Productivity Spillovers From Pollution Reduction: Reducing Coal Use Increases Crop Yields

Konstantinos Metaxoglou, and Aaron Smith

Air pollution reduces crop yields by slowing down photosynthesis. We estimate the increase in US corn and soybean yields attributed to the recent dramatic reductions in emissions of nitrogen oxides (NO_x) from electric power plants. In response to the observed changes in power plant NO_x emissions over the eight-year period from 2003–05 to 2011–13, we estimate that average corn yields improved by 2.46% and soybean yields by 1.62%. These improvements imply an increase in total surplus of $1.60 billion annually across the two crops. The estimated yield improvements vary substantially across states depending on the change in NO_x emissions. For corn, they range from 0.32% to 6.87% and for soybeans, they range from 0.21% to 4.30%. The demand for the two crops is quite inelastic, which means that prices decrease by more than production increases in response to this positive productivity shock and the implied rightward shift of the crop supply curve. Due to the low elasticities of supply and demand for U.S. corn and soybeans, we conclude from a welfare analysis that these changes made consumers better off and farmers worse off.

Key words: Crop yields, emissions, ozone pollution, electric power sector.

JEL codes: H53, I38, J22, J48, O12, Q12.

Agricultural productivity in the United States has grown substantially in the past 100 years. Farmers produce four times as much output from each unit of land and seventeen times as much output from each unit of labor, as they did a century ago (Andersen et al. 2018). Of the major crops, average corn yield increased eightfold and average soybean yield increased fivefold over this period. However, the rate of growth has slowed recently, which raises questions about how the world will meet the growing demand for agricultural products caused by increases in global population and wealth.

One way to increase land productivity is to reduce air pollution. High ground-level ozone in the summer slows photosynthesis and thereby reduces crop production per acre (yield). In this article, we quantify the crop yield increases attributed to the recent dramatic reductions in the emissions of nitrogen oxides (NO_x) from electric power plants in the United States. Large amounts of NO_x emissions from coal-fired power plants react with volatile organic compounds in the presence of sunlight to produce ozone. Exposure to ozone, alone or in combination with other pollutants, has been shown to be responsible for about 90% of the US crop loss due to air pollution (Heck et al. 1982). Given that both NO_x and ozone can travel hundreds of miles, power plant NO_x emissions significantly raise ozone levels in locations far from the pollution source.

In the past decade, the amount of coal used for electricity generation in the United States has decreased by more than a third. It has been replaced by technologies that emit less pollution—mostly natural gas but also wind and other renewables. Multiple government

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policies have targeted emissions from electric power plants, but the main driver of this move away from coal has been the declining price of natural gas due to hydraulic fracturing (fracking), which dramatically lowered the cost of natural gas extraction (Coglianese, Gerarden, and Stock 2017; Fell and Kaffine 2018). In addition, emissions from the remaining coal-fired power plants declined substantially over the same period due to adoption of abatement technology (Fowlie 2010).

We use a panel-data econometric approach to quantify the effects of NO_x emissions on crop yields. In particular, we estimate regression models to answer the following question: if power plants within a specified radius of an average county centroid reduce total NO_x emissions during the growing season, how much do we expect the crop yield to increase in that county, all else equal? An alternative approach would be to use calibrated atmospheric chemistry and agronomy models. These models assume particular functional forms for NO_x pollution dispersion, transformation into ozone, and the resulting effects on photosynthesis and crop yields. The main drawback of such calibrated models is that they require numerous assumptions regarding functional forms and parameter values. In contrast, our reduced-form regressions provide a transparent causal link between emissions and crop yields. A drawback of our approach is that it does not reveal the mechanisms underlying the detrimental effect of emissions on crop yields. However, these mechanisms are well known—our main contribution is to quantify their causal effects.

Using data for 2003–13, we estimate that average corn yield increased by 2.46% and soybean yield by 1.62% in response to the observed changes in power plant NO_x emissions over the eight-year period from 2003–05 to 2011–13. These yield improvements translate into an increase in total annual surplus of \$1.60 billion, \$1.07 billion of which are attributed to corn. Although consumers are better off, farmers are worse off because low elasticities imply a substantial decrease in price due to the rightward shift of the crop supply curves. The estimated yield increases vary substantially across states depending on the change in NO_x emissions. For corn, they range from 0.32% to 6.87% and for soybeans they range from 0.21% to 4.30%. As a benchmark to assess the magnitude of our estimated yield improvements, corn (soybean) yields increased by 2% (1.8%), on average, annually during the period of our analysis (USDA 2017).

Recent papers that employ regression techniques to evaluate the effects of pollution on crop yields include Carter et al. (2017), McGrath et al. (2015), Burney and Ramanathan (2014), and Auffhammer, Ramanathan, and Vincent (2006). Carter et al. study the effects of ozone on rice yields in China. Burney and Ramanathan study the effects of black carbon and ozone, and Auffhammer et al. study the effect of black clouds on rice yields in India. The work by McGrath et al. is the one that is most closely related to ours. Using US data from 1980 to 2011 and multivariate regressions controlling for weather, they find that ozone exposure reduced corn yields by 8.0–11.6% and soybeans by 3.3–7.7%. They also show that both crops are more sensitive to ozone in extreme temperatures and dry conditions, and corn is more sensitive to ozone than soybeans. Unlike our paper, McGrath et al. do not establish a formal relationship either between ozone and any of its precursors or between crop yields and NO_x emissions. Moreover, a direct comparison between our findings and the findings in McGrath et al. is not straightforward due to important differences in the calculation of the effects between the two papers.[1]

Regarding agricultural productivity spillovers from electricity generation, the closest paper to ours that we are aware of is Kaffine (2018). Following an empirical approach similar to ours, he estimates the spillover effect of wind farms on agriculture in the U.S. due to microclimate impacts, which arise from changes in local temperature, moisture, and CO_2 levels, due to vertical mixing, turbulence, and wakes created by wind turbines. According to his findings, an additional 100 megawatts of wind capacity increases corn yields by 0.5%–1%.

In addition to our main results, which are based on reduced-form regressions of crop yields on power plant NO_x emissions, we also quantify the two links in this causal chain. We show that ozone levels increase in response to power plant NO_x emissions and we estimate the effect of measured ozone levels on crop yields. To do so, we use a high-resolution

[1] There is an alternative strand of the literature that calculates yield and potential economic losses using ozone exposure indices and crop-specific dose response functions; see Mauzerall and Wang (2001), Mills et al. (2007), Van Dingenen et al. (2009), and Debage (2014), among others. Crop response functions are also employed in conjunction with regional and global atmospheric chemical transport models (ACTMs) as in Van Dingenen et al. (2009), Avnery et al. (2011b, 2011a), and Ghude et al. (2014), among others.

weather data set from the North American Regional Reanalysis dataset of the National Center of Environmental Prediction at the National Oceanic and Atmospheric Administration (NOAA). Based on conversations with NOAA staff, these are the most comprehensive historical daily weather data available at such a fine (approximately 0.3 degrees) spatial resolution.

The remainder of the paper is organized as follows. The next section provides some background on ozone and its effects on crop yields. Subsequently, we discuss the various data sources and presents our main results. In the following section, we quantify the social welfare implications of the crop yield improvements due to the reduction in NO_x emissions. Finally, we conclude. To accommodate space limitations, we relegate the analysis of the relationship between ozone and power plant NO_x emissions, as well as the analysis of the relationship between crop yields and ozone, along with a battery of robustness checks and some additional discussion, to the online supplementary material of the article.

How NO_x Affects Crop Yields

In the presence of sunlight, oxides of nitrogen (NO_x) react with volatile organic compounds (VOCs) to produce ground-level ozone.[2] In addition to a wide variety of health problems, especially for children, the elderly, and people with lung diseases, ozone can be particularly harmful for vegetation and ecosystems. A substantial amount of research has also demonstrated that ozone and its precursors can travel hundreds of miles away from their sources under appropriate meteorological conditions.

The primary source of NO_x is fossil-fuel combustion. Additional sources of NO_x include biomass burning, lightning, and soils. VOCs are emitted from a range of human activities, including fossil-fuel combustion, evaporation of fuel, solvent use, and chemical manufacturing. Terrestrial vegetation also provides a large natural source of VOCs (e.g., pinene from coniferous trees). The weather plays a significant role in ozone formation; hot sunny days provide the most favorable conditions for ozone production. For this reason, NO_x emissions are typically regulated during the summer (May 1–September 30) in the United States when sunlight intensity and temperatures are highest.

Wind speed and direction are important determinants of ozone transport. Low wind speeds lead to the buildup of high local concentrations. High wind speed prevents the local build-up near the sources, but contributes to long-range transport and regional ozone particularly during directionally persistent wind conditions. For example, the CUSAQC (1999) report documents ozone concentration patterns at different wind directions and speeds that are consistent with an atmospheric ozone lifetime of about one day and a corresponding transport distance of 200, 500, and 800 km at speeds of 2, 5, and 8 meters per second.

When enough ozone enters the leaves of a plant through the stomata, it reduces photosynthesis, the process that plants use to convert sunlight to energy to live and grow. It can also slow the plant's growth and increase the risk of disease, damage from insects, effects of other pollutants, and harm from severe weather. Some plants also show signs of visible damage, such as marks on their leaves, when ozone is present under certain conditions. Exposure to ozone, alone or in combination with other pollutants, has been shown to be responsible for about 90% of the US crop loss due to air pollution; see Heck et al. (1982), Murphy et al. (1999), Mauzerall and Wang (2001), Tong et al. (2007), among others.

Dose-response functions have been developed to quantify the effects of ozone on photosynthesis. The dose is the amount of ozone available during the response period and is defined as the ozone concentration multiplied by the duration of exposure (Felzer et al. 2007). Although the dose measures concentration over a period of time, ozone is often observed to affect vegetation only after surpassing certain threshold levels because of plants' antioxidant defenses. Under low antioxidant conditions, plants may have a much lower ozone threshold.

Data

NO_x Emissions

We measure emissions (thousands of tons) as accumulated totals during the growing season

[2] Ground-level or "bad" ozone is formed in the lower troposphere and is distinct from the beneficial stratospheric ozone. The material in this section draws heavily from chapter 6 in National Research Council (1991), the Introduction in Mauzerall and Wang (2001), US EPA (1991), and https://www.epa.gov/ozone-pollution; last accessed June 2019.

(April–September). Hourly electric generating unit (EGU)-level NO_x emissions are available from the US Environmental Protection Agency (EPA) Continuous Emission Monitoring System (CEMS). We limit our attention to NO_x emissions from coal and natural gas for EGUs owned by electric utilities. Electric utilities account for more than 95% of the emissions during the period of our analysis. We use the primary fuel type for each EGU to identify NO_x emissions from coal and natural gas.[3] As our main explanatory variable, we use total emissions from power plants within an assumed radius from each county centroid during the growing season.

Ozone

Hourly concentrations for the network of ozone monitors are readily available from the Air Quality System (AQS) data by EPA.[4] The same data contain information on the latitude and the longitude of the monitor site that is needed to construct county-level measures of ozone pollution. Following previous work—for example, Currie and Neidel (2005), Schlenker and Walker (2016)—we use monitor-level data to construct county-level measures of ozone pollution for each county with corn and soybeans yield data. Following the atmospheric science literature, we use the AOT40 cumulative index of ozone concentration during hours 10am–5pm, which we construct by summing ozone hourly concentrations exceeding 40 parts per billion (ppb), to measure ozone pollution.[5] A natural concern, which has also been raised before in related literature (Currie and Neidel 2005), is the variation in the number of ozone monitors over time, as well as the variation in the number of observations per monitor, both of which affect the variation in ozone pollution in our analysis. In our robustness checks, we show that changes in the number of monitors and the average distance to the monitors over time do not affect our results.

Crops

Annual county-level data on yields (bushels per acre) are available from the National Agricultural Statistics Service (NASS) of the US Department of Agriculture (USDA).[6] Following Schlenker and Roberts (2009) and Annan and Schlenker (2015) and to focus on rain fed agriculture, we limit our sample to counties east of the 100th meridian and exclude Florida.

We include crop prices (dollars per bushel) in some models to account for the possibility that expected prices may change agricultural land management practices. We use pre-planting futures prices from the Chicago Mercantile Exchange (CME). Although the futures prices are national, crop planting dates that exhibit variation across states are available from the USDA. Hence, we construct state-specific futures prices that better reflect the farmers' expectations during the planting season for prices received after harvest. As in Miao, Khanna, and Huang (2016), we first identify the most active usual planting dates for each state as reported in NASS (2010). For each state, we then calculate the average daily prices of December corn futures prices and November soybean futures prices over the range of usual planting dates. In our welfare analysis, we use annual state-level average prices received by farmers from USDA NASS.

Weather and Meteorological Variables

To account for the movement and concentration of emissions and pollution, we use fine-scale wind data. Daily data at a grid resolution of approximately 0.3 degrees (32 km) for a long list of weather variables are readily available from the North American Regional Reanalysis (NARR) data set of the National Center of Environmental Prediction (NCEP) at the National Oceanic and Atmospheric Agency (NOAA). Based on conversations with NOAA staff, these are the most

[3] Oil accounts for 1.8% of total NO_x emissions from electric utilities during 2003–13, which are the years relevant for our analysis.

[4] See https://aqs.epa.gov/aqsweb/airdata/FileFormats.html#_hourly_data_files; last accessed June 2019.

[5] In more detail, we first calculate the AOT40 index for each monitor. We then calculate the distance between each ozone monitor and the county centroid. Finally, we calculate a weighted average of concentrations across all monitors within an assumed radius from the county's centroid—we look at radii of 50, 100, and 200 miles—using the inverse of the distance to the monitor as the weight. The method, also known as inverse distance weighting, allows us to a construct an ozone concentration measure for each county during the ozone and growing seasons in every year during 2003–13. We use ozone-season (May–September) averages in the models linking ozone to NO_x emissions. We use growing-season (April–September) averages in the regressions that relate crop yields to ozone.

[6] Online supplementary material tables 1 and 2 present production and acres for corn and soybeans by state.

comprehensive historical daily weather data at this fine spatial resolution.[7]

There are two primary uses of this dataset in the paper. The first is to obtain measures of wind speed and direction for each power plant, which help us to construct explanatory variables in the regressions that link crop yields and ozone pollution to power plant NO_x emissions as in Schlenker and Walker (2016). The second is to obtain county-level weather-related controls, such as barometric pressure, relative humidity, and cloud area fraction in the regressions that link ozone pollution to power plant NO_x emissions. In terms of temporal and spatial aggregation of the data, we first calculate an average of the weather variable of interest (e.g., wind speed) for each grid point during the ozone season (May–September). We then calculate the distance between NARR grid points and county centroids or power plants. Finally, we use the data for the variable of interest associated with the grid point that is the closest to the county centroid or power plant.

For regressions that link crop yields to NO_x emissions and ozone pollution, we use the temperature and precipitation data from Annan and Schlenker (2015), an updated version of Schlenker and Roberts (2009), which are available for each county during the growing season. The data from Schlenker and Roberts have been used extensively in the literature on the effects of climate change on US agriculture and are discussed in great detail elsewhere (Roberts, Schlenker, and Eyer 2013). Following these papers, in the models for corn yields, we use precipitation, the square of precipitation, cumulative degree days between 10°C and 29°C (moderate heat), and cumulative degree days above 29°C (extreme heat). For soybeans, we use the same controls except we define the extreme heat threshold at 30°C rather than 29°C.

The Effect of NO_x Emissions on Crop Yields

In the following subsections, we start by describing our empirical approach for estimating the effect of NO_x emissions on crop yields. We then present our main results. Subsequently, we discuss additional results based on interactions of NO_x emissions with distance and meteorological variables. Having presented a series of robustness checks, we quantify the causal chain from NO_x emissions to crop yields through ozone.

Empirical Approach

We use fixed-effects models to establish a direct link between county crop yields and NO_x emissions from nearby power plants:

$$(1) \quad y_{ct} = a_c + \beta n_{ct} + \mathbf{z}'_{ct}\gamma + f_c(t) + \varepsilon_{ct},$$

where y_{ct} is the crop yield for county c in year t, $\mathbf{z}_{ct}$ denotes the temperature and precipitation controls, n_{ct} measures total NO_x emissions from plants within an assumed radius from the county centroid during the growing season (April–September), and ε_{ct} denotes the error term. We use a radius of 100 miles for our main results. There are an average of twenty-three power plants within 100 miles of a county centroid. The average county in our sample is about 600 square miles, or about 25×25 miles, so we are allowing NO_x emissions from several counties away to affect yield.

We estimate equation (1) separately for corn and soybeans via OLS. The county fixed effects, a_c, capture time invariant heterogeneity that matters for yield, such as the soil quality. We use $f_c(t)$ to denote different time-related functions, including county-specific linear trends and year fixed effects, to control for time-variant unobservables in various ways. To account for spatial correlation, we group the counties in our sample in three mutually exclusive geographical regions: the most northern (and coolest) states, the most southern (and warmest) states, and those in the middle.[8] We cluster the standard errors by region × year, which accommodates arbitrary correlation among unobservables within the same region and year. Our sample spans eleven years (2003–2013), so there are thirty-three clusters in total.

In earlier papers, which use longer samples than ours, time trends aim to capture technological changes, such as varieties with better yields due to selective breeding and changes in agronomic practices with a varying degree of flexibility depending on the specification.

[7] The reader should note that the mean county size in our sample is about 600 square miles (2010 Census land area). The NARR grid size is about 395 square miles. The mean distance to power plants within 100 miles is close to 66 miles. This means that the area of the circle around the county centroids is $A = \pi \times 66^2 \approx 13{,}684$ square miles, which is about 20 times as large as the mean county area. Given that the average number of plants within 100 miles is 23, there are $23 \times 395/13{,}684 \approx 0.67$ power plants in an area equal to the size of a NARR grid.

[8] Schlenker and Roberts (2009) use the same regions. See figure A.7 and section 7 of their supplemental appendix.

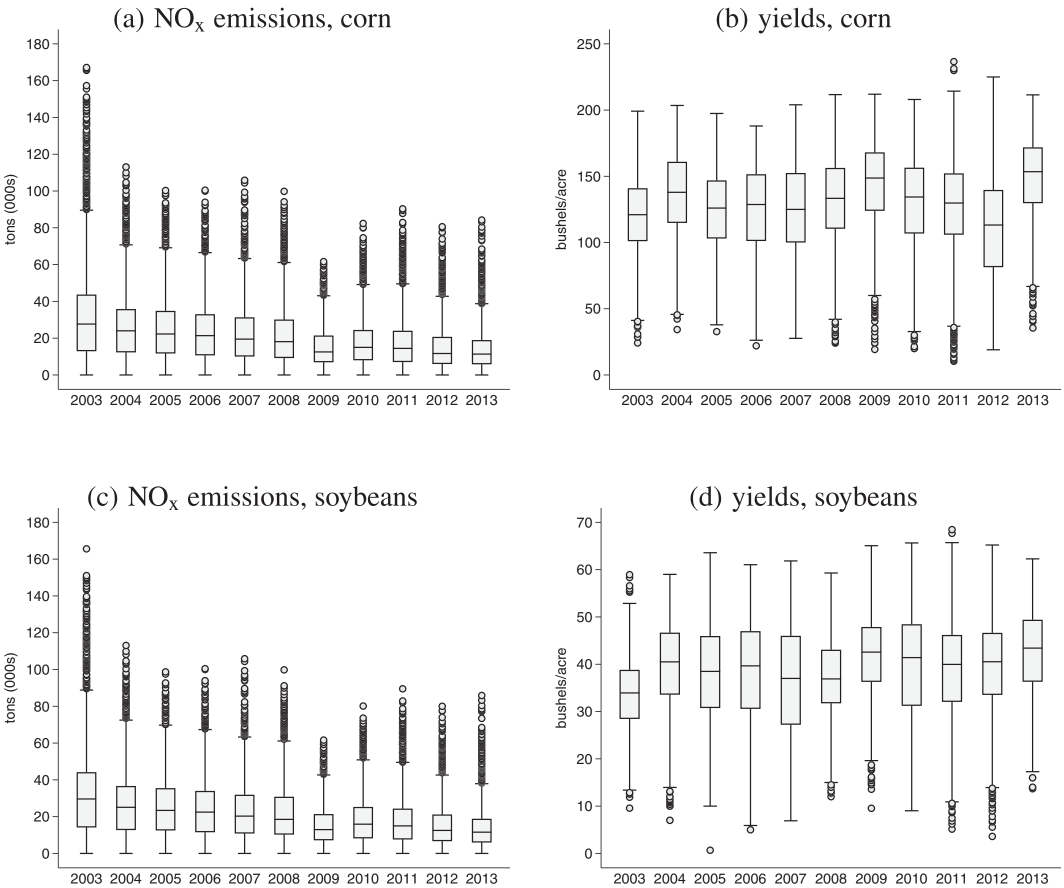

Figure 1. Crop yields and NO_x emissions

Note: The data points in all four plots are county-year combinations. We report total cumulated NO_x emissions within a 100-mile radius from the county centroids calculated following the approach in the Data section. Panels (a) and (b) pertain to counties growing corn. Panels (c) and (d) pertain to counties growing soybeans. For each of the box-and-whisker plots, the boxes cover the interquartile range, from the lower quartile to the upper quartile, and contain a vertical white line indicating the median. The whiskers, denoted by horizontal lines, intend to cover most or all the range of the data. The bottom whisker extends to a value that is the lower quartile minus 1.5 times the interquartile range, or the minimum should this be smaller. The top whisker extends to a value that is the upper quartile plus 1.5 times the interquartile range, or at the maximum, if this is smaller.

For example, Miao, Khanna, and Huang (2016) use a linear and a quadratic trend. Their sample spans the period 1977–2007. Annan and Schlenker (2015) use year fixed effects and county-specific quadratic trends. Their data are for 1989–2013. Schlenker and Roberts (2009) also use state-specific quadratic trends for a much larger sample period, 1950–2005, during which there was a threefold increase in yields. In our case, technological changes and changes in agronomic practices are not as pronounced given that our sample is for 2003–13. Our short time series dimension also limits the amount of flexibility we can reasonably allow in the trends. Thus, we do not use higher-order polynomial trends.

Figure 1 shows the temporal and spatial variation in yields and NO_x emissions in our regression sample. The within-county (between-counties) standard deviation of corn yields is 23 (29) bushels per acre. The within-county (between-counties) standard deviation of NO_x emissions is 8,718 (18,232) tons for the counties in the yield regressions that pertain to corn. The within-county (between-counties) soybean yield standard deviation is 6.6 (8) bushels per acre. The within-county (between-counties) standard deviation of NO_x emissions is 8,661 (17,740) tons in the yield regressions that pertain to soybeans.

Main Results

Table 1 presents the results of the yield regressions in equation (1) assessing the effect of

Table 1. Crop Yields and NO_x Emissions

	A. corn					
	(A1)	(A2)	(A3)	(A4)	(A5)	(A6)
NO_x	−0.1040	−0.3225***	−0.3721**	−0.3079*	−0.3859**	−0.2016
	(0.2099)	(0.1111)	(0.1758)	(0.1496)	(0.1701)	(0.1652)
Moderate heat		1.7801	6.0699	38.7182**	37.1235**	44.5489
		(15.3323)	(13.3410)	(16.7577)	(17.3765)	(35.5223)
Extreme heat		−36.7926***	−41.1446***	−85.5300***	−87.2518***	−89.5777***
		(8.5382)	(6.6218)	(13.6028)	(15.0375)	(16.9203)
Precip.		94.5057***	93.5231***	122.6831*	120.5622*	79.0083
		(33.0202)	(33.9374)	(59.7212)	(66.7239)	(72.7765)
Precip. Sq		−62.5746**	−62.2809**	−98.4008**	−98.2071*	−69.8762
		(23.7282)	(24.6992)	(44.9464)	(50.6343)	(55.9370)
R-squared	0.5986	0.7114	0.7724	0.7871	0.7739	0.7941
Observations	17,274	17,274	17,274	8,260	6,842	6,842
Counties	1,858	1,858	1,858	1,858	1,858	1,858
	B. soybeans					
	(B1)	(B2)	(B3)	(B4)	(B5)	(B6)
NOx	−0.1045**	−0.1444***	−0.0699	−0.1244***	−0.1393***	0.0617
	(0.0481)	(0.0296)	(0.0438)	(0.0308)	(0.0346)	(0.0464)
Moderate heat		16.3407***	16.5833***	22.9152***	23.3822***	17.1425
		(5.4673)	(5.1315)	(5.9539)	(6.1806)	(10.3689)
Extreme heat		−13.2173***	−15.2759***	−20.8792***	−21.3031***	−22.6374***
		(2.0513)	(1.9421)	(3.0759)	(3.2544)	(2.5211)
Precip.		52.2279***	48.5534***	42.8081***	43.4046***	39.6321***
		(11.4373)	(10.9539)	(14.4091)	(14.9774)	(13.1088)
Precip. Sq		−32.3131***	−30.6653***	−31.1032***	−32.0168***	−28.4784***
		(7.1948)	(7.1324)	(9.4648)	(9.8972)	(8.5405)
R^2	0.5913	0.7002	0.7571	0.7534	0.7389	0.8014
Observations	15,860	15,860	15,860	7,589	6,402	6,402
Counties	1,693	1,693	1,693	1,693	1,693	1,693
	C. specifications					
	(C1)	(C2)	(C3)	(C4)	(C5)	(C6)
County FE	Yes	Yes	Yes	Yes	Yes	Yes
County × trend	No	No	Yes	Yes	Yes	Yes
Top ten states	No	No	No	Yes	Yes	Yes
Balanced panel	No	No	No	No	Yes	Yes
Year FE	No	No	No	No	No	Yes

Note: The standard errors in parentheses are clustered by region × year. The asterisks denote statistical significance as follows: 10%(*), 5%(**), 1%(***).

NO_x emissions from power plants within 100 miles of the county centroids.[9] Panel A of the table pertains to corn, panel B pertains to soybeans, and panel C provides some information regarding the model specification.[10] We find negative and statistically significant estimates of the effect of NO_x emissions on yields.

[9] We address distance from the emissions source in the next section, where we interact NO_x emissions with distance from the power plant to the county centroid.

[10] Online supplementary material table 3 contains descriptive statistics for crop yields, NO_x emissions, power plants, and the weather variables that enter equation (1) for the 100-mile radius by crop.

We consider six alternative specifications for each crop. First, we omit weather ($\mathbf{z}_{ct}$) and the time-related controls ($f_c(t)$), so that the identification of the coefficient on NO_x emissions comes from deviations from county-specific means. Second, we add temperature and precipitation ($\mathbf{z}_{ct}$). In the third specification, $f_c(t)$ contains county-specific linear trends through interactions of a linear time trend with county fixed effects. The fourth and fifth specifications also include county-specific linear trends, but they restrict the sample to only the top ten producing states (fourth) and the balanced-panel of counties for which we have data for all years during 2003–13 (fifth).[11] Hence, in the third, fourth and fifth specifications, we identify the effects of NO_x emissions also using deviations from county-specific trends. In the final specification, we add year fixed effects.

Yield trends could vary across counties for many reasons other than variation in nearby NO_x emissions, including different climate trends (Burke and Emerick 2016), soil differences that make some regions more amenable to technological progress, and different trends in land use. Thus, it is important to allow heterogeneous trends in case these trends are correlated with NO_x emissions. Comparing columns A2 and A3 in table 1, the heterogeneous trends make a small difference for corn. The NO_x coefficient changes from −0.37 to −0.32, which is less than a one-standard-error difference. The NO_x coefficient for corn also changes little when we drop low-producing counties by restricting the sample to only the top ten producing states (column A4) and to the balanced-panel of counties (column A5).

For soybeans, including heterogeneous trends decreases the NO_x coefficient from −0.14 (column B2) −0.07 (column B3) which is a difference of about two standard errors. However, dropping the low-producing counties implies NO_x coefficients of −0.12 (column B4) and −0.14 (column B5). These estimates are larger in absolute value and have smaller standard errors than the full-sample estimate in column B3, which suggests that the low-producing counties introduce considerable noise in the soybean results.

The NO_x coefficient in column A3 implies that each 1,000 tons of NO_x emissions predicts 0.37 fewer bushels of corn per acre. Using this estimate, an increase in NO_x emissions equal to 1 within-county standard deviation implies a decrease in corn yields by 3.24 bushels per acre.[12] Assuming an average corn yield of 130 bushels per acre, this estimate implies a 2.49% decrease in yields.

A similar calculation for soybeans based on NO_x coefficient estimate in column B3 shows that an increase in NO_x emissions by 1 within-county standard deviation implies a decrease in soybean yields of 0.61 bushels per acre. Using the average yield of 40 bushels per acre, our estimates imply a 1.52% decrease in yields. The estimate for the effect of emissions on soybean yields doubles if we use estimates from the models in columns B4 and B5 that exclude low-producing counties.

One potential identification concern could be that hot weather is confounded with NO_x emissions. Specifically, high temperatures reduce crop yields and also raise the demand for air conditioning, which in turn increases electricity generation and NO_x emissions. If this mechanism were important, we would expect to see the negative NO_x coefficient decrease in absolute value when we control for temperature. We do not observe such a drop. Controlling for weather causes the NO_x coefficient to increase in absolute value for corn (columns A1 and A2).[13] However, the weather controls do soak up a substantial amount of variation and thereby reduce the standard errors.

For corn, the NO_x coefficient drops approximately in half and becomes statistically insignificant at 5% when we add year fixed effects (column A6). For soybeans, the NO_x coefficient is positive and statistically insignificant at conventional (less than or equal to 10%) levels in the presence of year fixed effects (column B6). After including year fixed effects, the regression asks whether a county's yield is further below its trend than the average county in years when nearby NO_x emissions are further above trend than the average county. In contrast, models that exclude year fixed effects ask merely whether county yield

[11] Online supplementary material table 4 provides the number of observations by state for the unbalanced and balanced panels.

[12] Recall from our discussion of figure 1 that an increase of 8,700 tons is approximately equal to one standard deviation increase in emissions within county.

[13] Online supplementary material table 5 shows the variation in the four weather variables by quartile of NO_x emissions. There is no indication that high NO_x emissions are associated with extreme heat.

is below its trend in years when nearby NO_x emissions are above trend. Our identification is weaker in the models with year fixed effects because changes over time in NO_x emissions are correlated across counties.

In all models, the coefficients on the weather variables are similar to those in Schlenker and Roberts (2009).[14] We estimate a small positive coefficient on moderate heat and a large negative coefficient on extreme heat. Using the specifications with the county-specific linear trends, the harmful effect of extreme heat is roughly seventy times as large as the beneficial effect of moderate heat for corn. The corresponding ratio for soybeans is about ten. Since there is very little irrigation in the counties in our sample, precipitation is an important determinant of yields. Similar to Schlenker and Roberts, we estimate a quadratic relationship between yield and rainfall. The optimal amount of precipitation is 29–32 inches depending on the specification and commodity.

In sum, based on the full-sample models in A3 and B3, we estimate that an increase in NO_x emissions by 8,700 tons (equal to 1 within-county standard deviation) within a 100-mile radius of the county centroid implies a decrease in corn yields by 2.49% and a decrease in soybean yields by 1.52%. Before evaluating the welfare impacts of these effects in a subsequent section, we interact NO_x with distance and meteorological variables, investigate the robustness of our findings, and quantify the causal chain from NO_x to yields through ozone.

Interacting NO_x Emissions with Distance and Meteorological Variables

Ozone and NO_x transport depend on the distance between counties and power plants, as well as meteorological conditions such as wind speed, wind direction, temperature, precipitation, cloud coverage, and solar radiation. In this section, we report results from models that vary the radius we use to define nearby NO_x emissions and that interact NO_x emissions with a set of meteorological variables identified from the atmospheric chemistry literature.[15]

In particular, using c to denote the county and t to denote a year, we use OLS to estimate the following fixed-effects model:

$$y_{ct} = a_c + \mathbf{x}'_{ct}\beta + \mathbf{z}'_{ct}\gamma + f_c(t) + \varepsilon_{ct}, \tag{2}$$

where y_{ct} is yield, a_c is a county fixed effect capturing time invariant unobservables, $\mathbf{x}_{ct}$ is a vector of variables related to NO_x emissions discussed below. The vector $\mathbf{z}_{ct}$ contains the same temperature and precipitation controls as in equation (1), and $f_c(t)$ contains county-specific linear trends. Finally, ε_{ct} is the error term.

We consider three alternative specifications of equation (2) that stem from different elements of $\mathbf{x}_{ct}$. In the simplest specification (I), $\mathbf{x}_{ct}$ contains a single element: total accumulated NO_x emissions across plants within an assumed radius (50, 100, or 200 miles) from each county centroid denoted by $n_{ct} = \sum_{p \in \mathcal{P}} nox_{pt}$. This is the regressor of interest in equation (1). The set of power plants $\mathcal{P}$ and the implied emissions that enter the summation depend on the assumed radius. In the second specification (II), we also interact NO_x emissions with the distance between the plant and the county centroid, that is, $\sum_{p \in \mathcal{P}} nox_{pt} d_{cp}$.

In the third specification (III), which is the richest, we fully interact NO_x emissions with wind speed and direction, since both contribute to ozone transport across space and time. The series of interaction terms in specification III involve wind direction and wind speed. For example, holding wind speed constant, counties downwind should be affected more by NO_x emissions relative to counties upwind. To capture this relationship between pollution and emissions, we use v_{pt} to denote the wind speed at the plant and cos_{cpt} to denote the cosine of the difference between the wind direction at the plant and the location of the county relative to the plant, which can differ for upwind ($cos_{cpt} > 0$) and downwind ($cos_{cpt} < 0$) counties. We measure the wind direction and the cosine of the difference between the

[14] Moderate heat is measured in 1,000 degree days, and extreme heat is measured in 100 degree days. The precipitation is measured in meters.

[15] See Thompson et al. (2001), Cox and Chu (1993), Camalier, Cox, and Dolwick (2007), and Dawson, Adams, and Pandis (2007), among others. See also Details of the Omnibus Meteorological Database at by the EPA Support Center for Regulatory Atmospheric Modeling at https://www.epa.gov/scram/air-modeling-observational-meteorological-data; last accessed June 2019.

wind direction at the plant and the county location as in Schlenker and Walker (2016).[16]

An approach in the atmospheric science tradition would likely employ emissions and dispersion modeling instead of the reduced-form regression approach we use. For example, the Air Pollution Emission Experiments and Policy (APEEP) model in Muller and Mendelsohn (2007) and Muller, Mendelsohn, and Nordhaus (2011) uses a Gaussian dispersion model to translate annual NO_x emissions from various sources such as power plants into annual NO_x concentrations in each county, a linear regression model to translate annual NO_x concentrations into average summer ozone concentrations, and a dose-response function to translate average summer ozone into crop yield (see the technical appendix to Muller and Mendelsohn 2007). To the best of our knowledge, APEEP is based on standard models in atmospheric science. The Gaussian dispersion model imposes a functional relationship on how wind speed, wind direction, and distance, affect pollution dispersion. The approach in Schlenker and Walker (2016), which we also employ, is, if anything, a more flexible way to model these interactions.[17]

Table 2 shows the marginal effects of a 1,000-ton increase in NO_x emissions on crop yields distinguishing between counties that are downwind and counties that are upwind from the relevant power plants. The table shows results from nine different regressions for each crop: specifications I, II, and III for each of three radii (50, 100, or 200 miles from the county centroid).[18] For corn, the estimated marginal effects are negative for all specifications for both upwind and downwind counties, and they are statistically significant at 5% for all but the most flexible specification in the case of the largest radius. For soybeans, although many of the estimated marginal effects are not significant at 5%, they are similar to those in the analogous specifications in column B3 of table 1.

For both crops, the marginal effects are largest for the 50-mile radius and smallest for the 200-mile radius. When we double the radius from 50 to 100 miles, which implies quadrupling the area of the circle, the estimated NO_x coefficients decrease by about 50%. When we double the radius from 100 to 200 miles, the NO_x coefficients again drop approximately in half.

The estimated marginal effects for corn are similar between the three specifications and between upwind and downwind counties. We classify a county as downwind in a given year if the average wind direction flowed from the power plants within the assumed radius and toward the county centroid. This average obscures substantial variation in wind direction across days within a year—a county that is downwind on average is likely to be upwind for a substantial fraction of the growing season. It also obscures variation in power plant locations—a county with power plants in all directions from the county centroid will experience emissions blowing toward the centroid no matter which direction the wind is blowing. As a result, it is reasonable to expect significant NO_x pollution effects on crop yields even in upwind counties.[19]

Contrary to corn, the soybean marginal effects for specification III are notably larger for the downwind counties than for the upwind counties. The difference is especially large at the 100- and 200-mile radii, where the marginal effects for the upwind counties are a small negative (100 miles) or positive (200 miles). These differences disappear when we repeat these regressions using a balanced panel of counties in the top ten states.[20] Thus, as in the results presented in table 1, the low-producing counties introduce considerable noise in the soybean results.[21]

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[16] The full set of variables entering $\mathbf{x}_{ct}$ is similar to that in Schlenker and Walker (2015) and is listed in the online supplementary material table 6. One difference between us and them when it comes to the construction of these variables is that they have a one-to-one match between pollution sources and sinks. In particular, each California zip code in their sample (sink) is linked to a single airport (source) given that they focus on a distance of at most 10 kilometers between the sink and the source. In our case, a many-to-many match between pollution sources (power plants) and sinks (counties) is possible, especially when we consider power plants that are located within 100 and 200 miles from the counties for which we have data on corn and soy yields.

[17] See also Wang, Ogden, and Chang (2007), Moretti and Neidell (2011), Nail, Hughes-Oliver, and Monahan (2011), and Chang, Hao, and Sarnat (2014) for a similar approach to modeling the relationship between ozone and NO_x using a regression framework.

[18] Online supplementary material tables 7 and 8 show the full regression results for corn and soybeans, respectively.

[19] To investigate the variation in the wind direction, we calculated the proportion of days in growing season for each year during 2003–12 that the wind was blowing from each of four directions (north, east, south, west); see Online supplementary material figures S1 and S2. The wind rarely blew from the same direction on more than half of days, and it rarely blew from any one direction for less than 10% of days.

[20] See the online supplementary material table 9.

[21] To explore spatial and temporal heterogeneity of the effects of NO_x emissions on crop yields, we interacted NO_x with dummy variables for the north, middle, and south regions in our sample using the regions in Schlenker and Roberts (2009). In the case of corn, the coefficients of all three interactions are negative.

Table 2. Marginal Effects of NO_x Emissions on Crop Yields

	A1. Corn, 50 miles					B1. Soybeans, 50 miles				
	(I.all)	(II.d)	(II.u)	(III.d)	(III.u)	(I.all)	(II.d)	(II.u)	(III.d)	(III.u)
Effect	–0.7059	–0.7033	–0.7039	–0.7761	–0.7487	–0.1248	–0.1250	–0.1250	–0.1589	–0.0871
s.e.	0.3283	0.3300	0.3296	0.3258	0.3788	0.0917	0.0921	0.0921	0.0820	0.0987
t-stat.	–2.1498	–2.1312	–2.1356	–2.3819	–1.9764	–1.3604	–1.3567	–1.3573	–1.9380	–0.8824
	A2. corn, 100 miles					B2. soybeans, 100 miles				
	(I.all)	(II.d)	(II.u)	(III.d)	(III.u)	(I.all)	(II.d)	(II.u)	(III.d)	(III.u)
Effect	–0.3721	–0.3727	–0.3729	–0.3668	–0.4548	–0.0699	–0.0699	–0.0700	–0.1228	–0.0049
s.e.	0.1760	0.1761	0.1762	0.2091	0.2319	0.0438	0.0437	0.0437	0.0358	0.0582
t-stat.	–2.1142	–2.1160	–2.1161	–1.7540	–1.9610	–1.5941	–1.5988	–1.6015	–3.4336	–0.0842
	A3. corn, 200 miles					B3. soybeans, 200 miles				
	(I.all)	(II.d)	(II.u)	(III.d)	(III.u)	(I.all)	(II.d)	(II.u)	(III.d)	(III.u)
Effect	–0.1430	–0.1421	–0.1417	–0.1553	–0.1462	–0.0371	–0.0384	–0.0393	–0.0761	0.0173
s.e.	0.0655	0.0652	0.0650	0.0987	0.1068	0.0194	0.0195	0.0197	0.0190	0.0281
t-stat.	–2.1836	–2.1800	–2.1785	–1.5734	–1.3695	–1.9181	–1.9734	–1.9999	–4.0073	0.6169

Note: The table shows the effect of an increase in NO_x emissions by 1,000 tons on yields. We report effects for counties that are upwind (u) and downwind (d) separately when needed. The former (latter) are counties for which the cosine of the difference between the wind direction at the power plants and the direction in which the county is located is positive (negative). The effects shown are based on the models in the online supplementary material table 7. In the case of interactions of NO_x emissions with distance and meteorological variables, we evaluate the effects at the means of the variables interacted with NO_x emissions (e.g., mean distance, mean wind speed, etc.). The standard errors are calculated using the delta method and are clustered by region × year.

Robustness Checks

The discussion that follows pertains to robustness checks for unbalanced-panel models. We focus on the most flexible specification with county-specific linear trends and the 100-mile radius unless stated otherwise. In table 2, we provide the NO_x coefficients for the robustness checks discussed below. We denote the various specifications using a series of mnemonics, with benchmark (BENCH) referring to the estimates in columns A3 and B3 of table 1, namely, –0.37 for corn, and –0.07 for soybeans.

A. Controlling for Crop Prices (PRIC). Miao, Khanna, and Huang (2016) argue that an increase in expected crop prices can steer farmers towards the adoption of improved crop practices, seed varieties, and other technologies, all of which can have a positive effect on yield. However, an increase in expected crop prices may also decrease yields if it leads, for example, to expanding acreage to low-quality areas. Hence, the net effect of crop prices on yields is an empirical question. When we control for CME futures prices, the NO_x coefficient changes little from the benchmark model. It is negative and significant at 5% and falls inside the 95% confidence interval of its benchmark counterpart for corn. The NO_x coefficient is not significant at conventional levels in the case of soybeans.

B. March-August Growing Season (MARC). We define the growing season as March–August following Miao, Khanna, and Huang (2016) and Schlenker and Roberts (2009) as opposed to April–September in our main results. In the case of corn, the NO_x coefficient becomes slightly smaller and is not significant at conventional levels.[22] For soybeans, the NO_x coefficient is slightly larger (–0.08) than its benchmark counterpart and is significant at 10%.

C. Non-irrigated counties (NOIR). We exclude observations for which the fraction of irrigated to total planted acres exceeds

However, only the coefficient of the $NO_x \times$ north interaction (–0.38) is significant at conventional levels (10%). For soybeans, the coefficient of the $NO_x \times$ north interaction is negative (–0.14) and significant at 1%. To explore the heterogeneity of the effects across time, we interacted NO_x with dummy variables for two time periods: 2003–08 and 2009–13. The main reason for interacting NO_x with these two dummy variables is that the EPA NO_x budget program (NBP) was terminated in 2008 and was replaced by the Clean Air Interstate Rule (CAIR) NO_x ozone season and NO_x annual programs in most states. In the case of corn, the coefficient of the $NO_x \times 2003-08$ is –0.37 and significant at 5%. The coefficient of the $NO_x \times 2009-13$ interaction is –0.30 but not significant at conventional levels. For soybeans, the coefficients for both interactions are not significant at conventional levels.

[22] The coefficient is negative and significant at 5% in a balanced panel model with the same specification.

20% for a county in a particular year. This change in the set of counties in our sample causes us to drop 2% of the observations in our corn models and 3% of our soybean observations and has no material implications for our estimates of the NO_x effects.

D. Counties in Annan and Schlenker (ANSC). Using data for the counties in Annan and Schlenker (2015) for 2003–13 we estimate a NO_x coefficient that is negative and significant at 5% in the case of corn. For soybeans, it is negative and not significant at conventional levels. For both crops, the NO_x coefficient is very similar to its benchmark counterpart.

E. Excluding 2012 (NO12). We estimated the regressions that link crop yields and NO_x emissions excluding 2012, which was characterized by the most adverse weather conditions during the growing season in recent years. At the same time, gas prices paid by electric power plants were at particularly low levels. In April 2012, gas-fired electricity generation accounted for 32% of all electricity generation. For the first time since EIA began collecting data, gas-fired generation was virtually equal to coal-fired generation.[23] Therefore, there were two countervailing forces in play in terms of their effects on yield: bad weather and lower NO_x emissions from power plants. The NO_x coefficient for corn decreases to –0.17 and it is not significant at conventional levels.[24] For soybeans, the NO_x coefficient is –0.10 and significant at 5%. It also falls inside the 95% confidence interval of its benchmark counterpart.

F. Controlling for other NO_x emissions (EPAT). Our benchmark models do not control for NO_x emissions from other sources that have a negative effect on crop yields and may be correlated with NO_x emissions from power plants. To do so, we replaced the linear trend with NO_x emissions attributed to sources other than fossil fuel combustion at electric utilities from the EPA Air pollutant Emissions Trends data, which we further interacted with county fixed effects. The NO_x coefficient is negative and significant at 5% for both commodities. In the case of corn, the point estimate is –0.25 and falls inside the 95% confidence interval of its benchmark counterpart. In the case of soybeans, the point estimate is –0.16 and falls outside the 95% confidence interval of its benchmark counterpart.

G. Kitchen Sink (KSIN). We consider a rich specification with the following controls in addition to the weather-related variables, the county-fixed effects, and the county-specific linear trends in columns A3 and B3 of table 1: (i) NO_x emissions from sources other than utility plants, (ii) CME futures crop prices (exhibit variation by state and year), (iii) USDA NASS fertilizer price index (exhibits variation by year), (iv) motor gasoline and petroleum prices (exhibit variation by state and year) from the EIA State Energy Data System (SEDS), (v) BEA series CA 30110 (per capita personal income), CA 45190 (production expenses on fertilizer and lime), CA 45370 (farm earnings), all of which exhibit variation by county and year.[25] For corn, the NO_x coefficient (–0.34) is significant at 5% and very simlar to its benchmark counterpart. In the case of soybeans, the NO_x coefficient (–0.07) is significant at 10% and also very similar to its benchmark counterpart.

H. Clustering. Clustering the standard errors by state (CLUS) implies a NO_x coefficient that is significant at 1% (5%) for corn (soybeans). This is an attempt to account for correlation of the unobservables in equation (1) across space and time. We also considered clustering by USDA Agricultural District (CLUU) as an alternative clustering scheme to account for correlation in unobservables across space and time.[26] The NO_x coefficient is now significant at 1% for both crops. These two clustering schemes are less conservative than our benchmark because they allow for less spatial correlation.

[23] https://www.eia.gov/todayinenergy/detail.php?id=6990; last accessed June 2019.

[24] As for MARC, the coefficient is negative and significant at 5% in a balanced panel model with the same specification.

[25] The data on emissions from sources other than power plants are the same as in robustness check F. The CME futures crop prices are the same as the ones used in robustness check A.

[26] Our regression samples contain more than 219 (207) agricultural districts in the case of corn (soybeans). According to the USDA, these districts are groups of counties in each state, by geography, climate, and cropping practices. The geographic attributes include soil type, terrain, and elevation (mountains). The basic components of climate are mean temperature, annual precipitation and length of growing season. These factors influence the crops grown, the need to conserve soil moisture, and the use of irrigation (cropping practices). See https://www.nass.usda.gov/Data_and_Statistics/County_Data_Files/Frequently_Asked_Questions/index.php#; last accessed June 2019.

Finally, we performed two additional robustness checks. We do not report these in figure 2 because they use different units. First, we constructed a distance-weighted sum of NO_x emissions across plants within 100-mile radius such that emissions from plants that are further away receive smaller weight (i.e., inverse-distance weighting). The NO_x coefficient is negative and significant at 5% in the case of corn except for the model specification in which we include a common linear trend (online supplementary material table 10). In the case of soybeans, the NO_x coefficient is negative and significant at 1% only for the baseline specification in which we only control for county fixed effects and weather. It is negative, albeit not significant at conventional levels, in the remaining specifications (online supplementary material table 11). For the corn specification with county-specific linear trends, the NO_x coefficient is –14.67, while for soybeans it is –2.60. Assuming an increase in distance-weighted NO_x emissions equal to 1 within-county standard deviation, which is equivalent to 190 tons, the implied decrease in corn yields is 2.14% when evaluated at the average yield of 130 bushels per acre. The same increase in NO_x emissions implies a

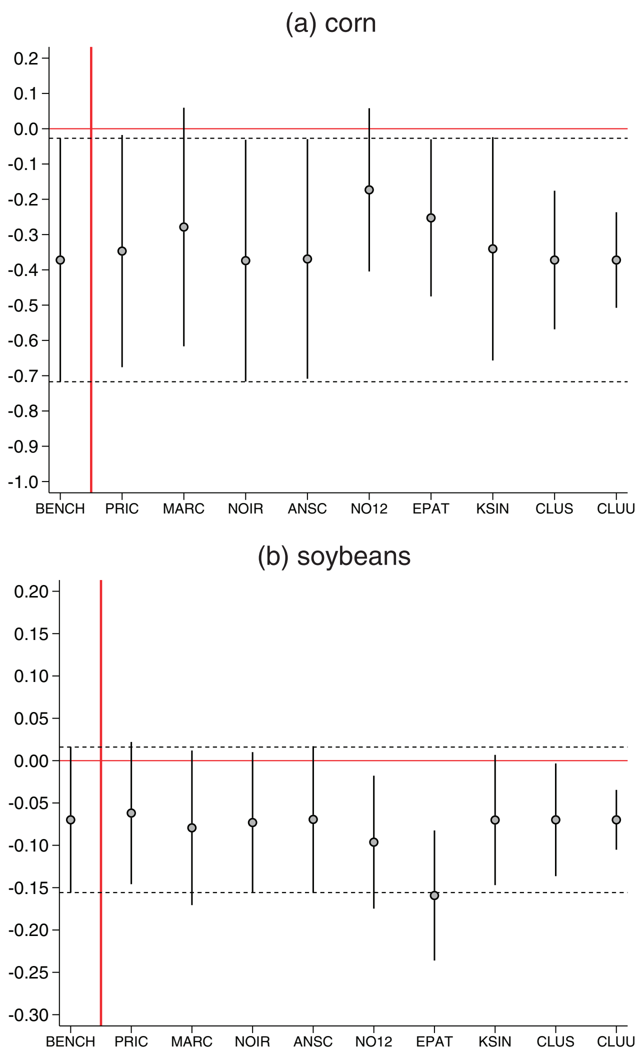

Figure 2. Crop yields and NO_x emissions, robustness checks

Note: The mnemonics on the horizontal axis correspond to various checks discussed in detail in the Robustness Checks section. With the exception of EPAT, we use the specification with county-specific linear trends and show the NO_x coefficients and the associated 95% confidence intervals. The dashed lines indicate the 95% confidence intervals of the NO_x coefficients for the benchmark models in the leftmost part of each graph. The confidence intervals are constructed using standard errors clustered by region × year. Panel (a) pertains to counties growing corn. Panel (b) pertains to counties growing soybeans.

decrease in soybean yields of 1.24% for the average yield of 40 bushels per acre. These effects are comparable to the benchmark estimates of 2.49% (corn) and 1.52% (soybeans).[27]

Second, we used log crop yields as dependent variables. In the specification with county-specific linear trends using the unbalanced panel, the NO_x coefficient is negative and significant at 5% in the case of corn (online supplementary material table 12). For soybeans, the coefficient is negative but not significant at conventional levels (online supplementary material table 13). Given that the NO_x coefficient estimates are –0.0036 (–0.0014) for corn (soybeans), the implied drop in yields due to an increase in NO_x emissions by 8,700 tons is 3.10% (1.24%) for corn (soybeans) based on average yields of 130 (40) bushels per acre. Once again these estimates are similar to their benchmark counterparts for both crops.[28]

Quantifying the Causal Chain through Ozone

NO_x emissions raise ozone levels, which slows down photosynthesis and thereby reduces crop yields. In this section, we present results from two sets of regressions that aim to quantify the effect of NO_x emissions on yields through ozone. First, we run regressions of ozone pollution on power plant NO_x emissions. Second, we regress crop yields on ozone pollution. We summarize the results of the two sets of regressions in table 3.[29] We measure ozone pollution using AOT40, a cumulative metric, which is the sum of hourly ozone concentrations exceeding 40 ppb over the growing season; see Tong et al. (2007), McGrath et al. (2015), and Carter et al. (2017), among others.[30] We report results for unbalanced-panel yield models with county-specific linear trends and controlling for weather.

Table 3 shows that regressions of yields on ozone pollution produce negative coefficients for both crops but with a substantially larger coefficient for corn. The soybean coefficient is not statistically significant at conventional levels. These results mirror those in our reduced form regressions of yield on NO_x. Given that the link between ozone and crop yields is well documented in the scientific literature, these results provide qualitative support for our main findings.

The NO_x coefficient in the regression of ozone on NO_x emissions is 0.05. We measure NO_x in 1,000 s of tons, so a 1,000 ton increase in NO_x emissions during the growing season implies an increase in total growing-season ozone pollution equal to 0.05 ppb. The coefficient on ozone in the corn model is −2.23, which implies a decrease in corn yields equal to $2.23 \times 0.05 \approx 0.11$ bushels per acre with a standard error of 0.03 bushels per acre. Similarly for soybeans, the ozone coefficient in the yield regression is −0.33, which implies a decrease of $0.33 \times 0.05 \approx 0.02$ bushels per acre with a standard error of 0.01 bushels per acre. These coefficients are less than a third of the corresponding estimates from the reduced form regression, which are −0.37 for corn and −0.07 for soybeans.

To assess the effects discussed in the previous paragraph, it is important to keep in mind that the intermediate variable in these calculations, ozone pollution, is measured as an average across monitors weighted by distance to the county centroid. As a measure of the ozone to which the crops in a county are exposed, this variable contains error. We expect the implied effects to be attenuated by this measurement error, so it makes sense that the implied effects from this two-step process are smaller than the reduced-form effects in table 1. In sum, we take these implied effects as a strong qualitative indication that NO_x emissions affect crop yields significantly through ozone, but likely underestimate the magnitude of these effects.

Welfare Implications of Yield Improvements

Tables 4 and 5 contain estimates of the welfare effects associated with the yield improvements attributed to the reduction in NO_x emissions during our sample period. For each county, we compute the change in average NO_x emissions from the first three years of our sample

[27] Similar to the sum of NO_x emissions, the distribution of the distance-weighted sum of NO_x emissions is heavily skewed to the right with a mean of 443 (450) tons and a standard deviation of 463 (455) tons in the corn (soybean regressions). The between-counties standard deviation is 0.426 (0.414) and the within-county standard deviation is 190 (187) tons.

[28] In the online supplementary material section S.1, we present a further robustness check in which we allow for flexible functional forms in the relationship between crop yields and NO_x emissions based on threshold effects and interactions of NO_x emissions with intraseason dummies. Our results are robust to this check.

[29] For details on these regressions, see the online supplementary material sections S.2.1 and S.2.2.

[30] Similar to Carter et al. (see their appendix), we only consider ozone concentrations during the 8-hour time window 10am–5pm each day in our calculation of AOT40.

Table 3. Causal Chain of the Effects of NO_x Emissions on Crop Yields Through Ozone

	A. Ozone and NO_x	B. Yields and Ozone		C. Yields and NO_x	
		corn	soybeans	corn	soybeans
NO_x	0.0479***			−0.3721**	−0.0699
	(0.0027)			(0.1758)	(0.0438)
Ozone		−2.2316***	−0.3301		
		(0.6350)	(0.2049)		
R^2	0.6368	0.8047	0.7766	0.7724	0.7571
Observations	89,197	9,716	9,048	17,274	15,860
Counties	1,865	1,637	1,513	1,858	1,693

Note: Panel A: We report the NO_x coefficient in column (I) of panel B of the online supplementary material table 17. Panel B: We report the ozone coefficient in columns A8 and B8 of the online supplementary material table 22. for corn and soybeans, respectively. Panel C: We reproduce the NO_x coefficients in columns A3 and B3 of table 1 for corn and soybeans, respectively. The details of the regression for panels A and B are available in the online supplementary material sections S.2.1 and S.2.2, respectively.

to the last three years of our sample. Using our regression estimates, we then compute the predicted change in yield attributable to these NO_x changes. We report the results by state.

In particular, using j to denote the state, we compute the estimated change in yields due to reductions in NO_x emissions using the following expression:

$$(3) \quad \Delta yield_j = \hat{\beta} \times (\bar{x}_{1j} - \bar{x}_{0j}),$$

where $\bar{x}_{1j}$ is a weighted average of NO_x emissions for counties in the state for 2011–13, $\bar{x}_{0j}$ is a weighted average of NO_x emissions for counties in the state for 2003–05, and $\hat{\beta}$ is the NO_x coefficient in columns A3 and B3 of table 1 for corn and soybeans, respectively. We use bushels as weights. To convert the estimated yield changes to dollar values, we multiply the estimated yield changes by average quantities (bushels) and prices (dollars per bushel) in 2014–16.

Averaged across the states in our sample, we estimate yield improvements of 4.33 bushels per acre of corn (2.46%) and 0.83 bushels per acre of soybeans (1.62%). The estimates are quite heterogeneous across states. The largest corn yield effects are those for Kentucky, where we estimate a 6.87% yield improvement. The smallest effects are those for North Dakota, for which the yield improvement is 0.32%. Similarly, for soybeans, we estimate yield improvements ranging from 0.21% in North Dakota to 4.30% in Kentucky. These differences in yield improvements reflect the varying changes in exposure to NO_x emissions. Since a small number of coal power plants operate near North Dakota farms, those farms experienced only small changes in exposure to NO_x emissions. In contrast, states in the eastern corn belt (e.g., Ohio) experienced a substantial decrease in NO_x emissions as coal use by power plants in these states declined. When we limit our analysis to the top-ten producing states for both crops, we see similar yield improvements (4.57 bushels per acre) for corn but much larger yield improvements for soybeans (1.58 bushels per acre).[31]

The incidence of an improvement in agricultural productivity such as the one we estimate in this paper depends on the elasticity of demand. If demand is relatively inelastic, then an increase in supply will reduce prices by so much that farm revenue declines. In that case, most of the benefits flow to consumers. In a comprehensive assessment of the effects of agricultural productivity improvements, Alston (2018) concludes that “American farmers as a group, supplying land, labor, and managerial inputs used in agriculture, have been made worse off by the changes in technology that transformed American agriculture.” This conclusion is drawn partly from the lack of evidence that demand elasticities are large enough to allow farmers to capture the benefits of improving productivity and partly from the fact that farming has not become more profitable over time even though agricultural productivity has increased substantially. Real net farm income in the United States has remained relatively constant at about $60 billion per year (in 2009 dollars) over the past ninety years; it has declined from 50% of the value of agricultural production in the 1930s to around 20% currently. Global population and incomes have soared over this

[31] See Online supplementary material table 15.

Table 4. Welfare Implications of Reduced NO_x Emissions, Corn

Rank (1)	State (2)	Bushels (3)	Yield (4)	Price (5)	*Δyield* (6)	%*Δyield* (7)	*ΔTR* (8)	Weight (9)	*ΔCS* (10)	*ΔPS* (11)	*ΔTS* (12)
1	IA	2537.833	192.213	3.527	2.500	1.301	−309.535	0.095	239.275	−137.282	101.993
2	IL	2206.050	193.911	3.618	6.845	3.530	−276.010	0.225	564.349	−323.790	240.559
3	MN	1382.850	182.162	3.414	4.576	2.512	−163.264	0.100	251.783	−144.458	107.325
4	NE	1664.900	183.036	3.565	2.304	1.259	−205.265	0.061	151.865	−87.131	64.734
5	IN	951.023	173.975	3.743	6.463	3.715	−123.109	0.102	256.054	−146.909	109.145
6	SD	799.127	161.113	3.281	0.950	0.590	−90.669	0.014	34.149	−19.593	14.556
7	OH	544.733	165.262	3.759	8.810	5.331	−70.813	0.084	210.457	−120.748	89.709
8	WI	516.773	168.792	3.481	5.302	3.141	−62.213	0.047	117.656	−67.504	50.152
9	MO	545.513	167.250	3.519	5.779	3.455	−66.382	0.055	136.605	−78.376	58.229
10	MI	337.143	161.645	3.576	4.199	2.597	−41.701	0.025	63.466	−36.413	27.053
11	KS	615.000	149.963	3.558	5.231	3.488	−75.676	0.062	155.477	−89.203	66.273
12	ND	386.020	144.062	3.248	0.457	0.317	−43.361	0.004	8.870	−5.089	3.781
13	KY	224.620	164.453	3.842	11.293	6.867	−29.845	0.045	111.795	−64.141	47.654
14	PA	139.783	148.628	3.973	3.603	2.424	−19.206	0.010	24.556	−14.088	10.467
15	MS	98.332	176.830	3.993	0.947	0.535	−13.578	0.002	3.816	−2.189	1.626
16	NC	102.237	128.648	4.184	2.839	2.207	−14.793	0.007	16.353	−9.382	6.971
17	TN	127.750	161.326	3.787	6.989	4.332	−16.731	0.016	40.109	−23.012	17.097
18	TX	288.155	156.182	4.127	1.093	0.700	−41.127	0.006	14.617	−8.386	6.230
19	LA	74.968	174.337	3.946	1.420	0.814	−10.230	0.002	4.425	−2.539	1.886
20	NY	81.941	142.361	3.995	1.624	1.141	−11.321	0.003	6.775	−3.887	2.888
21	AR	98.580	182.133	3.995	1.313	0.721	−13.621	0.002	5.150	−2.954	2.195
22	MD	66.123	165.887	3.784	8.365	5.042	−8.653	0.010	24.165	−13.864	10.300
23	GA	52.512	172.098	3.967	2.092	1.216	−7.203	0.002	4.627	−2.655	1.972
24	VA	49.790	152.774	3.897	5.048	3.304	−6.710	0.005	11.923	−6.841	5.082
25	SC	33.797	118.579	3.884	6.793	5.729	−4.540	0.006	14.032	−8.051	5.981
26	AL	39.710	146.656	3.658	7.009	4.779	−5.024	0.005	13.754	−7.891	5.863
27	DE	30.989	188.443	3.787	8.257	4.382	−4.058	0.004	9.841	−5.646	4.195
28	OK	39.467	142.622	3.812	2.115	1.483	−5.203	0.002	4.241	−2.433	1.808
29	NJ	11.094	152.183	3.737	5.702	3.747	−1.434	0.001	3.012	−1.728	1.284
30	WV	5.206	149.362	3.792	9.183	6.148	−0.683	0.001	2.320	−1.331	0.989
	ALL	14052.020	176.856	3.584	4.333	2.460	−1741.958	1.000	2505.516	−1437.517	1067.999

Note: For each state, we report average annual total quantity (*bushels*), average yield (*yield*), and average price (*price*) for 2014–16. The average yields are bushel-weighted. Annual state-level prices are readily available from the USDA. We calculate the change in yield (*Δyield*) using equation (3). The state-specific percentage change in yield (%*Δyield*) is equal to $100 \times \Delta yield/yield$. We also report the change in total revenue (*ΔTR*), change in consumer surplus (*ΔCS*), change in producer surplus (*ΔPS*), and change in total surplus (*ΔTS*), in dollars. For each state, we calculate *ΔCS* and *ΔPS* using equations (5) and (6), respectively. The *weight* column corresponds to the term w_j in the two equations. In the last row ("ALL"), we report the average yield, the average price, and the average change in yield, across states. The three averages are bushel-weighted. The percentage change in yield is calculated using equation (4). We also report the sum of *bushels*, *ΔTR*, *weight*, *ΔCS*, *ΔPS*, and *ΔTS*. The states are ordered in term of total production for 2003–13. The bushels and dollars are in millions. The yield is in bushels per acre and the price is in dollars per bushel.

Table 5. Welfare Implications of Reduced NO_x Emissions, Soybeans

Rank (1)	State (2)	Bushels (3)	Yield (4)	Price (5)	$\Delta yield$ (6)	$\%\Delta yield$ (7)	ΔTR (8)	Weight (9)	ΔCS (10)	ΔPS (11)	ΔTS (12)
1	IA	541.232	56.475	9.425	0.473	0.838	−116.726	0.069	87.517	−50.692	36.825
2	IL	561.463	57.758	9.750	1.352	2.341	−125.262	0.201	253.598	−146.890	106.708
3	MN	355.785	49.912	9.331	0.714	1.430	−75.961	0.078	98.162	−56.858	41.304
4	IN	300.407	54.919	9.688	1.177	2.144	−66.598	0.099	124.262	−71.976	52.286
5	NE	302.543	58.289	9.230	0.527	0.904	−63.896	0.042	52.769	−30.565	22.204
6	OH	249.002	52.802	9.709	1.513	2.866	−55.320	0.109	137.690	−79.753	57.937
7	MO	237.477	46.350	9.622	1.017	2.194	−52.285	0.080	100.508	−58.217	42.291
8	SD	240.033	47.663	9.030	0.172	0.360	−49.595	0.013	16.671	−9.656	7.015
9	AR	150.748	49.603	10.006	0.258	0.521	−34.515	0.012	15.152	−8.776	6.375
10	ND	211.471	37.171	9.016	0.079	0.212	−43.629	0.007	8.632	−5.000	3.632
11	KS	160.557	42.369	9.212	1.169	2.758	−33.844	0.068	85.448	−49.493	35.954
12	MI	95.846	47.980	9.499	0.802	1.671	−20.834	0.025	30.905	−17.901	13.004
13	MS	104.782	50.162	10.203	0.210	0.419	−24.464	0.007	8.464	−4.902	3.561
14	WI	92.858	50.721	9.367	0.996	1.964	−19.904	0.028	35.183	−20.379	14.804
15	KY	86.938	49.259	9.865	2.111	4.285	−19.625	0.057	71.884	−41.637	30.247
16	NC	60.887	36.694	9.591	0.569	1.552	−13.363	0.014	18.230	−10.559	7.671
17	TN	75.510	45.939	9.878	1.187	2.583	−17.068	0.030	37.635	−21.799	15.836
18	LA	64.508	51.083	10.197	0.289	0.566	−15.051	0.006	7.049	−4.083	2.966
19	PA	25.367	46.930	9.362	0.669	1.425	−5.434	0.006	6.976	−4.041	2.935
20	VA	22.505	37.491	9.356	0.816	2.175	−4.818	0.007	9.446	−5.471	3.975
21	MD	21.734	43.173	9.400	1.532	3.548	−4.675	0.012	14.878	−8.618	6.260
22	SC	12.587	31.811	9.545	1.368	4.299	−2.749	0.008	10.440	−6.047	4.393
23	NY	13.126	43.347	9.437	0.333	0.768	−2.835	0.002	1.945	−1.126	0.818
24	AL	17.337	39.148	9.651	1.467	3.746	−3.829	0.010	12.531	−7.258	5.273
25	DE	7.459	43.506	9.407	1.555	3.573	−1.606	0.004	5.143	−2.979	2.164
26	OK	11.424	30.437	9.389	0.435	1.428	−2.454	0.002	3.147	−1.823	1.324
27	GA	10.710	40.170	10.034	0.523	1.302	−2.459	0.002	2.691	−1.559	1.132
28	NJ	3.785	38.777	9.316	1.144	2.950	−0.807	0.002	2.155	−1.248	0.907
29	TX	2.989	32.969	9.188	0.249	0.754	−0.629	0.000	0.435	−0.252	0.183
30	WV	1.287	49.713	9.378	1.573	3.165	−0.276	0.001	0.786	−0.455	0.331
	ALL	4042.357	51.084	9.519	0.828	1.616	−880.510	1.000	1260.328	−730.012	530.316

Note: For each state, we report average annual total quantity (*bushels*), average yield (*yield*), and average price (*price*) for 2014–16. The average yields are bushel-weighted. Annual state-level prices are readily available from the USDA. We calculate the change in yield ($\Delta yield$) using equations (3). The state-specific percentage change in yield ($\%\Delta yield$) is equal to $100 \times \Delta yield / yield$. We also report the change in total revenue (ΔTR), change in consumer surplus (ΔCS), change in producer surplus (ΔPS), and change in total surplus (ΔTS), in dollars. For each state, we calculate ΔCS and ΔPS using equations (5) and (6), respectively. The *weight* column corresponds to the term w_j in the two equations. In the last row ("ALL"), we report the average yield, the average price, and the average change in yield, across states. The three averages are bushel-weighted. The percentage change in yield is calculated using equations (4). We also report the sum of *bushels*, ΔTR, *weight*, ΔCS, ΔPS, and ΔTS. The states are ordered in term of total production for 2003–13. The bushels and dollars are in millions. The yield is in bushels per acre and the price is in dollars per bushel.

period fueling the demand for agricultural products which, all else equal, would have increased the returns to farming. The fact that net income in the agricultural sector has remained stagnant implies that farmers as a whole are net losers from increasing agricultural productivity.

Although numerous elasticity estimates exist in the literature, most are not suitable for the purpose of assessing the incidence of a yield improvement coming from a simultaneous long-run productivity shock to corn and soybeans in the United States. Some papers in the literature generate estimates based on short-run shocks, some estimate the response of supply or demand of one crop holding the price of the others constant, and others estimate elasticities that apply at a global or regional scale. We need both supply and demand elasticities because, all else equal, a percentage increase in supply equal to $\%\Delta s$ decreases the equilibrium price by $-(\frac{\%\Delta s}{\eta_s - \eta_d})$ and increases the equilibrium quantity by $-(\frac{\eta_d \%\Delta s}{\eta_s - \eta_d})$, where η_s is the supply elasticity and η_d is the demand elasticity.[32]

We obtain our elasticity estimates using a modified version of Roberts and Schlenker (2013), who estimate the global demand and supply elasticities for a calorie-weighted index of corn, wheat, soybeans and rice. Using their publicly available code and data from the American Economic Review website, we limit their sample to corn and soybeans for the United States only and estimate the same models as in their table 1. Thus, we obtain supply and demand elasticities for an index of US corn and soybeans. We use the instrumental variables estimates for the model with four knots in the cubic spline trend and obtained a supply elasticity $\eta_s = 0.196$ and a demand elasticity $\eta_d = -0.295$.[33] We use these elasticities for both commodities.

The supply elasticity estimate is very similar to Hendricks, Smith, and Sumner (2014), who use field-level data from satellite imaging to estimate the elasticity of corn and soybean supply in Iowa, Illinois, and Indiana. They obtain long-run elasticities of 0.3. The demand estimate is somewhat smaller than others in the literature, but prior papers typically include storage as a source of demand and they use short-run price shocks for identification. Firms can mitigate short-run price shocks by adjusting inventory, which implies that inventory demand is very elastic with respect to short-run shocks. However, firms cannot mitigate long-run shocks through inventory management. For example, Adjemian and Smith (2012) estimate elasticities of total demand for corn and soybeans equal to −0.8 and −1.0, respectively, but they present evidence that the elasticities are much smaller when inventory levels are low because consumption is the only available margin of adjustment.

With the demand and supply elasticity estimates in hand, we perform a welfare analysis assuming constant elasticity demand and supply curves of the form $Q = a_d P^{\eta_d}$ and $Q = a_s P^{\eta_s}$. We calibrate the values of a_d and a_s for each commodity using the 2014–16 US prices and quantities (bushels) shown in row "ALL" in tables 4 and 5. Next, we calculate the counterfactual prices and quantities that would have been realized in 2014–16 in the absence of the NO_x pollution reduction. We calculate the percentage change in the US average price $(\%\Delta p = -\frac{\%\Delta yield}{\eta_s - \eta_d})$ and the percentage change in US quantity $(\%\Delta q = -\frac{\eta_d \%\Delta yield}{\eta_s - \eta_d})$ using:

$$(4) \quad \%\Delta yield = \sum_j \frac{Q_{j1}}{Q_1} \%\Delta yield_j,$$

where Q_{j1} is average quantity over 2014–16 and $\%\Delta yield_j$ is the estimated percent change in yield for state j calculated using equation (3).

The counterfactual equilibrium price and quantities implied by these percentage changes allow us to calculate the change in consumer, producer, and total surplus, due to crop yield improvements attributed to the reduction in NO_x emissions. To do so, we integrate under the relevant curves in figure 3. We also compute state-level changes in consumer and producer surplus, which are proportional

[32] Roberts and Schlenker (2013) use a similar expression to calculate the effect of a shift in demand (as opposed to supply) on the equilibrium price. In general, $\%\Delta Q_d = \%\Delta d + \eta_d \%\Delta P$, where $\%\Delta Q_d$ is the percentage change in the quantity demanded, $\%\Delta d$ is the shift in demand in percentage terms, $\%\Delta P$ is the percentage change in price, and η_d is the demand elasticity. An analogous expression holds for the supply curve, $\%\Delta Q_s = \%\Delta s + \eta_s \%\Delta P$, where $\%\Delta Q_s$ is the percentage change in the quantity supplied, $\%\Delta s$ is the shift in supply in percentage terms, $\%\Delta P$ is the percentage change in price, and η_s is the supply elasticity. In equilibrium, $\%\Delta Q_d = \%\Delta Q_s$, which implies $\%\Delta P = \frac{\%\Delta d - \%\Delta s}{\eta_s - \eta_d}$ and $\%\Delta Q = \frac{\eta_s \%\Delta d - \eta_d \%\Delta s}{\eta_s - \eta_d}$.

[33] We report full regression results in Online supplementary material table 14.

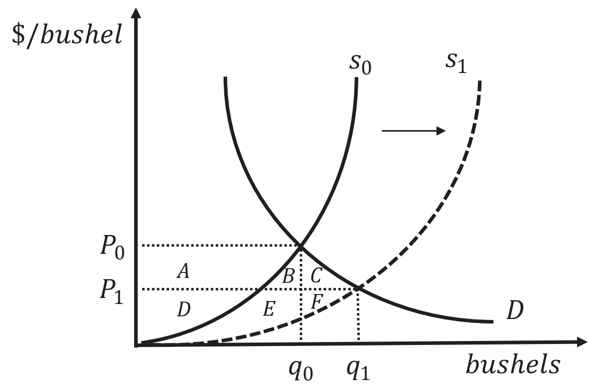

Figure 3. Shift in crop supply curve due to yield improvements following NO_x reductions.

Note: The figure shows the implication of crop yield improvements due to a reduction in NO_x emissions. The subscript 1 (0) denotes the actual (counterfactual) equilibrium. The change in consumer surplus is given by $\Delta CS = CS_1 - CS_0 = A + B + C$. The change in producer surplus is given by $\Delta PS = PS_1 - PS_0 = D + E + F - (A + D) = E + F - A$.

to the state's contribution to the change in supply:

$$\Delta CS_j = w_j \times \Delta CS = \frac{Q_{j1}}{Q_1}\frac{\%\Delta yield_j}{\%\Delta yield} \times \Delta CS \tag{5}$$

$$\Delta PS_j = w_j \times \Delta PS = \frac{Q_{j1}}{Q_1}\frac{\%\Delta yield_j}{\%\Delta yield} \times \Delta PS. \tag{6}$$

We provide details of these computations in the online supplementary material section S.2.5.

In the case of corn, annual consumer surplus increases by \$2.51 billion and producer surplus decreases by \$1.44 billion. Therefore, total surplus increases by \$1.07 billion per year. For soybeans, consumer surplus increases by \$1.26 billion, while producer surplus decreases by \$0.73 billion with an implied increase of \$0.53 billion in total surplus per year. Total revenue decreases by \$1.74 billion for corn and by \$0.88 billion for soybeans.

As a comparison, Muller and Mendelsohn (2007) report gross annual damages to US agriculture from 2002 NO_x emissions equal to \$700 million per year in their table 1. Their estimates are based on the Air Pollution Emission Experiments and Policy Analysis (APEEP) model, which translates VOC and NO_x emissions into ozone and uses dose-response functions to estimate the effects of ozone on crop yields. Across the two crops, we have estimated a decrease in total revenue (producer surplus) for US farmers equal to \$2.62 (\$2.17) billion, which is substantially larger than the damage figure reported by Muller and Mendelsohn. Although there is a difference between our and their estimates of the harmful effects of NO_x emissions on US agriculture, a precise comparison between their damages and ours is not straightforward due to several differences in the calculation of the effects of NO_x emissions between the two papers.[34]

As a final remark, a case can be made for a larger net demand elasticity than assumed here. Econometric methods may underestimate the elasticity with respect to long-run shocks because samples are too short and long-run shocks too infrequent to properly identify their effects. Moreover, US corn and soybean farmers compete in a global market, which implies that export markets can absorb fluctuations in US production without substantial price impacts. The United States exports

[34] First, Muller and Mendelsohn use nationwide NO_x emissions from all sources in the 2002 EPA National Emissions Inventory, whereas we use NO_x emissions from power plants in the eastern United States that lie within a 100-mile radius from the centroids of counties growing corn and soybeans. In 2002, nationwide emissions due to fuel combustion from electric utilities accounted for about 20% of all NO_x emissions. Second, Muller and Mendelsohn include a wide variety of crops, whereas we focus on corn and soybeans. Based on the 2002 USDA summary of crop values, corn and soybeans accounted for approximately 66% of the value of the crops they use. Third, they use 2002 prices of \$2.25 for corn and \$5.19 for soybeans (see table 10 in their appendix), whereas we use 2014–16 prices of \$3.59/bushel and \$9.51/bushel. Finally, US production of corn and soybeans in 2002 was 8.97 and 2.76 billion bushels, whereas in 2014–16 the average US production was 14.05 and 4.04 billion bushels.

about 15% of its corn crop and 50% of its soybean crop annually. Net demand elasticities greater than one would imply substantial gains to farmers from the reduction in NO_x emissions. However, such high elasticities appear difficult to justify given the available empirical evidence.

Conclusions

The advent of fracking, along with various policies and the declining cost of renewables, has caused a dramatic reduction in the amount of coal used in the US electric power sector in recent years. The resulting reduction in pollution has had widespread effects on human health and welfare. In this paper, we study the effects of the decrease in NO_x emissions from power plants on agricultural productivity focusing on two crops of paramount importance to the United States and world agriculture: corn and soybeans. We find substantial effects, and we validate the causal channel through which they occur. Lower NO_x emissions imply lower ground-level ozone, which accelerates photosynthesis and increases crop yields.

Over the eight-year period from 2003–05 to 2011–13, our estimates show that average corn yields increased by 2.46% and soybean yields increased by 1.62% in response to the observed changes in NO_x emissions from power plants. Our findings are robust to alternative specifications of our baseline equations, the use of alternative controls, the way we measure exposure to NO_x emissions, how we handle the distance between counties growing corn and soybeans and power plants, as well as the role of meteorological conditions, such as wind direction and speed, and also alternative clustering schemes for the purpose of inference. Moreover, we show that there is a strong link between NO_x emissions from power plants and ozone pollution in a flexible econometric framework, and it is robust to a wide array of checks performed.

According to our estimates, the observed reduction in emissions translates into an increase in total surplus of $1.60 billion annually. Based on recent demand and supply elasticity estimates, the implied rightward shift of the crop supply curves due to yield improvements leads to an increase in consumer surplus by $3.77 billion and a decrease in producer surplus by $2.17 billion. Additionally, there is a decrease in farmers' revenue equal to $2.62 billion.

We focus on the effects of power plant NO_x emissions on corn and soybeans grown primarily in the Midwestern United States, but the two crops are only a small fraction of the biomass in this area. Thus, to the extent that reducing NO_x emissions and ozone levels benefits other plants, the productivity spillovers we study in this paper have a much larger scope. Although these effects may be challenging to estimate and may include negative effects such as weed growth, we believe that reducing NO_x (and other harmful) emissions from power plants can be beneficial not only for human morbidity and mortality but also for agriculture and is a research agenda worth pursuing.

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Supplementary Material

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

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