric transport model using ARP-regulated power plant-level SO2 emissions as inputs. Crop yield per acre is total yield per acre divided by planted acres. The first stage of IV regressions corresponds to variations in the model in Panel A of Figure 2. Column (1) repeats our main instrument. Column (2) adds Phase II updates. Columns (3) and (4) follow a similar pattern, but interact our original instrument with boiler-level SO2 output in 1985. Columns (5) and (6) replace 1985 SO2 output with 1985 heat output. See Section 7 for details.

Table A-3
Reduced Form Estimates With Alternate Standard Errors

	(1) Baseline	(2) Unweighted	(3) State Cluster	(4) Conley	(5) Bootstrap
Panel A: Corn					
SC X Post	-0.050	-0.056	-0.056	-0.056	-0.056
	(0.014)	(0.011)	(0.014)	(0.016)	(0.026)
Panel B: Soybean					
SC X Post	-0.048	-0.050	-0.050	-0.050	-0.050
	(0.016)	(0.016)	(0.017)	(0.014)	(0.017)

Note: We weight crop regressions by annual county-level acreage. Outcome for corn and soybean is log of crop yield per planted acre. We derive airborne sulfate measures from the APEEP atmospheric transport model using ARP-regulated power plant-level SO2 emissions as inputs. Baseline model in Column (1) corresponds to Column (3) of Table 2. Column (2) omits weights. Column (3) clusters standard errors at the level of state. Column (4) uses geospatially correlated Conley standard errors, using a radius of 200 miles. Column (5) uses bootstrapped standard errors with 10,000 replications, stratified on years with replacement.

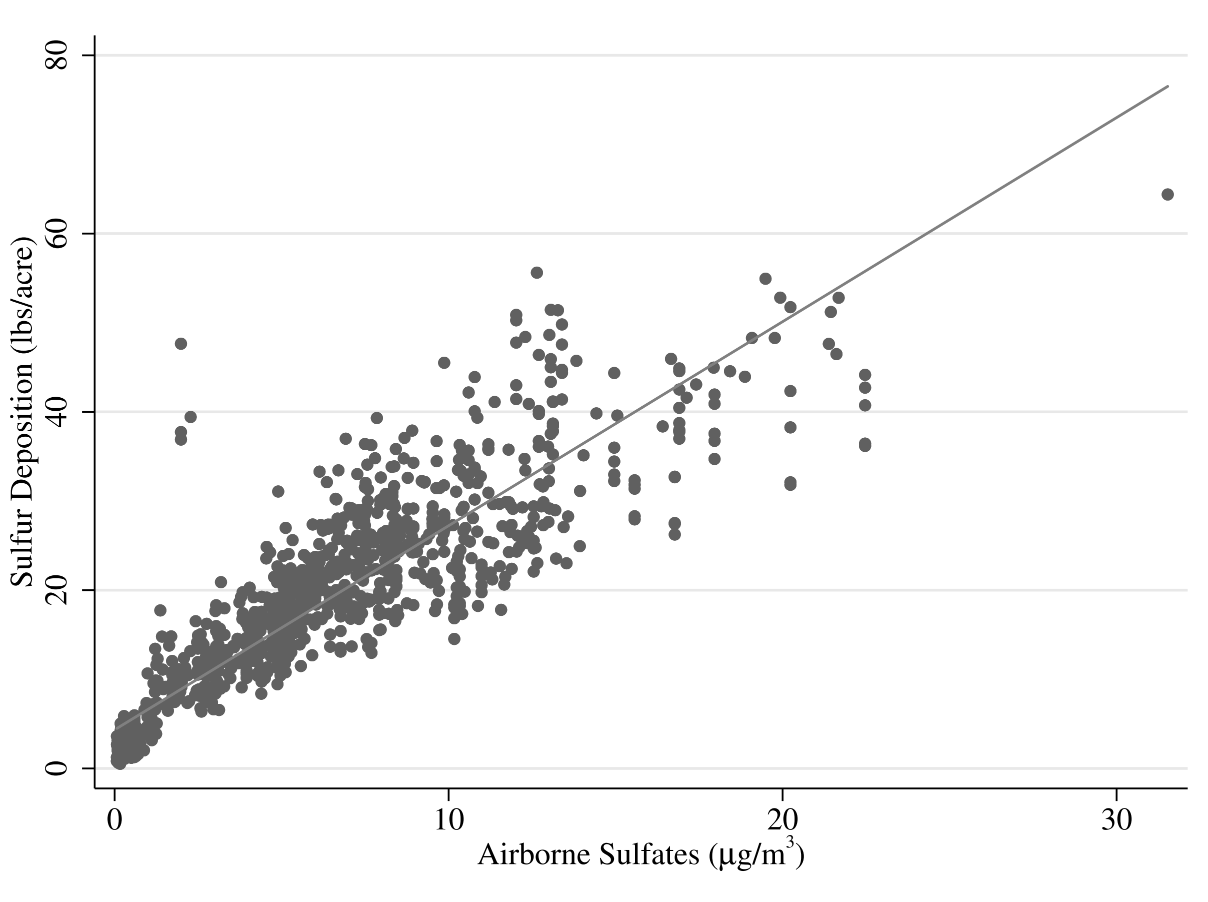
Table A-4
Expanded Pollutants

	(1)	(2)	(3)	(4)	(5)
	LUR Data			Monitor Data	
Panel A: Corn					
Sulfates ($\mu g/m^3$)			0.055	0.023	0.026
			(0.007)	(0.005)	(0.005)
Airborne SO2 (LUR)	0.004	0.004	0.001		
	(0.002)	(0.002)	(0.002)		
Airborne NO2 (LUR)		-0.006	-0.006		
		(0.003)	(0.003)		
Airborne O3 (LUR)		-0.003	-0.003		
		(0.001)	(0.001)		
Airborne SO2 (Monitor)					-0.008
					(0.003)
Airborne NO2 (Monitor)					0.004
					(0.002)
Airborne O3 (Monitor)					-1.107
					(1.420)
Clusters	211	211	211	96	96
Observations	41,964	41,964	41,964	11,180	11,180
Panel B: Soybean					
Sulfates ($\mu g/m^3$)			0.042	0.013	0.013
			(0.007)	(0.004)	(0.004)
Airborne SO2 (LUR)	0.002	0.003	-0.000		
	(0.002)	(0.002)	(0.002)		
Airborne NO2 (LUR)		0.002	0.001		
		(0.002)	(0.002)		
Airborne O3 (LUR)		-0.004	-0.004		
		(0.002)	(0.001)		
Airborne SO2 (Monitor)					-0.001
					(0.003)
Airborne NO2 (Monitor)					0.000
					(0.001)
Airborne O3 (Monitor)					-5.276
					(1.433)
Clusters	175	175	175	73	73
Observations	34,944	34,944	34,944	8,320	8,320

Note: We weight crop regressions by annual county-level acreage. Outcome for corn and soybean is log of crop yield per planted acre. We derive airborne sulfate measures from the APEEP atmospheric transport model using ARP-regulated power plant-level SO2 emissions as inputs. Monitor pollutant measures come from air monitor data we aggregate to the county level. Land Use Regression (LUR) data are from the Center for Air, Climate and Energy Solutions (CACES). See Section 7.1 for details.

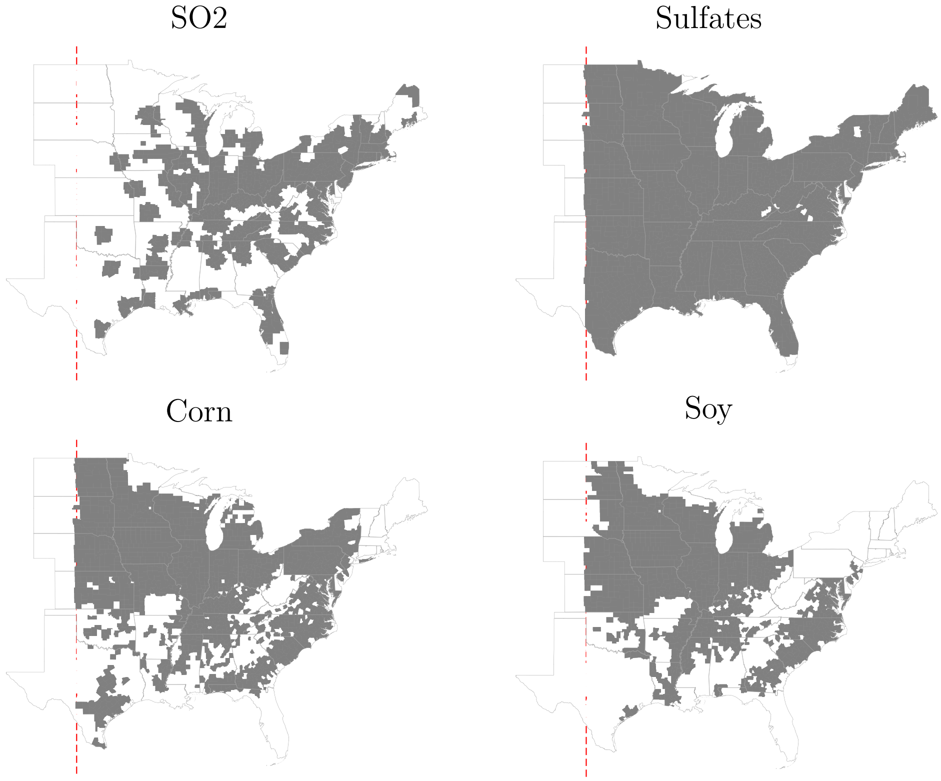
Figure A-1

Correlation Between Airborne Sulfates and Sulfur Deposition



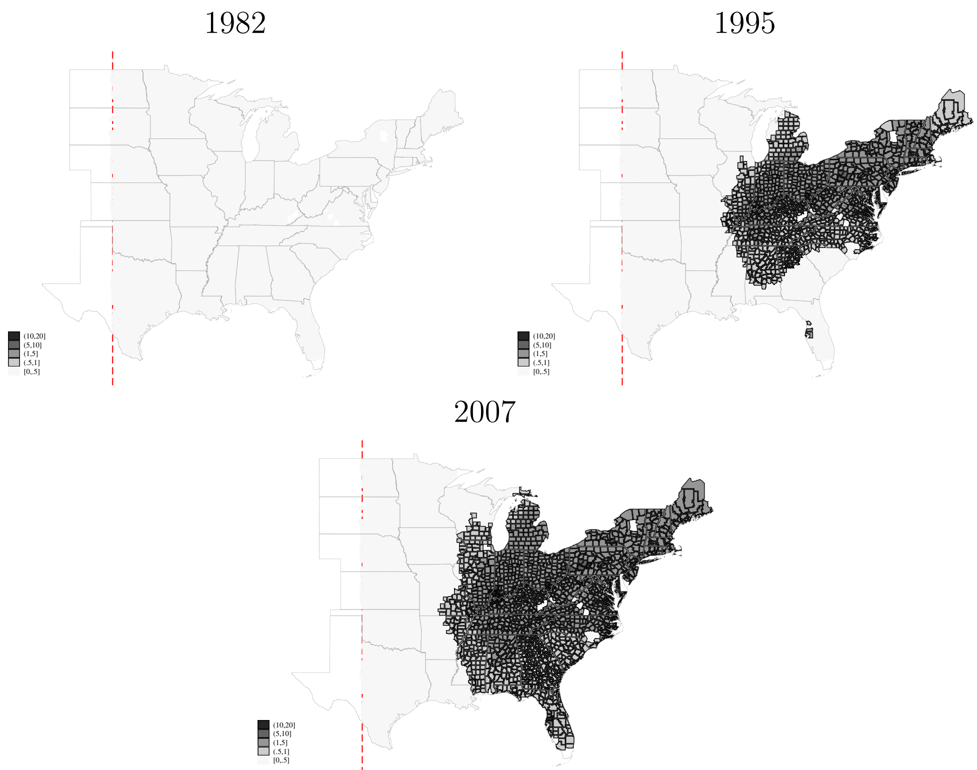
Note: We generate predicted sulfate levels using boiler-level SO2 emissions and the APEEP atmospheric conversion matrix which takes as inputs SO2 and provides as output estimated sulfates, which include sulfate and ammonium sulfate. Sulfur deposition data are from the Clean Air Markets Division, Clean Air Status and Trends Network (CASTNET). Data shows raw values across multiple sensors and multiple years with a simple correlation. We match deposition monitors to atmospheric sulfates using county of monitor.

Figure A-2
Analysis Counties by Outcome



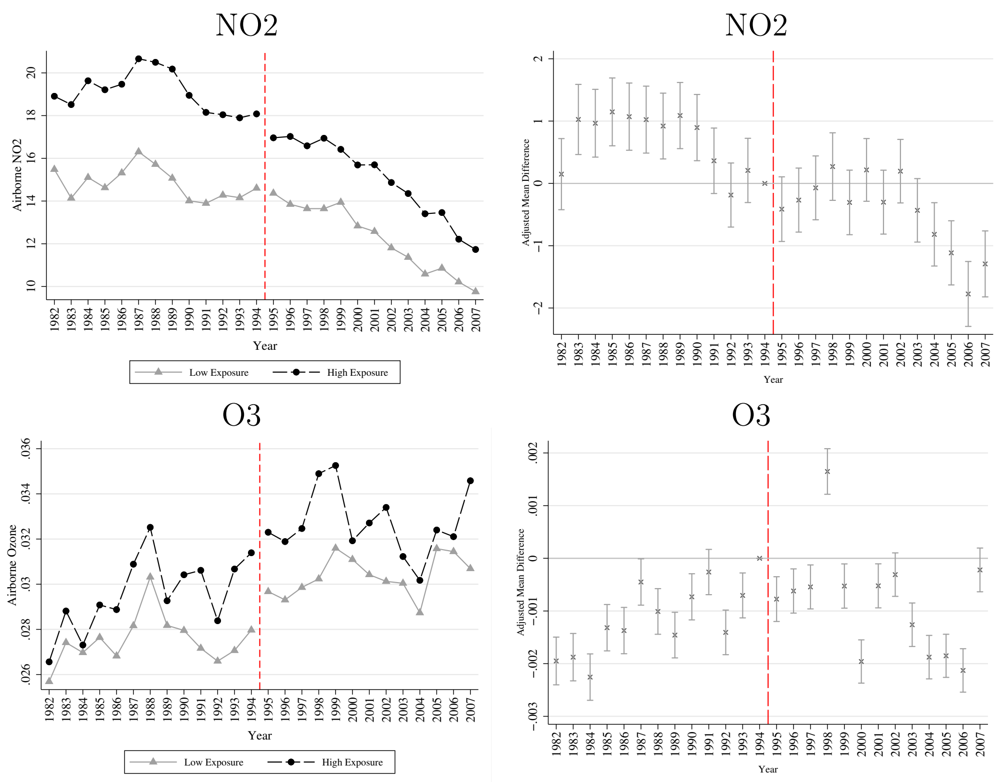
Note: Graphs shade counties used in our main regressions for each noted outcome east of 100 degrees longitude. See Section 3 for details.

Figure A-3
County-Level Variation in Weighted Number of ARP Plants With Technology Upgrades



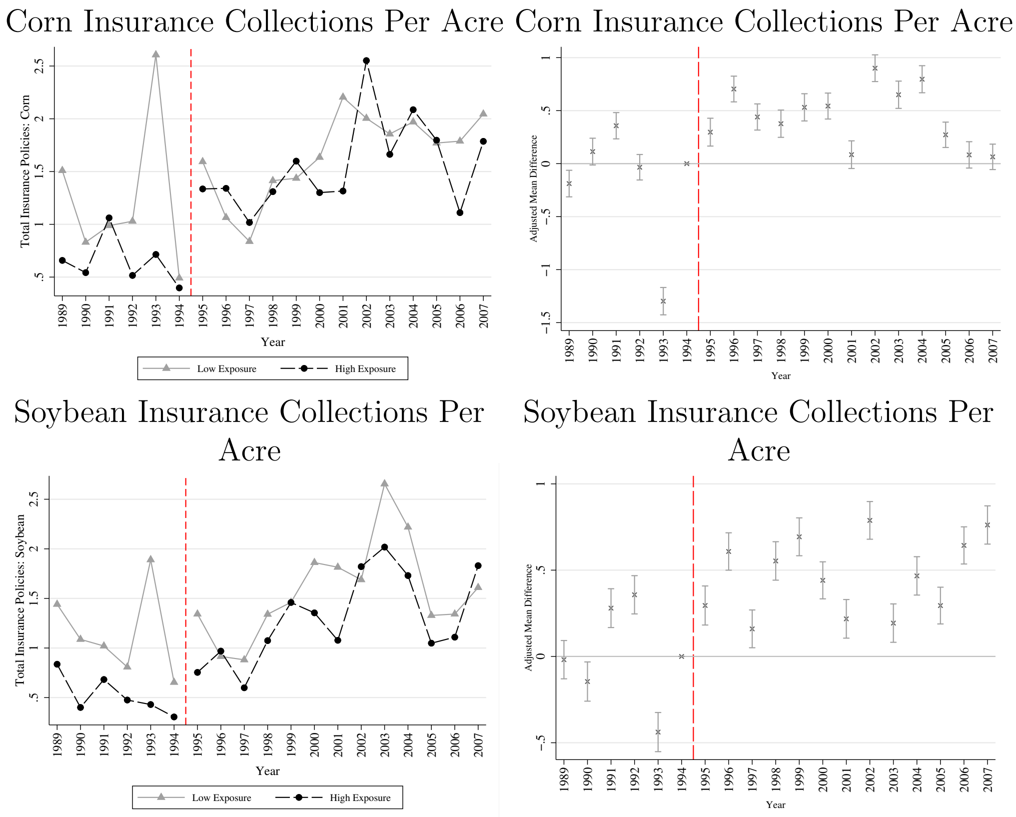
Note:.Our measure of treatment is the number of sulfur control boiler upgrades installed at ARP-treated power plants, weighted by the APEEP atmospheric dispersion matrix for SO2 emissions to ambient sulfates, and multipled by 100,000 for ease of reading. See Section 4 for details.

Figure A-4
Trends and Event Studies in Other Pollutants



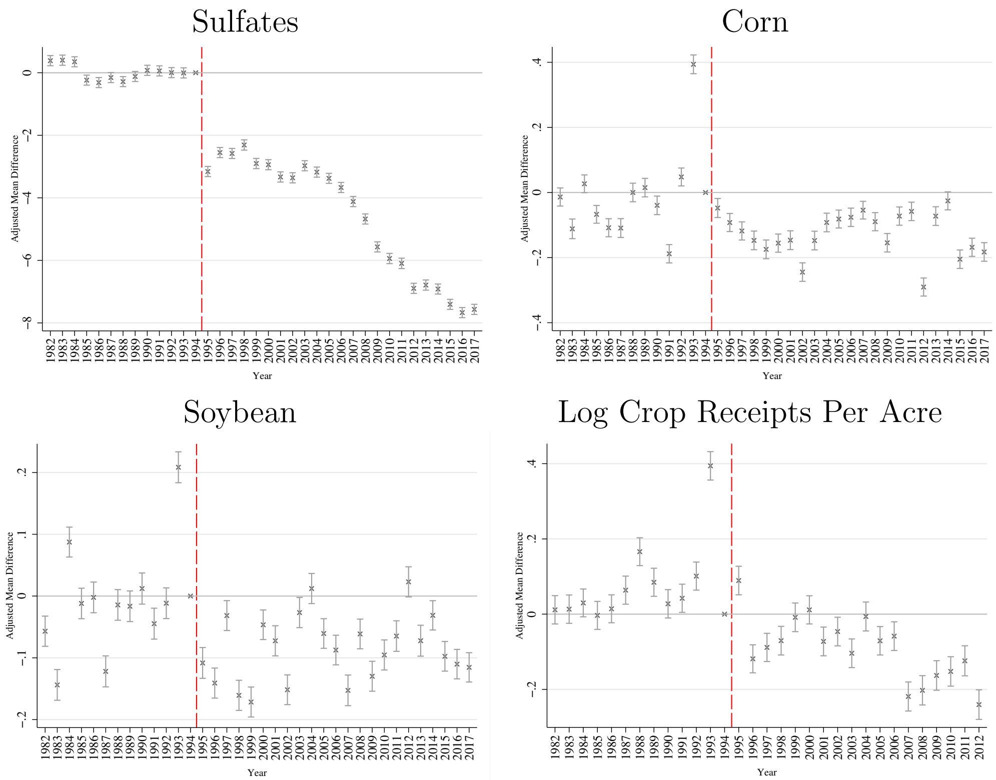
Note: Event studies show the annual marginal effect of an additional unit of our treatment measure as we describe in Section 4. We use 1994, the year prior to the enforcement of the ARP, as baseline for comparison, and treatment levels in 1995 as our measure of marginal treatment intensity. All estimates include 95% confidence intervals, where we cluster standard errors by crop reporting district. Emissions data are from EPA air quality monitors, which we aggregate to the county level.

Figure A-5
Trends and Event Studies in Corn and Soybean Indemnity Collections



Note: Trend figures show outcome trends split by above vs. below the median level of treatment intensity in 1995 for all available counties east of the 100th degree meridian. Event studies show the annual marginal effect of an additional unit of our treatment measure as we describe in Section 4. We use 1994, the year prior to the enforcement of the ARP, as baseline for comparison, and treatment levels in 1995 as our measure of marginal treatment intensity. All estimates include 95% confidence intervals, where we cluster standard errors by crop reporting district. Insurance indemnities are from the USDA REIS data.

Figure A-6
Extended Outcomes



Note: Event studies show the annual marginal effect of an additional unit of our treatment measure as we describe in Section 4. We use 1994, the year prior to the enforcement of the ARP, as baseline for comparison, and treatment levels in 1995 as our measure of marginal treatment intensity. All estimates include 95% confidence intervals, where we cluster standard errors by crop reporting district. We derive atmospheric sulfate projections using the APEEP transport model. Corn and soybean outcomes are log of yield per planted acre from the USDA NASS. Crop receipts are from BEA data and are divided by total crop acreage from the Census of Agriculture. We linearly impute between-COA crop acreage at the county-level.

Appendix B Sulfur as an Input and the Marginal Product

Despite its importance in the growth process, prior to the ARP testing yielded little gains from the use of sulfur fertilizers, potentially because the sulfur deposition vector provided sufficient baseline levels. Morrison (2009) notes research in the 1970s and 80s showed little gains to application of additional sulfur, suggesting sulfur as an input had a low marginal product. Figure B-1 illustrates a basic model for the marginal productivity of sulfur. If, after sufficient ground sulfur, additional application yields no gains, the marginal productivity of sulfur eventually zero and yields are unchanged even with additional application. After the ARP, the sulfur flow decreased due to lower deposition, pushing the marginal product up into a region of positive gains.

Appendix B.1 Sulfur Deficiencies and Agricultural Productivity Before the Acid Rain Program

Agricultural science suggests both the stock and flow of sulfur are important. Crops draw soil sulfur, which needs replenishment to maintain high growth yields. Sulfur loss can also occur through water drainage and irrigation, which can be more of a problem in high drainage soils. Productive regions may start with large amounts of ground sulfur, but absent replenishment, could lose productivity over time due to sulfur deficiencies. Such deficiencies appear as stunted growth and yellowed leaves due to a lack of chlorophyll coloring (Sawyer, 2004; Stevens et al., 2002).

While there is no consensus regarding the association between the ARP and sulfur deficiencies, a 2007 North Carolina State University report from the College of Agricultural and Life Sciences, *SoilFacts: Sulfur Fertilization of North Carolina Crops*, specifically notes, “Today [sulfur] deficiency may be more of a concern due to several factors that farmers may not have considered: 1) tighter air quality standards for atmospheric emissions mean less sulfur falls onto the landscape [. . .]".[34] Through this channel, in the absence of adaptive behavior, ARP-associated reductions in soil-level sulfur flows may lead to reduced output.

Research from the 1970s and 1980s found little benefit to using sulfur fertilizer (Morrison, 2009). By the mid-2000s, experiments suggested a newly-found positive relationship between additional sulfur and yields for most crops studied (Camberato, Maloney and Casteel, 2012), presenting a shift from prior findings that sulfur levels were sufficiently high without additional fertilizers (Sawyer et al., 2009). In addition to the ARP, a number of industry changes could explain shifts in baseline sulfur flows. Adoption of newer fertilizer and pesticide technologies, both with decreased sulfur content compared to older versions, removed a common flow of ground sulfur over time. Field burning, now less common, was another potential mechanism for returning sulfur to the soil for the following season.[35]

Sulfur flow also came in the form of acid raid and general sulfuric deposition, which decreased substantially with the CAAA. As of yet, there is little work on how the CAAA, and specifically the ARP, affected agricultural through this channel. The EPA considered the effect the program had via benefits of O3 reductions, and estimated gains in crop yields between 1990 and 2010 valued at approximately $7.5 billion due to reductions in O3 (see the Appendix of EPA (1999)). In a follow-up 2008 report, the EPA further discussed theoretical effects of sulfur and oxides of nitrogen on plants, but did not expand models to the assessment of the ARP due to a lack of valuation studies linking said pollutants to the productivity of agricultural land (EPA, 2008). Extension literature began writing of a potential link between the ARP and sulfur deficiencies during the late 2000s. The following quotes (from reports by the Purdue University Department of Agronomy, the Cornell University Cooperative Extension, and North Carolina State University) show a recent move to the hypothesis of a potential link between the ARP and reduced sulfur:

[34] Extension report E07-50255 , available online at `http://www.soil.ncsu.edu/publications/Soilfacts/AG-439-63W.pdf`.

[35] "The Skinny of Sulfur", Agronomy Insider, 3/05/2015.

> Sulfur deficiency of corn and other crops may be becoming more prevalent because less [sulphur] is deposited from the troposphere to the soil due to reductions in power plant [sulphur] emissions. ("Sulfur Deficiency in Corn", 2012)[36]

> Since the Clean Air Act was passed in 1970, emissions of sulfur dioxide have decreased dramatically resulting in reduced sulfur deposition in many parts of the state. ("Sulfur for Field Crops", 2007))[37]

> There are several factors that have resulted in the increasing number of cases where sulfur is being diagnosed as deficient or limiting in young corn plants. First, there is the fact that we have had an extended period of frequent and intense rainfall events starting in the fall of 2002 and continuing through the spring of 2003. Since sulfur is a mobile nutrient and is water soluble, this sulfur in the upper soil profile (top 2 to 4 inches) has been leached into the lower rooting zone. The reduction in sulfur emissions brought about by the clean air act means that these same rainfall events are not replacing the sulfur leached [. . .] ("Sulfur Deficiency Symptoms in Emerging Corn, 2003)[38]

> Yellow striping on corn leaves is more prevalent this year than in the past, possibly because of sulfur deficiency in the soil, says a Purdue Extension soil fertility specialist.
>
> Yellow, green-yellow or yellow-white striping on the leaves of corn plants can indicate a variety of nutrient deficiencies or other damage, said Jim Camberato. Analysis of soil and tissue samples shows that many cases of striping are due to sulfur deficiency.
>
> "We used to get quite a bit of sulfur from rainfall. The power plants would burn coal that had sulfur in it, so sulfur would be deposited in rainfall or absorbed directly from the air by the soil," Camberato said. "But over the last 20-25 years, these emissions have been reduced, so perhaps now the amounts in rainfall and atmosphere deposition are low enough that plants are not getting enough that way anymore." ("Soil fertility specialist says yellow striping in corn may be linked to sulfur deficiency", 2016)

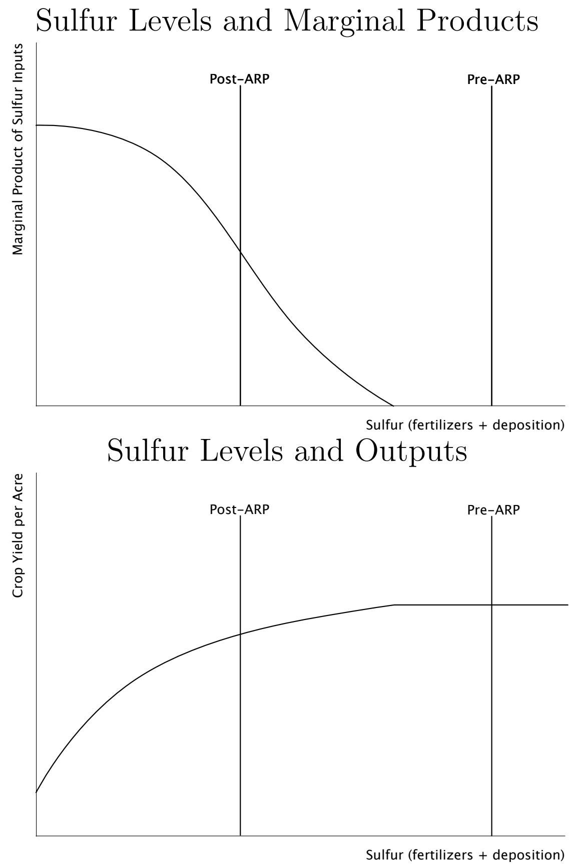
Appendix B.2 Trends in Agriculture Around the Time of the ARP

Figure B-2 shows the long-run trend in both corn and soybean output across time — in both cases, yields per acre have been regularly increasing. Around the time of the ARP,

[36] Camberato, Maloney and Casteel (2012)
[37] Place et al. (2007)
[38] `http://www.ces.ncsu.edu/plymouth/cropsci/docs/sulfur.html`.

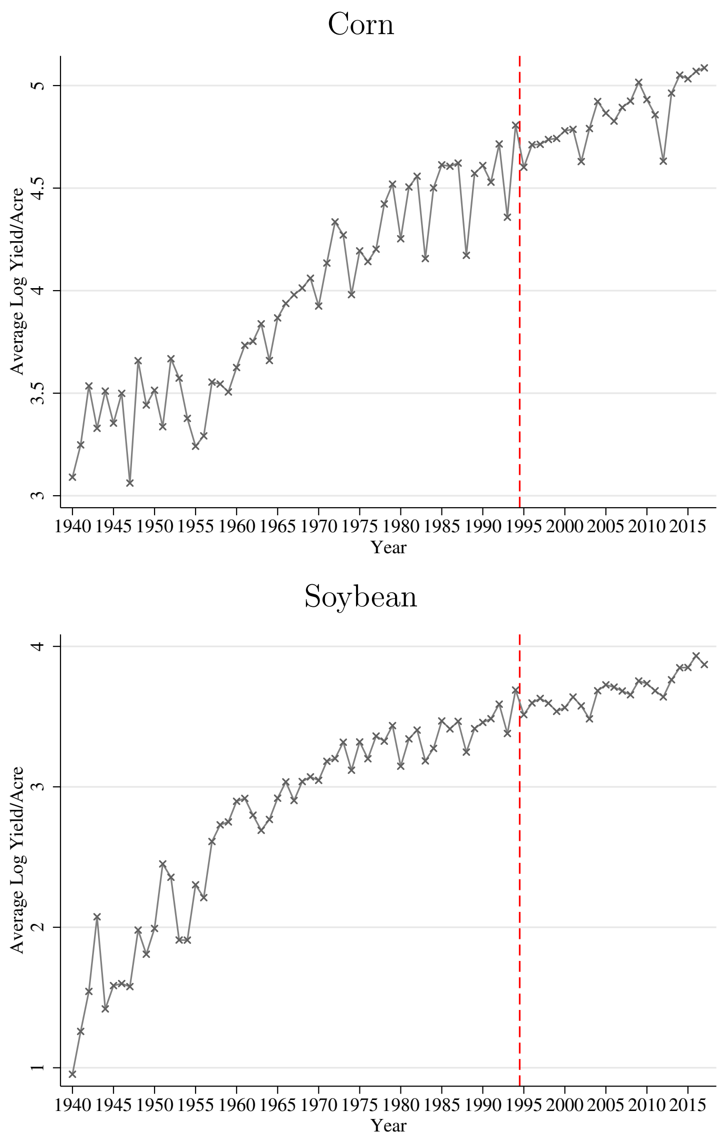
productivity and prices were volatile both nationally and globally. Figure B-3 shows the global price of corn and soybean across time (in 2015 dollars). Weather drove supply losses and price spikes in the 1990s, as did sharp changes in demand on global markets. China left the corn export market in 1994, leading to speculative price increases. By early 2000, prices had returned to 1994 levels (Stevens, 1999). Our research design controls for these confounders to the extent they affect all areas in a similar fashion over time. There was a drought in 1991 and a combination of freezes, unusual rainfall, a Midwestern flood, a drought, and insects in 1993 (Kliesen, 1994; Lott, 1994). A high-production year followed in 1994, but yields fell again in 1995 due to heat waves and late planting seasons. Starting in 1996, yields stabilized, followed by a number of consistently high-yield years (Stevens, 1999).

Figure B-1
Potential Model of Sulfur Inputs



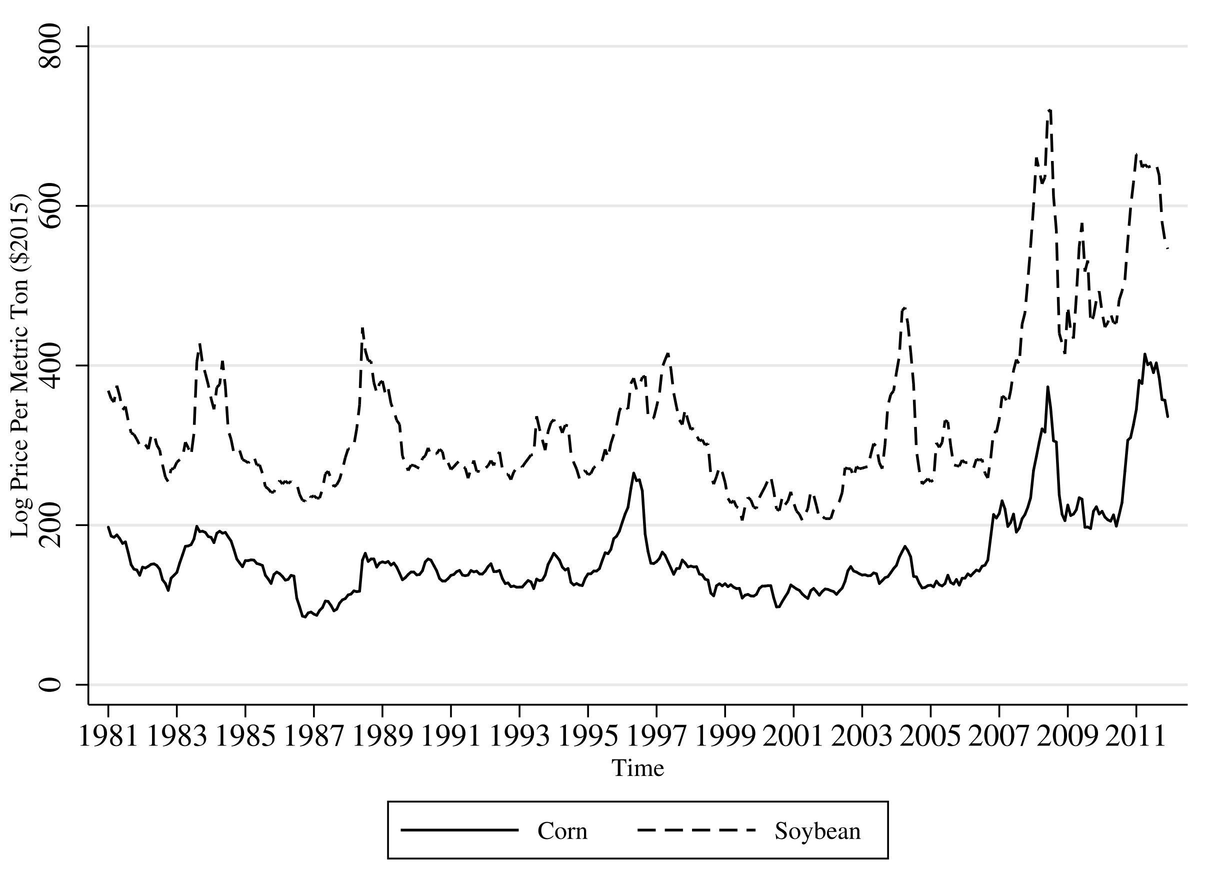
Note: Panel A shows potential relationship between the marginal product of sulfur inputs and sulfur levels from both applied fertilizers and provision via deposition. Panel B shows potential relationship between the output and sulfur levels from both applied fertilizers and provision via deposition. “Pre-ARP” and “Post-ARP” present potential levels corresponding with pre- and post-regulatory soil sulfur levels in a field.

Figure B-2
Historical Log Annual Crop Yield



Note: Historic crop data are in log yield per planted acre. Data come from the U.S. Department of Agriculture's National Agricultural Statistical Service.

Figure B-3
Historical Global Prices for Corn and Soy



Note: Global price data come from the International Monetary Fund historic primary commodity data and are inflated to 2015 dollars.

Appendix C Cost Calculations

Our primary independent variable is airborne sulfates as predicted using the APEEP atmospheric transport model. This includes both SO4 and (NH4)2SO4. To convert this to a measure of ground deposition of SO4, we use data from the EPA Clean Air Markets Division, Clean Air Status and Trends Network (CASTNET) Total Deposition data. We merge ground deposition monitors to air sulfate measures using monitor county information. We then run the following regression, which includes year fixed effects, county fixed effects, and a county-specific linear year trend:

$$SO4 = \beta sulfates + \delta_{year} + \lambda^1_{county} + \lambda^2_{county} Xtrend.$$

We find $\beta = 0.6835$, which implies each additional $\mu g/m^3$ of airborne sulfates correlates with an additional 0.68 pounds of ground SO4 deposition.

To convert this reduced SO4 to reduced crop yields, we use data on how much sulfur each crop removes from the soil — our assumption is that removing S deposition is equivalent to preventing crop take-up of the required sulfur. The Purdue University Soil Fertility Update (July 11, 2017) notes that soybean removes about 0.17 pounds of sulfur per bushels of grain, and corn grain is around 0.05 pounds per bushel. This suggests that each $\mu g/m^3$ of airborne sulfates lost reduces yields per acre by:

$$0.68/0.05 = 13.6 \text{ corn bushels per acre}$$

$$0.68/0.17 = 4 \text{ soybean bushels per acre}$$

To calculate replacement costs, we use data on fertilizer use and price from the Economic Research Service in the United States Department of Agriculture. While they do not have direct data on pure sulfur costs, they do track ammonium sulfate, which is 24% sulfur. We assume to replace a pound of sulfur, producers must purchase 4.17 (1/0.24) pounds of ammonium sulfate. To find average cost per county to replace lost sulfur, we multiply the price of ammonium sulfate by the lost sulfur per acre by the number of acres for each relevant crop. This provides us with an approximate county-level measure of the replacement cost of lost sulfur.

To calculate lost crop receipts, we first repeat our primary reduced form regressions using levels of corn and soybean yields per acre. We find a per-unit reduction of 3.99 corn bushels per acre and 1.61 soybean bushels per acre. As pricing data are often in tons, we convert our bushel measure to tons: data suggest approximately 40 bushels per ton for corn and 37 bushels per ton for soybean. This implies the average county lost approximately 0.04 tons of corn yield per acre and 0.02 tons of soybean yield per acre. To obtain total lost revenues, we multiply these values by the price per ton in a given year and the number of acres in a given county-year.