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Ambient Ozone and Planting Decision: Evidence From US Crop Acreage

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ABSTRACT

This study leverages the variation in upwind ozone as an arguably exogenous shock for identification and quantifies the impact of ambient ozone on planted acreage of corn and soybeans. Highlighting the importance of behavioral responses, this study finds that a one-additional ppb of average ambient ozone reduces subsequent plantings of corn and soybean acreage by 1.59%–1.97%. Such ozone-induced acreage shrinkage is partially achieved through acreage shifts to less-ozone-sensitive crops. My prediction results suggest that, when ozone concentrations are projected to fall, the expected rise in corn and soybean production by 2050 would be underestimated by 43.41%–49.72% without considering acreage adjustment.

JEL Classification: Q15, Q18, Q24, Q52, Q53

1 | Introduction

Ambient ozone harms plant cells' antioxidant protection by interacting with them at the extracellular matrix (Baier et al. 2005), resulting in observed chlorosis and necrosis of plant tissue (Lucas et al. 1993; Rich 1964). These ozone-induced biological damage effects have been well documented, particularly for corn and soybeans. Boone et al. (2019) and Liu and Lu (2023), for example, discovered that a one-ppb rise in ozone concentrations reduces corn yields by 2.2%–2.6% and soybean yields by 1.9%–2.0%. Although elevated ambient ozone levels reduce crop yields, ozone concentrations in the US have been falling in recent decades as a result of the Clean Air Act and its subsequent amendments, as well as the reduction of vehicle and industrial emissions (EPA 2024a), which has positively contributed to crop productivity. Da et al. (2022) and McGrath et al. (2015), studying the time periods of 1980–2018 and 1980–2011, respectively, attributed 8.2%–11.7% of the corn production rise and 2.9%–6.3% of the soybean production rise to reduced ozone levels. Taking additional air pollutants into account, Lobell and Burney (2021) identified reductions in ozone and other pollution levels as key factors behind the yield gains of one-fifth for corn and soybeans from 1999 to 2019, corresponding to approximately $5 billion per year.

Soybeans and corn are two principal crops that are essential to global food security, fuel supply, and livestock feed. In this study, I focus on these two crop types, for which the US produces more than one-third of the global supply (Schlenker and Roberts 2009). Specifically, the empirical context of this study centers on the US acreage of corn and soybeans combined, east of the 100°W meridian (D'Agostino and Schlenker 2016; Mérel and Gammans 2021; Schlenker et al. 2006; Schlenker and Roberts 2009), where the corn and soybean production are mostly non-irrigated and constitutes the vast majority of the national production. Many factors have been demonstrated to be associated with the planting decisions of corn and soybeans, such as climate variability, prices, and insurance subsidy (Claassen et al. 2017; Cui 2020b; Goodwin et al. 2004; Haile et al. 2016; Miao et al. 2016; Yu et al. 2018). Motivated by a conceptual framework built upon a crop grower's decision-making process, this study innovatively investigates how the corn and soybean acreage is influenced by the aforementioned ozone-induced damage effects.

The empirical analysis of this work is based on a county-by-year panel dataset primarily constructed from two sources: the corn and soybean acreage, obtained from the National Agricultural Statistics Service (NASS), and the satellite-based reanalysis data on pollution and weather conditions, retrieved from the European Centre for Medium-Range Weather Forecasts (ECMWF). The planted acreage is preferred over the harvested counterpart, as the former more accurately reflects the acreage allocation decision made by crop growers prior to the current growing season (Cui 2020b). The satellite-based reanalysis data are preferred over the ground-based observations, as the majority of ground-based monitors are urban and population-focused (EPA 2019), but the main focus of this study is cropland instead.

The endogeneity concern and measurement errors in ambient ozone are the key hurdles to estimating the causal effect of ambient ozone on the planted acreage. Overcoming these challenges require finding an exogenous variation to instrument for ozone. Specifically, I rely on the variation in ambient ozone from upwind neighbor counties as an exogenous shock for identification, a common approach to correct for the endogeneity of air pollution in the literature (Barwick et al. 2018; Carneiro et al. 2021; Chen et al. 2021; Deryugina et al. 2019; Wang et al. 2022). Other pollutant controls are also instrumented by their corresponding upwind counterparts to ensure that the exclusion restriction criterion is not violated.

This study utilizes an IV approach to provide evidence that a one-ppb increase in average ambient ozone reduces the subsequent plantings of corn and soybean acreage by 1.59%–1.97%. Given real-world trends of decreasing ozone and expanding acreage, this finding implies that a one-ppb decline in ozone concentrations would increase corn and soybean acreage by 1.59%–1.97%. Such an acreage change is partially achieved through substitution with less-ozone-sensitive crops, including winter wheat, sorghum, and barley. The prediction results suggest that as ambient ozone concentrations are projected to decline, corn and soybean production is expected to increase by 3.03%–7.34% by 2050, accounting for ozone-driven yield changes alone. Further estimation underlines the importance of acreage adjustments when evaluating the agricultural production benefits of falling ozone concentrations. When considering both yield and acreage changes, corn and soybean production is anticipated to rise by 5.36%–14.61% by mid-century. That is, comparing with the predicted production change from both channels, the predicted production change from the biological channel alone would, therefore, be underestimated by 43.41%–49.72%.

This study makes an important contribution to the understanding of ozone damage on crop production by providing the first causal estimate of ambient ozone effects on the corn and soybean acreage. An existing strand of literature has well documented the damage effects of ambient ozone exposure on crops via biological mechanisms, including reduced photosynthesis and accelerated senescence (Ainsworth 2017; Avnery et al. 2011; Boone et al. 2019; Carter et al. 2017; Da et al. 2022; Feng et al. 2022; Ghude et al. 2014; Hong et al. 2020; McGrath et al. 2015; Metaxoglou and Smith 2020; Montes et al. 2022; Yi et al. 2018). Providing estimates on the yield losses caused by ozone biologically, extant studies primarily focus on the ozone effects on crop production at the intensive margin. Different from them, this study centers on the ozone-induced shrinkage in the planted acreage that has been previously overlooked, highlighting the importance of such ozone effects on crop production over the extensive margin. In addition, my re-estimated crop production benefits from ozone control, after taking account of acreage adjustment, also link to the policy discussions of pollution management targeting at ambient ozone and related pollutants (Aldy et al. 2022; Deschênes et al. 2017; Fowlie et al. 2012; Greenstone 2003; Schmalensee and Stavins 2019).

This study also contributes to a better understanding of the environmental and economic factors that lead to a crop acreage response. An established body of literature has thoroughly examined the crop acreage responses to weather characteristics or climate variability (Arora et al. 2020; Cohn et al. 2016; Cui 2020b; Cui and Tang 2023; Miao et al. 2016), crop insurance (Claassen et al. 2017; Goodwin et al. 2004; Yu et al. 2018), and crop prices (Haile et al. 2016; Miao et al. 2016). Showing evidence that exposure to elevated ambient ozone shrinks the total acreage of corn and soybeans combined, this study stresses the role that ambient ozone plays in crop acreage allocation. Moreover, further analyses indicate that the acreage shrinkage is partially achieved through acreage shifts to less-ozone-sensitive crops. This finding joins the recent discussions of comparative advantage and crop substitution (Arora et al. 2020; Cui 2020b; Livingston et al. 2015), suggesting that special attention should be paid to the cross-type variations and cross-variety variations in sensitivity to elevated ozone (Mills et al. 2007, 2018).

The remainder of this study is structured as follows. The next section includes a conceptual model that motivates the empirical analyses. Section 3 introduces the background of ambient ozone and lays out data sources. Section 4 shows the empirical strategies for identification, including the panel fixed effect model and upwind-based IV method. Section 5 includes the results, checks for robustness, and make predictions. Section 6 examines nonlinearity and spatial heterogeneity. The last section discusses policy implications and concludes.

2 | Conceptual Model

This conceptual model shows the mechanism through which exposure to ambient ozone affects the optimal planted acreage of crops.[1] Suppose a crop grower, who is a price taker in a perfect competitive market, owns both agricultural land and nonagricultural land within a county. To maximize the total profit, this grower allocates acreage among planting crop i, planting crop j, and an outside option that yield returns of p_i, p_j, and r, respectively. The cost of producing crops on an additional unit of land is indexed by a constant c. The total amount of land owned by the grower and the amount of land used for nonagricultural purposes are indexed by $\bar{A}$ and A_n, respectively.

I assume that crop production (y_k, $k = i$ or j and $i \neq j$) is a function of both the planted acreage (A_k, $k = i$ or j and $i \neq j$) and ambient ozone (O). Specifically, the production of a specific crop is assumed as an increasing, concave function of its planted acreage ($\frac{\partial y_k}{\partial A_k} > 0$ and $\frac{\partial^2 y_k}{\partial A_k^2} < 0$, $k = i$ or j and $i \neq j$). Since ozone has adverse effects on crop yields (Boone et al. 2019; Carter et al.

2017; Da et al. 2022; Hong et al. 2020; McGrath et al. 2015), the marginal crop production on per unit of land is assumed to be negatively affected by ambient ozone ($\frac{\partial^2 y_k}{\partial A_k \partial O} < 0$, $k = i$ or j and $i \neq j$).

The crop grower hence seeks to maximize the total revenue earned by producing crops and the total return on nonagricultural land, less the total cost from crop production:

$$\max_{A_i,\ A_j, A_n} p_i y_i (A_i, O) + p_j y_j \left(A_j, O\right) + r A_n - c\left(A_i + A_j\right), \tag{1}$$

subject to $A_i + A_j + A_n = \bar{A}$, where $i \neq j \neq n$ and $\bar{A}$ is a constant.

Regarding the flexibility of making adjustments on nonagricultural land, there are two possible scenarios that could occur. First, if we assume that land can be switched between agricultural and nonagricultural uses, the profit maximization problem turns into

$$\max_{A_i,\ A_j} p_i y_i (A_i, O) + p_j y_j \left(A_j, O\right) + r\left(\bar{A} - A_i - A_j\right) - c\left(A_i + A_j\right), \tag{2}$$

where $i \neq j$. The optimal acreage is determined based on the first-order condition of the above objective function with respect to A_i and A_j:

$$p_i \frac{\partial y_i \left(A_i^*, O\right)}{\partial A_i} - r - c = p_j \frac{\partial y_j \left(A_j^*, O\right)}{\partial A_j} - r - c = 0. \tag{3}$$

The comparative statics of ozone effects on optimal crop acreage are then derived by total differentiating the above first order condition, suggesting that the optimal planted acreage is negatively affected by elevated ambient ozone:

$$\frac{dA_i^*}{dO} = -\frac{\frac{\partial^2 y_i}{\partial A_i \partial O}}{\frac{\partial^2 y_i}{\partial A_i^2}} < 0, \tag{4}$$

$$\frac{dA_j^*}{dO} = -\frac{\frac{\partial^2 y_j}{\partial A_j \partial O}}{\frac{\partial^2 y_j}{\partial A_j^2}} < 0. \tag{5}$$

Second, when land cannot be switched between agricultural and nonagricultural uses, A_n becomes fixed in this case, and the profit maximization problem turns into:

$$\max_{A_i,\ A_j} p_i y_i (A_i, O) + p_j y_j \left(A_j, O\right) + r\overline{A_n} - c\left(A_i + A_j\right), \tag{6}$$

subject to $A_i + A_j = \overline{A - A_n}$, where $i \neq j \neq n$, and $\overline{A_n}$ and $\overline{A - A_n}$ are constants.

Under this scenario, the comparative statics of ozone's effect on the optimal planted acreage are:

$$\frac{dA_i^*}{dO} = -\frac{p_i \frac{\partial^2 y_i}{\partial A_i \partial O} - p_j \frac{\partial^2 y_j}{\partial A_j \partial O}}{p_i \frac{\partial^2 y_i}{\partial A_i^2} + p_j \frac{\partial^2 y_j}{\partial A_j^2}}, \tag{7}$$

$$\frac{dA_j^*}{dO} = -\frac{p_j \frac{\partial^2 y_j}{\partial A_j \partial O} - p_i \frac{\partial^2 y_i}{\partial A_i \partial O}}{p_i \frac{\partial^2 y_i}{\partial A_i^2} + p_j \frac{\partial^2 y_j}{\partial A_j^2}}. \tag{8}$$

These comparative statics suggest that when lands used for agricultural and nonagricultural purposes are not interchangeable, the impact of ambient ozone on optimal planting decision is determined based on the ozone-driven relative change in marginal revenue product (MRP) of land between different crop types. When the ozone-driven MRP of planting crop i is higher in magnitude than that of planting crop j ($|p_i \frac{\partial^2 y_i}{\partial A_i \partial O}| > |p_j \frac{\partial^2 y_j}{\partial A_j \partial O}|$, or $p_i \frac{\partial^2 y_i}{\partial A_i \partial O} < p_j \frac{\partial^2 y_j}{\partial A_j \partial O}$), the planted acreage of crop i is negatively affected by ozone stress ($\frac{dA_i^*}{dO} < 0$), and vice versa.

The conceptual model proposes that, while ambient ozone is invisible, crop growers respond to ozone-induced yield losses by reallocating the optimal planted acreage to maximize profits. Note that it simplifies crop growers' behaviors to provide intuition for the empirical analyses that follow. Overall, it provides two important takeaways. First, ambient ozone has an arguably negative impact on optimal planted acreage when land can be switched between agricultural and non-agricultural uses. Second, the optimal planted acreage is determined based on the ozone-driven relative change in MRP of land across crops when land cannot be switched between agricultural and nonagricultural purposes. That is, the ozone-induced acreage shrinkage of some crops is partially offset by substitution with others. The remaining analyses seek to empirically examine the extent to which exposure to ambient ozone influences planted acreage in the US context.

3 | Background and Data

3.1 | Background of Ambient Ozone

I begin with introducing the daily, seasonal, and annual cycles of ozone.[2] Ozone concentrations peak during the day, a consequence of photochemical reactions triggered by sunlight (EPA 2024b). Seasonally, Figure A1 illustrates that ambient ozone levels are greater in spring and summer, which correspond to the growing season for corn and soybeans; the rises in solar radiation and temperatures drive the seasonal pattern by accelerating the photochemical reactions that produce ozone (Jacob and Winner 2009). The most important temporal pattern, at least for this study, is the annual variation, as I rely on year-by-year ozone variations over the corn and soybean growing season. Effective regulatory actions and emission reduction initiatives have lowered ambient ozone concentrations across my study period, as shown by Figure A1 (Aldy et al. 2022; Deschênes et al. 2017).

In addition to the aforementioned temporal variations, ambient ozone also exhibits spatial variations. As noted by Ainsworth (2017), Brauer et al. (2016), and Ramankutty et al. (2008), croplands in China, India, and the US are subject to considerably higher levels of ambient ozone exposure than those in Australia or

Brazil. Figure A2 indicates, within the US, high average ambient ozone levels along the East Coast, Kentucky, Tennessee, and Alabama. By contrast, Texas, Louisiana, the Dakotas, and the southern shore of Lake Michigan show rather low concentrations. Figure A2 also shows the change rate of ambient ozone across my study period; the southern shore of Lake Michigan and Lake Erie, the East Coast, and the southern border have shown a notable elevation in ozone concentrations. Ozone levels have meanwhile dropped noticeably in the Dakotas, Missouri, Oklahoma, Arkansas, and Mississippi.

Both natural and anthropogenic emissions drive the spatial variations in ambient ozone levels. A large amount of nitrogen oxides (NO_X) and volatile organic compounds (VOCs), which are key ozone precursors, are emitted by natural sources such as wildfires (Jaffe and Wigder 2012; Kleinman et al. 2001). Forests also contribute to the formation of ozone by releasing biogenic VOCs (Guenther et al. 2006). Further influencing ambient ozone levels are ozone intrusion events, in which ozone from the stratosphere enters the troposphere (Hocking et al. 2007).

On the human side, industrial activities and traffic generate NO_X emissions. Internal combustion engine vehicles–cars, trucks, buses, and motorcycles–emit NO_X during fuel combustion (Pastorello and Melios 2016). Also greatly contributing to NO_X emissions are chemical manufacture, oil refining, metal production, and coal-fired power generation (Ma et al. 2016; Seinfeld and Pandis 2016). Although variations from natural sources could be seen as exogenous, emissions produced by humans are essentially endogenous. This stresses the need of identifying an exogenous shock to serve as an instrumental variable for ozone. The variation in ambient ozone transmitted from upwind counties, as described in the Appendix, provides such an exogenous shock for identification that addresses ozone's endogeneity issues.

3.2 | Data Sources and Description

The dataset used for this study is primarily gathered from two sources. First, the county-level planted acreage of corn and soybeans are obtained from the NASS at the US. Department of Agriculture (USDA).[3] Note that the harvested acreage may be impacted by current-growing-season environmental conditions, and the planted acreage reflects the acreage allocation decision made before the current growing season and is hence preferred over the harvested acreage (Cui 2020b). The NASS releases data on a wide range of agricultural production-related variables, which have been extensively utilized by a large number of studies (Annan and Schlenker 2015; Claassen and Just 2011; Cui 2020a, 2020b; Goodwin and Mishra 2006; Hendricks et al. 2014; Hornbeck and Keskin 2014; Kuwayama et al. 2019; Metaxoglou and Smith 2020; Roberts et al. 2017; Sanders and Barreca 2022; Yu et al. 2018). Given that croplands in certain regions heavily rely on irrigation, I limit the data sample to counties east of the 100°W meridian, except from Florida (D'Agostino and Schlenker 2016; Schlenker and Roberts 2009; Mérel and Gammans 2021), to prevent irrigation from driving the results, as irrigated crops may be subject to higher yield losses caused by ozone (Pandey et al. 2023). As a result, there are 1924 counties covered in the final data sample. As depicted in Figure A3, the change rate of the total acreage of corn and soybeans combined is relatively low for the Midwestern states, or Corn Belt states, over the study period. Data on the planted acreage of other crop types, used in the substitution analysis, are collected from the same source.

Second, the ECMWF-released reanalysis data provides information on ambient ozone, also known as ground-level ozone.[4] The average ambient ozone concentration, as shown in Table B1, is roughly 38.5 ppb throughout the growing seasons during 2003–2001. Based on the European Envisat satellite and the American Aqua and Aura satellite retrievals, the ECMWF reanalysis data are validated and assimilated by observations from sondes and ground-based monitors through an array of difficult and costly reanalysis efforts (Auffhammer et al. 2013; Inness et al. 2019). Having been identified as an extensively-utilized high-quality reanalysis product (Auffhammer et al. 2013; Harari and Ferrara 2018), the ECMWF reanalysis data have been used by a wide range of empirical studies (Axbard 2016; Ayesh 2023; Cervellati et al. 2022; Colmer 2021a, 2021b; Cook et al. 2023; Heyes and Saberian 2022; Meier et al. 2023; Michler et al. 2022; Rahimi et al. 2022; Sarmiento 2023; Xie and Yuan 2023; Yin et al. 2023). Data on additional pollutants, including PM_{10}, SO_2, CO, $PM_{2.5}$, and NO_2, are retrieved from the same source.

The satellite-based reanalysis dataset is preferred over the ground-based Environmental Protection Agency (EPA) observations, as the majority of ground-based air quality monitors are urban and population-focused (EPA 2019), but the main focus of this study is cropland instead. Figure A1 compares ambient ozone concentrations retrieved from the ECMWF reanalysis data and the EPA ground-based data, which suggests that the ambient ozone data collected from two different data sources are highly consistent. The ground-based ambient ozone observations from the EPA are also used for robustness checks in the Results section. In addition, there exists another satellite-based data source for ambient ozone, the Modern-Era Retrospective Analysis for Research and Applications, Version 2 (MERRA-2). But as Da et al. (2022) and Liu and Lu (2023) have discussed, the MERRA-2 ambient ozone values are skewed higher by roughly 15 ppb than their EPA or ECMWF counterparts. I have hence excluded this data source from the analyses in this study.

Weather data are also retrieved from the ECMWF-released reanalysis data.[5] The baseline weather conditions include degree days and precipitation. Assuming that the within-day temperature follows a sine distribution (Baskerville and Emin 1969; Chen et al. 2016; Chen and Gong 2021; Roberts et al. 2013, Roberts et al. 2017; Xie et al. 2019), I calculate the moderate degree days (from 8°C to 32°C) and extreme degree days (over 34°C) over each growing season (Schlenker et al. 2006; Fisher et al. 2012). Wind direction and wind speed, used for IV construction and robustness checks, are calculated from wind speeds at the u- and v-components (ECMWF 2023). Additional weather characteristics retrieved from the ECMWF, used for robustness checks, include relative humidity, net solar radiation, and surface pressure.

Gridded data on pollution and weather are matched to counties based on the inverse of their squared distances to each county centroid (Deschênes and Greenstone 2011); grid points closer to the county centroid arguably contribute more to the pollution levels and weather conditions there than those that are further away. Specifically, data from the four closest gridded points, weighted based on the inverse square of their distances, are mapped to county centroid coordinates (He et al. 2016). In addition, as aforementioned, pollution and weather data are averaged or aggregated over the growing season of soybeans and corn, which is specified as March to August (Metaxoglou and Smith 2020; Miao et al. 2016; Schlenker and Roberts 2009), as these months cover the key stages of planting, growth, and harvesting for these crops. Alternative growing seasons are specified for robustness checks, given that some states may experience a later growing-season period.

4 | Empirical Strategy

4.1 | Panel Fixed Effects Estimation

I first rely on a panel fixed effects estimation model to assess the effect of ambient ozone on planting decisions. The outcome variable, A_{ct}, is specified as the acreage of corn and soybeans combined in logarithm in county c at year t (Cui 2020b). This specification is attributable to the two reasons listed below. First, ambient ozone produces similar biological damage to both corn and soybeans (McGrath et al. 2015; Mills et al. 2007). Second, as the dominant crop types in the US, the corn-soybean rotation is a common cropping practice (Hennessy 2006; Livingston et al. 2015; Porter et al. 1997; Seifert et al. 2017; Kluger et al. 2022), which suggests that separating the acreage of two crops may confound the estimated effect on the planted acreage (Cui 2020b).

The explanatory variable of interest, $O_{ct_{pre}}$, is the average ozone concentrations during the past one to three growing seasons. For example, for the acreage in 2010 within county c, ozone exposure is defined as the growing-season-average ozone concentrations in 2009, from 2008 to 2009, and from 2007 to 2009 for that county. The following reasons have explained this setup. First, given that growers allocate crop acreage at the start of each growing season, the current-growing-season ozone exposure should have no effect on the planting decision—the current growing season's ozone-induced damage occurs after the planting decision is made. Second, ambient ozone over non-growing seasons cannot cause damage to crops and thus would not affect acreage allocation based on the conceptual model. Third, crop growers tend to make decisions based on recent crop damage and yield losses, and growers within a county may enter and exit the market over time, making it challenging to assess the long-term ozone effect on the planting decision. In the Results section, I present estimates over alternative-growing-season lengths, further supporting this argument. The panel fixed effects estimation is formally written as:

$$A_{ct} = \beta_0 + \beta_1 O_{ct_{pre}} + \boldsymbol{W}_{ct_{pre}}\gamma + \boldsymbol{P}_{ct_{pre}}\eta + \sigma_c + \tau_t + \varepsilon_{ct}. \quad (9)$$

This model includes weather characteristics ($\boldsymbol{W}_{ct_{pre}}$) and other air pollutants ($\boldsymbol{P}_{ct_{pre}}$) as control variables. Weather controls include the quadratics of degree days from 8°C to 32°C and precipitation, as well as the square root of degree days exceeding 34°C (Schlenker et al. 2006; Fisher et al. 2012). The degree-day variables capture the effects from moderate temperature ranges and intense heat. They are built by fitting a sine curve through the temperature thresholds for each day of the growing seasons (Baskerville and Emin 1969; Chen et al. 2016; Chen and Gong 2021; Roberts et al. 2013, Roberts et al. 2017; Xie et al. 2019). This is because, as a sine curve, temperatures follow a daily pattern: they start at lower levels in the early morning, climb to a peak in the afternoon, and then decline in the evening. The included air-pollutant control variables are sulfur dioxide (SO_2), carbon monoxide (CO), and particulate matter less than 10 microns (PM_{10}). Not included are particulate matter less than 2.5 microns ($PM_{2.5}$) and nitrogen dioxide (NO_2); they either have a high correlation with PM_{10} (Gehrig and Buchmann 2003) or serve as an ozone precursor (Sillman 1999).

This model includes the county (σ_c) and the year (τ_t) fixed effects. The county fixed effects absorb county-specific attributes, such as soil features and agricultural institutions (Blanc and Schlenker 2017; Botzen et al. 2019). The year fixed effects absorb nationwide year-by-year variations, such as fluctuations in crop prices and advances in agricultural technology (Blanc and Schlenker 2017; Zhang et al. 2018). The error terms (ε_{ct}) are clustered at the year level to correct for the within-year autocorrelation in the errors.

4.2 | 2SLS Approach

Endogeneity and measurement errors in ambient ozone are two main challenges for the panel fixed effects model. Variations in ozone are not random even with weather and additional air pollution controls. For example, emissions from ethanol plants or fossil-fuel power plants might form ambient ozone; building and expanding these plants could reduce the acreage available for agricultural purposes. In this case, the magnitude of the estimated coefficient $\hat{\beta}_1$ would be biased upward. By contrast, assigning ozone exposure to each county from fixed grid cells introduces classical measurement errors, and such measurement errors would bias the estimated coefficient $\hat{\beta}_1$ toward zero (Aizer and Currie 2019; Arceo et al. 2016; Currie and Neidell 2005; Deryugina et al. 2019; Deschênes et al. 2020; Knittel et al. 2016).

Overcoming these challenges require finding an exogenous variation to instrument for ambient ozone. My approach is to rely on the variation in ambient ozone spread from upwind neighbor counties as an exogenous shock for identification, an approach having been used by a wide range of recent studies to correct for endogeneity (Barwick et al. 2018; Carneiro et al. 2021; Chen et al. 2021; Deryugina et al. 2019; Liu 2025a, 2025b; Liu et al. 2023; Liu and Lu 2023, 2024; Lu 2023; Wang et al. 2022). The aforementioned panel-fixed-effect estimation equation is rewritten as the following two-stage least squares (2SLS) estimation equation after instrumenting for ozone and other air pollutants:

$$A_{ct} = \beta_0 + \beta_1 \hat{O}_{ct_{pre}} + \boldsymbol{W}_{ct_{pre}}\gamma + \hat{\boldsymbol{P}}_{ct_{pre}}\eta + \sigma_c + \tau_t + \varepsilon_{ct}, \quad (10)$$

where the first stages are

$$O_{ct_{pre}} = \alpha_0 + \alpha_1 O^{uw}_{ct_{pre}} + \boldsymbol{W}_{ct_{pre}}\gamma + \boldsymbol{P}_{ct_{pre}}\eta + \sigma_c + \tau_t + \mu_{ct}, \quad (11)$$

$$P_{ct_{pre}} = \varphi_0 + \varphi_1 O_{ct_{pre}} + \boldsymbol{W}_{ct_{pre}}\gamma + \boldsymbol{P}^{uw}_{ct_{pre}}\theta + \sigma_c + \tau_t + \zeta_{ct}. \quad (12)$$

TABLE 1 | Baseline findings.

	Log planted acreage of corn and soybeans					
	One growing season		Two growing seasons		Three growing seasons	
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: OLS						
O_3	−0.0148***	−0.0144***	−0.0187***	−0.0155***	−0.0212***	−0.0136***
	(0.0016)	(0.0020)	(0.0022)	(0.0025)	(0.0026)	(0.0029)
Panel B: 2SLS (Second Stage)						
O_3	−0.0135***	−0.0159***	−0.0199***	−0.0197***	−0.0228***	−0.0161***
	(0.0022)	(0.0029)	(0.0030)	(0.0037)	(0.0039)	(0.0047)
Observations	30,383	30,383	28,589	28,589	26,787	26,787
Pollutant controls	YES	YES	YES	YES	YES	YES
Weather controls	NO	YES	NO	YES	NO	YES
County FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
KP *F*-Statistics	50.97	52.22	76.80	76.95	66.46	62.60

Note: Panels A and B report OLS estimates and 2SLS estimates (the second stage), respectively. This table presents the estimated ozone effects on the total acreage of corn and soybeans combined. The outcome variable for both panels is the total acreage of corn and soybeans combined in logarithm. The explanatory variables of Columns (1)–(2), (3)–(4), and (5)–(6) are during the past growing season, the past two growing seasons, and the past three growing seasons, respectively. Pollutant controls include PM_{10}, SO_2, and CO. Weather controls include $DD_{8\text{–}32^\circ C}$, $DD_{8\text{–}32^\circ C}$ squared, the square root of $DD_{34+^\circ C}$, precipitation, and precipitation squared. In Panel B, ozone is instrumented by upwind ozone within the radius band of 300–400 km; PM_{10}, SO_2, and CO are also instrumented by upwind PM_{10}, SO_2, and CO within the radius band of 300–400 km. Fixed effects include county FE and year FE. Standard errors are clustered at the year level (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$).

5 | Results

5.1 | Baseline Findings

Table 1 presents the estimated effects of ambient ozone pollution on the total acreage of corn and soybeans combined. The exposure time windows are specified as the past one, two, and three growing seasons in Columns (1)–(2), (3)–(4), and (5)–(6), respectively. The specification in both of the two panels and across all columns includes the county fixed effect and the year fixed effect. Panel A of Table 1 presents estimates from the panel fixed effects model, which does not take account of the endogeneity or measurement errors of pollution. For completeness, I show the estimated coefficients both without and with weather controls, in the odd and even columns, respectively; both yield negative results, and the estimated coefficients of interest after controlling for weather characteristics suggest that a one-additional ppb of average ambient ozone in the past one to three growing seasons is correlated with a decrease in corn and soybean planted acreage of 1.36%–1.55%.

To correct for the potential biases from endogeneity issues and measurement errors, I rely on the aforementioned upwind-based IV approach. Table B2 shows that upwind pollutants within the 300–400 km radius band are powerful predictors of pollutants in the focal county; the estimated coefficients on upwind O_3, PM_{10}, SO_2, and CO are significantly positive across all specifications. In addition, the Kleibergen-Paap Wald rk *F*-Statistics, for weak instrument identification, are 52.22–76.95 (Kleibergen and Paap 2006), which are above 16.38, the Stock–Yogo critical value for weak identification test (Stock and Yogo 2005). These results suggest that upwind pollutants are strongly predictive to the pollutants in the focal county, and the 2SLS estimators are not subject to weak instrument bias.

Panel B of Table 1 shows the second-stage results of the 2SLS estimation, correcting for endogeneity issues and measurement errors. The specifications without and with weather controls both yield significantly negative estimated coefficients at 1% significance level. Given that controlling for weather characteristics is preferred, I focus on the specification with weather controls throughout the rest of the analyses. Columns (2), (4), and (6) indicate that a one-additional ppb of average ambient ozone during the past one to three growing seasons decreases corn and soybean planted acreage by 1.59%–1.97%, slightly higher in magnitude compared to the ordinary least squares (OLS) results. The 2SLS estimation—which is arguably free of endogeneity bias and measurement errors—is preferred over the OLS estimation and will be the main specification for the remainder of this study. In terms of SDs,[6] these 2SLS estimates suggest that a one-SD elevation of average ambient ozone during the past one to three growing seasons decreases the acreage of corn and soybeans combined by 5.14%–6.54%.

Based on the assessed ozone effects on yields and acreage, I draw inferences about the historical variations in crop production and acreage that have been driven by ambient ozone.[7] Specifically, relying on year-by-year variations of ozone, I compute changes in acreage and crop production (from yield change alone and from both yield and acreage changes) for each county and then sum across all counties in the data sample. My back-of-the-envelope estimations indicate that, across the study period of my data sample, changing ozone concentrations could explain approximately 7.40% of the historical elevation in corn and soybean production when considering yield change alone. About 4.37%–5.42% of the historical acreage expansion of corn and soybeans combined could be explained by changes in ozone concentrations over my study period. After taking account of this acreage adjustment, ozone-driven increases in corn and soybean production account for 12.79%–14.08% of the total historical rise in corn and soybean production.

To compare the assessed ozone effects on acreage with other factors in the literature, such as prices, insurance, and climate variability, I convert the point estimates into acreage elasticities. Specifically, the estimated effects correspond to elasticities between ambient ozone and planted acreage of −0.61 to −0.76. Comparing with the insurance subsidy elasticity of corn and soybean acreage found by Yu et al. (2018),[8] the acreage shrinkage caused by ozone is less responsive relative to the acreage expansion induced by premium subsidy. More efforts have been conducted in the literature to assess price acreage elasticities, and the own-price acreage elasticities differ across studies. For instance, Miller and Plantinga (1999) finds that the price acreage elasticity is 0.95 for both corn and soybeans, greater in magnitude compared to my acreage elasticities of ozone; Miao et al. (2016) believes that the price acreage elasticities should be around 0.45–0.63, suggesting ambient ozone and prices lead to likewise responses to the planted acreage, though in the opposite directions. Additionally, due to the nonlinear nature of climate or weather variables, such as temperature and precipitation, studies estimating the acreage elasticities of climate or weather are absent. Only Cui (2020b) computes the semi-elasticities, rather than elasticities, of temperature and precipitation, which are hence not comparable to the acreage elasticity of ozone in this study.

5.2 | Robustness Checks

Here I discuss the robustness of the baseline results to alternative specifications, as shown in Table 2. Recall that to mitigate the irrigation-related confounding effect, I focus on the rainfed counties by limiting the data sample to counties east of the 100°W meridian, except for Florida (D'Agostino and Schlenker 2016; Mérel and Gammans 2021; Schlenker and Roberts 2009). To test whether the results are sensitive to this criterion for rainfed counties, I expand the sample by including all counties located east of the Rocky Mountains in Column (2).[9] Alternatively, rather than using a geographical boundary as the rainfed criterion, Column (3) excludes counties with an irrigated cropland acreage of more than 20%. Rather than solely focusing on the rainfed counties, Column (4) includes all corn and soybean-growing counties in the US. In addition, as discussed in the Data section, the baseline results rely on the reanalysis ambient ozone data from the ECMWF. Although it has been demonstrated in Figure A1 that ambient ozone data from the ECMWF and the EPA's ground-based observations are in line with each other, to further show that the baseline results still hold under alternative data sources, Column (5) relies on the EPA's ambient ozone data to replicate the results. As shown in Columns (2)–(5), my baseline findings hold up well to the alternative county sample or the alternative data source.

Next, I test the robustness of the baseline results to alternative growing seasons. For the baseline specification, pollution and weather data are averaged or aggregated over March to August (Metaxoglou and Smith 2020; Miao et al. 2016; Schlenker and Roberts 2009). Alternatively, there are also studies that specify the corn and soybean growing seasons as April to September (Annan and Schlenker 2015; Belasco et al. 2020; Cui 2020b) and May to October (Adjemian and Smith 2012; Cornaggia 2013). Columns (6) and (7) specify the growing season as April–September and May–October, respectively, which yield similar estimates compared to the baseline counterpart.

Subsequently, I test the robustness of the baseline results to additional control variables. Recall the baseline specification only includes the growing-season environmental factors; non-growing-season environmental factors should have no effects on crop production and, therefore, would not influence crop acreage allocation as suggested by the conceptual model. To confirm that the results are not influenced by environmental factors over the non-growing seasons, Column (8) further includes ambient ozone, other air pollutants (PM_{10}, SO_2, and CO), and weather characteristics (moderate degree days and its squared term, the square root of extreme degree days, and precipitation and its squared term) over the corresponding non-growing seasons.[10] In addition, to show that the baseline results are not sensitive to additional weather characteristics or air pollutants, Column (9) further controls for net solar radiation, relative humidity, wind speed, and surface pressure; Column (10) further controls for instrumented NO_2 and $PM_{2.5}$. To verify that the baseline results are not sensitive to the temperature thresholds of the degree-day variables, Column (11) specifies the temperature thresholds as 8–30°C for moderate degree days and above 30°C for extreme degree days. The results relying on alternative degree-day variables are similar to the baseline results. As indicated in Columns (8)–(11), all four specifications yield qualitatively similar results to the baseline counterparts.

Further, I conduct a falsification test by including explanatory variables over the current growing season. My empirical estimation relies on the assumption that current-growing-season ozone exposure should have no effect on crop acreage allocation, as farmers determine planting choices at the start of the current growing season. However, if the current-growing-season ozone has a significant effect on the planted acreage, then the aforementioned assumption would not hold, and the baseline estimated ozone effects would be confounded by ozone over the current growing season. To cross out this possibility, Column (12) shows the estimated coefficients on ambient ozone over the current growing season, which holds up my assumption that current-growing-season ozone has no effect on the planting decisions.

5.3 | 3SLS Estimation

Recall the conceptual model proposes that crop growers reallocate their optimal planted acreage in response to ozone-induced yield losses to maximize profits. To embed yields into the empirical model, I alternatively rely on a 3SLS estimation model.

TABLE 2 | Robustness checks.

	Baseline	East of rocky	Irrig. acres <20%	All counties	EPA data	Alt. GS: Apr.–Sept.	Alt. GS: May–Oct.	Add. controls: Non-GS	Add. controls: Weather	Add. controls: Pollutants	Alt. DDs	Placebo: Curr. GS
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Panel A: One growing season												
O_3	−0.0159***	−0.0152***	−0.0186***	−0.0158***	−0.0140***	−0.0164***	−0.0135***	−0.0170***	−0.0159***	−0.0163***	−0.0159***	−0.0019
	(0.0029)	(0.0029)	(0.0034)	(0.0029)	(0.0026)	(0.0031)	(0.0029)	(0.0029)	(0.0029)	(0.0029)	(0.0029)	(0.0031)
Observations	30,383	32,159	25,623	33,208	29,699	30,383	30,383	30,383	30,383	30,383	30,383	28,842
KP *F*-Statistics	52.22	53.83	41.22	51.52	56.66	170.08	198.91	26.91	36.84	26.60	52.25	45.09
Panel B: Two growing seasons												
O_3	−0.0197***	−0.0201***	−0.0271***	−0.0206***	−0.0204***	−0.0215***	−0.0217***	−0.0197***	−0.0194***	−0.0203***	−0.0193***	−0.0016
	(0.0037)	(0.0038)	(0.0044)	(0.0037)	(0.0038)	(0.0040)	(0.0039)	(0.0040)	(0.0037)	(0.0037)	(0.0036)	(0.0032)
Observations	28,589	30,227	24,093	31,144	27,962	28,589	28,589	28,589	28,589	28,589	28,589	27,047
KP *F*-Statistics	76.95	80.85	74.38	82.46	74.21	152.28	172.45	24.34	55.21	28.25	76.95	27.96
Panel C: Three growing seasons												
O_3	−0.0161***	−0.0180***	−0.0296***	−0.0193***	−0.0218***	−0.0183***	−0.0153***	−0.0181***	−0.0148***	−0.0164***	−0.0166***	−0.0009
	(0.0047)	(0.0047)	(0.0055)	(0.0046)	(0.0059)	(0.0049)	(0.0049)	(0.0054)	(0.0049)	(0.0048)	(0.0045)	(0.0037)
Observations	26,787	28,295	22,561	29,091	26,217	26,787	26,787	26,787	26,787	26,787	26,787	25,244
KP *F*-Statistics	62.60	70.60	76.11	72.98	46.77	125.54	146.77	15.42	43.94	23.93	62.25	20.39

Note: The outcome variable is the total acreage of corn and soybeans combined in logarithm. Panels A, B, and C report the estimated effects of ozone in the past growing season, past two growing seasons, and past three growing seasons on the acreage of corn and soybeans combined. Column (1) replicates the baseline results. Column (2) expands the sample by including all counties in states east of the Rocky Mountains. Column (3) relies on an alternative criterion for rainfed counties by including counties with less-than-20% irrigated cropland acreage. Column (4) expands the sample in including all counties growing corn and soybeans. Column (5) relies on an alternative data source (ozone data from the EPA). Columns (6) and (7) specify the growing season as April–September and May–October, respectively. Column (8) further controls for explanatory variables in the non-growing season. Column (9) further controls for net solar radiation, relative humidity, wind speed, and surface pressure. Column (10) further controls for instrumented NO_2 and $PM_{2.5}$. Column (11) specifies the temperature thresholds as 8–30°C for moderate degree days and above 30°C for extreme degree days. Column (12) conducts a placebo test by showing the estimated coefficients on ozone concentrations during the current growing season. In this column, all explanatory variables during the current growing season and the past growing seasons (one for Panel A; two for Panel B; three for Panel C) are included (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$).

TABLE 3 | 3SLS estimation results.

	One growing season	Two growing seasons	Three growing seasons
	(1)	(2)	(3)
Panel A: 3SLS (2nd Stage)	**Average yield of corn and soybeans**		
O_3	−1.5305***	−1.7878***	−1.8465***
	(0.1974)	(0.2567)	(0.3284)
Panel B: 3SLS (3rd Stage)	**Log planted acreage of corn and soybeans**		
Yield	0.0104***	0.0110***	0.0087***
	(0.0020)	(0.0023)	(0.0025)
Observations	30,383	28,589	26,787
Pollutant controls	YES	YES	YES
Weather controls	YES	YES	YES
County FE	YES	YES	YES
Year FE	YES	YES	YES

Note: Panel A reports the second-stage results of 3SLS estimates, in which the outcome variable is the average yield of corn and soybeans in the past growing season. Panel B reports the third-stage results of 3SLS estimates, in which the outcome variable is the total acreage of corn and soybeans combined in logarithm in the current growing season. The explanatory variables of Columns (1), (2), and (3) are during the past growing season, the past two growing seasons, and the past three growing seasons, respectively. Pollutant controls include PM_{10}, SO_2, and CO. Weather controls include $DD_{8–32°C}$, $DD_{8–32°C}$ squared, the square root of $DD_{34+°C}$, precipitation, and precipitation squared. Ozone is instrumented by upwind ozone within the radius band of 300–400 km; PM_{10}, SO_2, and CO are also instrumented by upwind PM_{10}, SO_2, and CO within the radius band of 300–400 km. Fixed effects include county FE and year FE (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$).

Specifically, the first stage remains the same as the 2SLS model, which instruments ozone and additional air pollutants with their upwind counterparts. The second stage estimates the ozone effect on the average yields of corn and soybeans ($Y_{ct_{pre}}$), and the third stage estimates the yield effect on the acreage of corn and soybeans. The second-stage and third-stage equations are numbered by (13) and (14), respectively:

$$Y_{ct_{pre}} = \varrho_0 + \varrho_1 \hat{O}_{ct_{pre}} + \boldsymbol{W}_{ct_{pre}}\gamma + \hat{\boldsymbol{P}}_{ct_{pre}}\vartheta + \sigma_c + \tau_t + \varepsilon_{ct}, \tag{13}$$

$$A_{ct} = \varsigma_0 + \varsigma_1 Y_{ct_{pre}} + \boldsymbol{W}_{ct_{pre}}\gamma + \hat{\boldsymbol{P}}_{ct_{pre}}\omega + \sigma_c + \tau_t + \varepsilon_{ct}. \tag{14}$$

Table 3 presents the estimated three-stage least squares (3SLS) results. As indicated by Table 3, a one-additional ppb of ambient ozone decreases the average corn and soybean yield by 1.53–1.85 bushels per acre, and a one-additional bushel per acre in yield elevates the corn and soybean acreage by 0.87%–1.10%. These estimates suggest that a one-additional ppb of ambient ozone decreases the corn and soybean acreage by 1.59%–1.97%, which is in line with the baseline 2SLS results.

5.4 | Predictions

The empirical findings reveal that higher ambient ozone concentrations significantly reduce corn and soybean planting acreage; what does this acreage change suggest for agricultural production? Ignoring this planted acreage change, existing welfare analyses mostly focus on the biological channel (i.e., yield change) via which ozone reduces crop production (Hong et al. 2020; McGrath et al. 2015; Tai et al. 2014). To what degree does disregarding this acreage adjustment underestimate the crop production loss? This section answers these questions by (1) predicting the saved crop production under four Representative Concentration Pathway (RCP) emission scenarios and (2) predicting by how much disregarding the acreage adjustment underestimates crop production changes.

The prediction procedures are as follows. First, I retrieve projected ambient ozone changes by 2050 in North America from Wild et al. (2012). The projected ambient ozone changes are based on four simulated emission scenarios: RCPs 2.6, 4.5, 6.0, and 8.5. Comparing to 2021, ambient ozone level is projected to decrease by approximately 3.5, 1.6, and 1.5 ppb by the middle of this century under RCPs 2.6, 4.5, and 6.0, three scenarios of which the fossil-fuel dependence increases in order; ambient ozone level is projected to increase by 0.4 ppb under RCP 8.5, a high-emission scenario heavily relying on fossil fuels. Second, I separately fit the ozone-yield 2SLS model and the ozone-acreage 2SLS model and extract the coefficients of interest. Third, based on the projected ambient ozone data, I predict the ozone-induced change in corn and soybean production from (1) the yield change alone and (2) both the yield change and acreage adjustment for each county. Note that the harvested ratios are taken into account,[11] as a small proportion of the planted acreage would be abandoned during harvesting (Cui 2020a). Fourth, the predicted county-level saved production is summed over all the sampled counties.

Figure 1 presents the predicted corn and soybean production changes. The dot-dashed and solid curves represent the predicted production changes compared to 2022, resulting from yield change alone (i.e., biological channel) and yield change plus acreage adjustment (i.e., biological and behavioral channels), respectively. Since ambient ozone concentrations are projected to fall under RCPs 2.6, 4.5, and 6.0 and rise under RCP 8.5, corn and soybean production is expected to increase under the former three scenarios and decline under RCP 8.5. Specifically, as indicated by Column (1) of Table 4, when considering ozone-driven biological

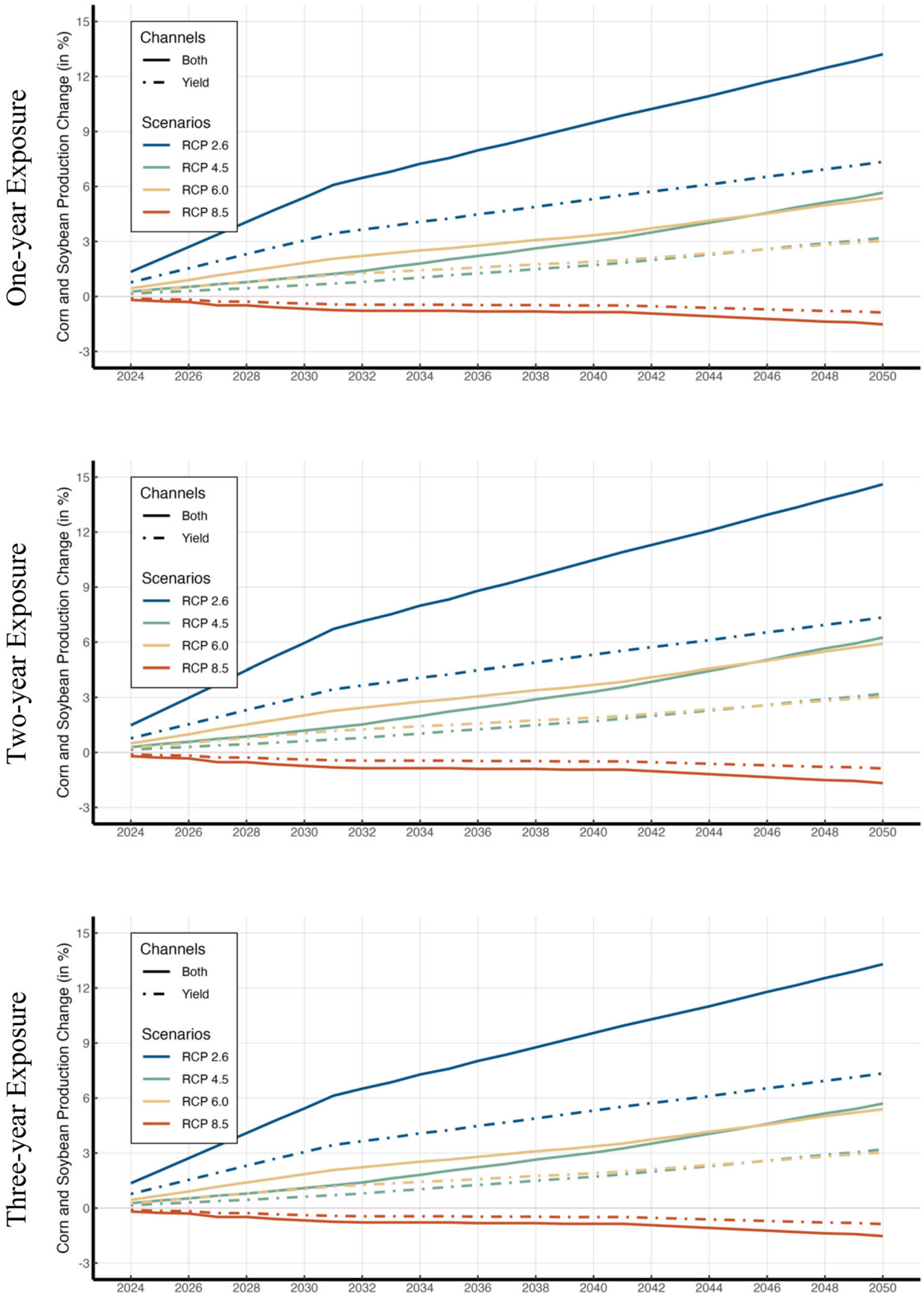

FIGURE 1 | Predicted production changes. This figure presents the predicted corn and soybean production change, compared to 2022, under the four RCP emission scenarios. The predictions are based on the baseline 2SLS estimates. The dot-dashed curves represent the predicted production changes resulting from yield change alone (i.e., biological channel). The solid curves represent the predicted production changes resulting from yield change plus acreage adjustment (i.e., biological and behavioral channels).

channel alone, corn and soybean production is predicted to rise by 7.34%, 3.20%, and 3.03%, respectively, under RCPs 2.6, 4.5, and 6.0, and to decline by 0.88% under RCP 8.5 by 2050. On the other hand, as shown by Columns (2), (4), and (6) of Table 4, when considering both ozone-driven biological and behavioral channels, corn and soybean production is predicted to rise by 13.21%–14.61%, 5.66%–6.25%, and 5.36%–5.91%, respectively, under RCPs 2.6, 4.5, and 6.0, and to decline by 1.52%–1.67% under RCP 8.5 by the middle of this century.

That is, comparing with the predicted production change from both channels, the predicted production change from the biological channel alone would, therefore, be underestimated. Without taking account of acreage adjustment, the predicted corn and soybean production rise would be underestimated by 44.42%–49.72%, 43.45%–48.74%, and 43.41%–48.70%, respectively, under RCPs 2.6, 4.5, and 6.0; the predicted corn and soybean production decline would be underestimated by 42.46%–47.73% under RCP 8.5. This shows the importance of considering both biological and

TABLE 4 | Predicted production changes.

		1-year exposure		2-year exposure		3-year exposure	
	Production change from yield only (in %)	Production change from both (in %)	Under-estimated production change (in %)	Production change from both (in %)	Under-estimated production change (in %)	Production change from both (in %)	Under-estimated production change (in %)
Year	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: RCP 2.6							
2025	1.15	2.02	42.95	2.23	48.24	2.03	43.32
2030	3.05	5.40	43.41	5.95	48.70	5.43	43.78
2035	4.25	7.55	43.69	8.33	48.99	7.60	44.06
2040	5.32	9.48	43.95	10.47	49.25	9.55	44.31
2045	6.32	11.32	44.18	12.51	49.48	11.40	44.55
2050	7.34	13.21	44.42	14.61	49.72	13.30	44.78
Panel B: RCP 4.5							
2025	0.23	0.41	42.73	0.45	48.01	0.41	43.10
2030	0.62	1.08	42.82	1.19	48.11	1.09	43.19
2035	1.15	2.02	42.95	2.23	48.24	2.03	43.32
2040	1.71	3.00	43.09	3.31	48.38	3.02	43.45
2045	2.43	4.29	43.26	4.73	48.55	4.32	43.63
2050	3.20	5.66	43.45	6.25	48.74	5.70	43.81
Panel C: RCP 6.0							
2025	0.38	0.67	42.77	0.74	48.05	0.68	43.13
2030	1.05	1.83	42.93	2.02	48.21	1.84	43.29
2035	1.49	2.62	43.04	2.89	48.32	2.64	43.40
2040	1.90	3.34	43.13	3.68	48.42	3.36	43.50
2045	2.46	4.33	43.27	4.77	48.56	4.36	43.63
2050	3.03	5.36	43.41	5.91	48.70	5.39	43.77
Panel D: RCP 8.5							
2025	−0.15	−0.26	42.64	−0.29	47.92	−0.26	43.00
2030	−0.38	−0.67	42.58	−0.74	47.86	−0.67	42.94
2035	−0.45	−0.78	42.56	−0.86	47.84	−0.79	42.93
2040	−0.49	−0.85	42.55	−0.94	47.83	−0.86	42.92
2045	−0.66	−1.15	42.51	−1.27	47.79	−1.16	42.88
2050	−0.88	−1.52	42.46	−1.67	47.73	−1.53	42.82

Note: This table presents the prediction results under four RCP scenarios. Columns (1) presents the predicted corn and soybean production change from the yield channel. Columns (2), (4), and (6) present the predicted corn and soybean production change from both yield and acreage channels. Columns (3), (5), and (7) present by what percentage does ignoring the acreage channel underestimate the corn and soybean production change.

behavioral channels when evaluating the agricultural production benefits of ozone pollution management.

My predictions have, so far, been based on estimates extracted from a linear specification. This specification assumes that the effect of ozone on crop growth and production is linear (Betzelberger et al. 2012). Nonetheless, some studies show that the ozone impact on crop productivity could be nonlinear with a critical threshold of 40 ppb (Mills et al. 2011) and employs AOT40 to capture cumulative ozone exposure higher than 40 ppb (McGrath et al. 2015). Based on the estimated coefficients for AOT40, which assume that ozone causes crop damage at concentrations higher than 40 ppb, Figure A4 depicts projected changes in corn and soybean production.[12] Despite a slightly smaller scale, the predicted production changes show a similar pattern to the linear case.

Specifically, as indicated by Column (1) of Table B5, when considering the biological channel alone, corn and soybean production is expected to rise by 4.79%, 2.27%, and 2.15%, respectively, under RCPs 2.6, 4.5, and 6.0, and to decline by 0.67% under RCP 8.5 by 2050. On the other hand, as shown by Columns (2), (4), and (6) of Table B5, when considering both biological and behavioral channels, corn and soybean production is predicted to rise by 8.60%–9.95%, 4.02%–4.62%, and 3.82%–4.40%, respectively, under RCPs 2.6, 4.5, and 6.0, and to decline by 1.17%–1.34% under RCP 8.5 by the middle of this century. This demonstrates that, similar to the linear case, when assuming that ozone causes crop injury only at concentrations above 40 ppb, the predicted production change from the biological channel alone would likewise be underestimated compared to both channels.

5.5 | Ozone-Induced Crop Substitution

As suggested by the conceptual model, the ozone-induced acreage shrinkage of some crop types could be partially achieved through substitution with other types; the crop allocation pattern is presumably determined by the ozone-driven relative change in the MRP of land. This differentiation in the relative change across crop types could be partially attributed to the fact that various crops respond to ambient ozone exposure differently; some types exhibit tolerance to ambient ozone, while others are more sensitive to elevated ozone concentrations (Da et al. 2022; Li et al. 2023; Mills et al. 2007). Additionally, the NASS statistics (2004, 2023) indicate that over the last two decades, the corn and soybean acreage changes in the opposite direction to the total acreage of principal crops, in line with this crop substitution hypothesis.

This section aims to empirically test the impact of ozone on the acreage of corn and soybeans combined relative to other principal crops. Specifically, the outcome variable is constructed as $\frac{A_{ct}^c+A_{ct}^s}{A_{ct}^c+A_{ct}^s+A_{ct}^a}$ (Cui 2020b), which is a ratio of the corn (A_{ct}^c) and soybean acreage (A_{ct}^s) to the total acreage of corn, soybeans, and an alternative crop type (A_{ct}^a). The alternative crop types are specified as winter wheat, spring wheat, sorghum, barley, and cotton, respectively; together with corn and soybeans, these crops constitute about three-quarters of the US cropland acreage (Cui 2020b). The estimation model to estimate the crop substitution effect is formalized as the following equation, where all specifications remain the same as Equation (10) except for the outcome variable:

$$\frac{A_{ct}^c + A_{ct}^s}{A_{ct}^c + A_{ct}^s + A_{ct}^a} = \beta_0 + \beta_1 \hat{O}_{ct_{pre}} + \boldsymbol{W}_{ct_{pre}}\gamma + \hat{\boldsymbol{P}}_{ct_{pre}}\eta + \sigma_c + \tau_t + \varepsilon_{ct}. \tag{15}$$

The estimated results of the ozone-induced crop substitution are shown in Table 5. The alternative crop types are winter wheat, spring wheat, sorghum, barley, and cotton in Columns (1)–(5), respectively. These results suggest the following findings. First, relative to winter wheat, sorghum, or barley, a one-ppb rise in ambient ozone concentrations during the past one to three growing seasons decreases the total acreage of corn and soybeans combined by 0.84%–1.42%, 0.49%–0.70%, or 0.04%–0.11%, respectively. The smaller magnitude in the acreage change relative to barley, as opposed to winter wheat or sorghum, could be explained by the fact that barley's main producing regions are almost entirely distinct from those of corn and soybeans, yielding higher switching cost relative to winter wheat and sorghum. Second, and by contrast, relative to spring wheat or cotton, the corn and soybean planted acreage is not significantly affected by elevated ambient ozone. This difference is in line with the findings of Da et al. (2022) on crop sensitivity to ambient ozone; spring wheat and cotton are more sensitive to ambient ozone exposure, while winter wheat, sorghum, and barley are classified as resistant to or moderately sensitive to elevated ozone.

5.6 | Alternative Time Windows

Given that this is the first study estimating the impact of ambient ozone on the planting acreage, it is uncertain about the most appropriate time window over which exposure to ambient ozone affects crop growers' planting decisions. The baseline specification specifies the time windows for ambient ozone exposure as one to three growing seasons, assuming that crop growers determine planting choices based on crop damage and yield losses over the latest growing seasons (Aragón et al. 2021). To test whether ambient ozone exposure over a longer time window still affects the planting acreage, I rely on the approach recorded in Deschênes et al. (2020) and Liu (2025b). Specifically, based on the 2SLS specification model, I vary the time window of all explanatory variables, from the past one to six growing seasons, and present the estimated coefficients of interest in Figure A5.

The estimated effects of ambient ozone during the past one to three growing seasons, in Figure A5, replicate the baseline results in Panel B of Table 1. These significantly negative point estimates show that elevated ambient ozone over the most recent three growing seasons prior to sowing significantly decreases the corn and soybean planted acreage, holding up my hypothesis that recent ozone-induced crop damage have an influence on crop growers' planting decision. As the time window for ambient ozone exposure gets longer, from the preceding four to six growing seasons as indicated in Figure A5, the point estimates shrink in magnitude and becomes statistically not significant. This could potentially be attributed to two reasons. First, crop growers within a county may enter and exit the market as time goes on, making the estimated effects on ambient ozone over longer time windows shrink toward zero. Second, crop growers could weight more on the most recent growing seasons, during which the ozone-induced crop damage may be moderate if ambient ozone concentrations drop over the course of the time window.

5.7 | Limitations

There are some limitations in the empirical analysis of this work. First, the findings reveal that ozone-induced yield losses affect the subsequent planting decisions of crop growers; nonetheless, it is not clear if these actions are totally rational. Certain growers might misread or react incorrectly to yield signals or might be less sensitive to yield reductions. This emphasizes the complexities of decision-making processes in agricultural production. Second, since consistent signals have a greater predictive value, long-term estimates tend to be more reliable than short-term ones for prediction. However, the limited time span of my data sample prevents me from empirically analyzing the long-term impacts, which I will leave to future research. Depending on the scenario,

TABLE 5 | Substitutions with alternative crops.

	Winter wheat (1)	Spring wheat (2)	Sorghum (3)	Barley (4)	Cotton (5)
Panel A: One growing season					
O_3	−0.0084***	−0.0005	−0.0049***	−0.0004**	0.0007
	(0.0007)	(0.0004)	(0.0006)	(0.0002)	(0.0008)
Observations	30,383	30,383	30,383	30,383	30,383
KP *F*-Statistics	52.22	52.22	52.22	52.22	52.22
Panel B: Two growing seasons					
O_3	−0.0120***	−0.0004	−0.0065***	−0.0010***	−0.0005
	(0.0009)	(0.0005)	(0.0007)	(0.0002)	(0.0009)
Observations	28,589	28,589	28,589	28,589	28,589
KP *F*-Statistics	76.95	76.95	76.95	76.95	76.95
Panel C: Three growing seasons					
O_3	−0.0142***	0.0009	−0.0070***	−0.0011***	−0.0011
	(0.0012)	(0.0006)	(0.0008)	(0.0002)	(0.0011)
Observations	26,787	26,787	26,787	26,787	26,787
KP *F*-Statistics	62.60	62.60	62.60	62.60	62.60

Note: Columns (1)–(5) report the estimated ozone effects on the corn-and-soybean acreage relative to alternative crops. The alternative crops are winter wheat, spring wheat, sorghum, barley, and cotton in Columns (1)–(5), respectively. The explanatory variables of interest in Panels A, B, and C are instrumented ozone in the past one to three growing seasons, respectively. Pollutant controls include instrumented PM_{10}, SO_2, and CO. Weather controls include $DD_{8-32°C}$, $DD_{8-32°C}$ squared, the square root of $DD_{34+°C}$, precipitation, and precipitation squared. Fixed effects include county FE and year FE. Standard errors are clustered at the year level (***$p < 0.01$, **$p < 0.05$, *$p < 0.1$).

my projections for future crop production could be perceived as an upper or lower bound as detailed in the Appendix. Third, although wind is considered as random and the upwind-based IV offers an exogenous shock, empirical verification of this claim is difficult, and I thus acknowledge this as another limitation.

6 | Nonlinearity and Heterogeneity

6.1 | Nonlinearity

Throughout the main empirical analysis, I rely on a linear specification to estimate the effects of ozone exposure on the acreage adjustment, assuming ambient ozone's negative impact on crop growth and production as linear (Betzelberger et al. 2012; Liu and Lu 2023). Nonetheless, it has been found that the dose-response relationship between crop growth and exposure to certain environmental stresses, such as heat, is nonlinear (Lobell et al. 2011; Schlenker and Roberts 2009). Some studies have suggested that crop production response to ambient ozone pollution may also exhibit a nonlinear relation (Pleijel et al. 1995). To explore the potential nonlinearity, this section presents the estimated effect of exposure to ambient ozone on the total acreage of corn and soybeans combined by allowing for a nonlinear response.

Evaluating the estimated effects at various concentration levels requires a binned approach (Chang et al. 2016, 2019; Graff Zivin and Neidell 2012; Liu 2025b; Wang et al. 2022). I specifically apply the following specification equation, which omits less-than-30 ppb as the reference bin and includes indicator variables for each one-half-ppb bin of ambient ozone:

$$A_{ct} = \beta_0 + \sum_j \beta_j O^j_{ct_{pre}} + \boldsymbol{W}_{ct_{pre}}\gamma + \boldsymbol{P}_{ct_{pre}}\eta + \sigma_c + \tau_t + \varepsilon_{ct}. \quad (16)$$

The indicator variable $O^j_{ct_{pre}}$ equals to one if ambient ozone concentration falls under the-jth-specific bin. The coefficient $\hat{\beta}_j$ is hence interpreted as the proportional change in the acreage of corn and soybeans, compared to the reference bin, for ambient ozone falling into the-jth-specific concentration bin. The rest remains the same as the baseline specification.

Figure 2 presents the estimated effects of ambient ozone exposure on the corn and soybean acreage, allowing for a nonlinear response.[13] The upper half of each plot includes a dark solid step function and a shallow band, representing the estimated coefficients $\hat{\beta}_j$ and the corresponding confidence intervals, respectively. Note that the estimated coefficients should be interpreted with caution, as ambient ozone falling into the-jth-specific concentration bin is not instrumented. Chang et al. (2016, 2019), Graff Zivin and Neidell (2012), and Wang et al. (2022) likewise make this compromise, as exogenous shocks cannot be separated across different concentration levels. Approximately normally distributed, the lower half of each plot shows the average number of days falling into the-jth-specific concentration bin across the

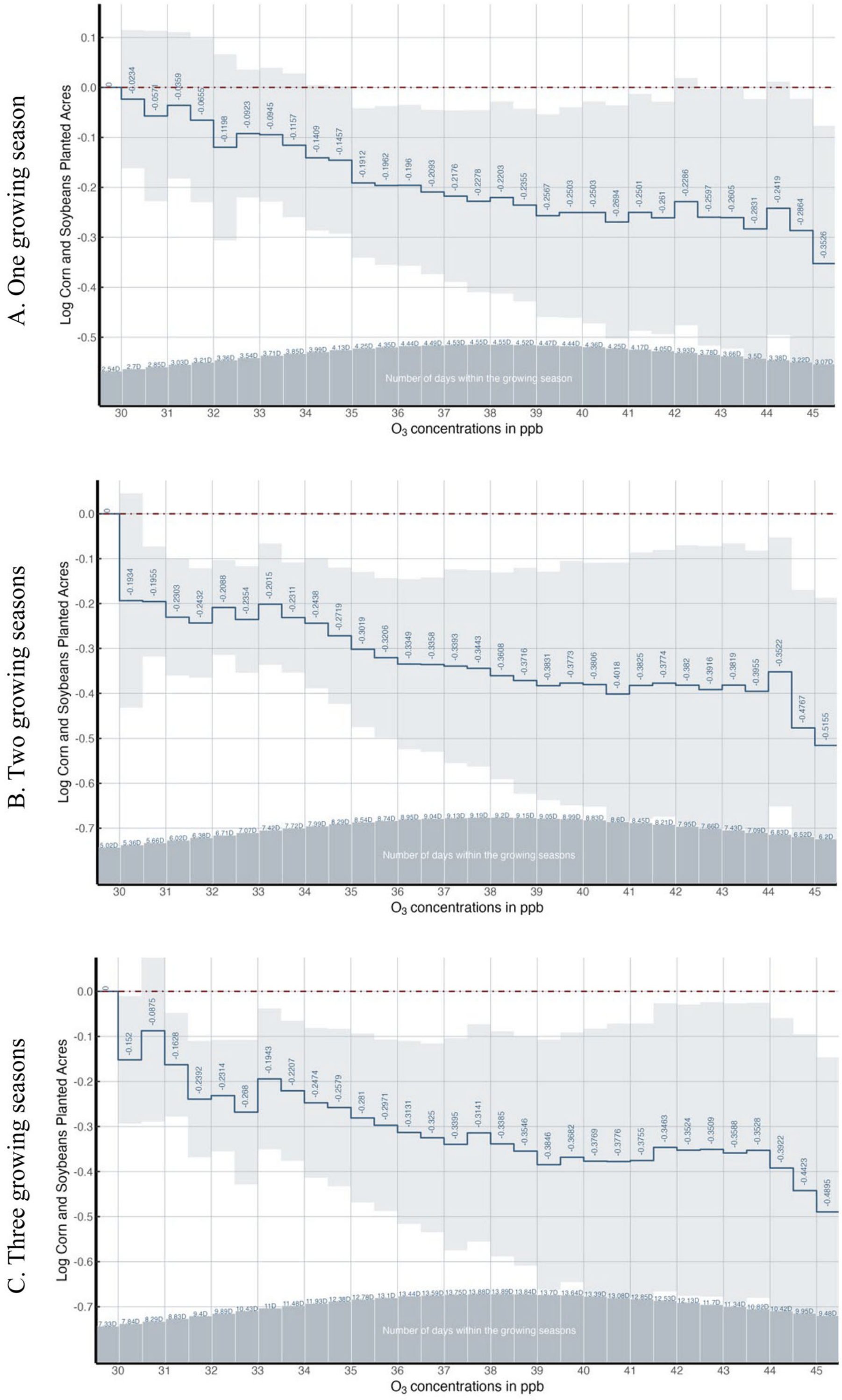

FIGURE 2 | Nonlinearity. This figure presents the estimated effects of ozone on the total acreage of corn and soybeans combined based on the binned approach. Ozone less than 30 ppb is omitted as the reference category. The 95% confidence intervals are constructed based on standard errors clustered at the year level.

growing seasons. Supporting the baseline linear specification, Figure 2 suggests that the decline in the corn and soybean acreage caused by elevated ambient ozone is relatively linear and steady.

6.2 | Spatial Heterogeneity

The ozone-induced acreage change may exhibit spatial heterogeneity, depending on whether corn and soybeans are dominant

TABLE 6 | Spatial heterogeneity.

	Log planted acreage of corn and soybeans		
	One growing season	Two growing seasons	Three growing seasons
	(1)	(2)	(3)
O_3	-0.0145^{***}	-0.0171^{***}	-0.0139^{***}
	(0.0029)	(0.0037)	(0.0047)
$\times \mathbb{1}_{\text{Corn Belt}}$	-0.0066^{***}	-0.0151^{***}	-0.0160^{***}
	(0.0021)	(0.0028)	(0.0041)
Observations	30,383	28,589	26,787
Pollutant controls	YES	YES	YES
Weather controls	YES	YES	YES
County FE	YES	YES	YES
Year FE	YES	YES	YES
KP *F*-Statistics	41.51	60.66	48.06

Note: This table reports the heterogeneous effects of ozone on the total acreage of corn and soybeans combined between Corn Belt states and non-Corn Belt states. The primary explanatory variables of Columns (1)–(3) are ozone in the past one to three growing seasons, respectively. The interaction term is ozone × indicator for Corn Belt states. Ozone is instrumented by upwind ozone within the 300–400 km radius band. Pollutant controls include instrumented PM_{10}, SO_2, and CO. Weather controls include $DD_{8\text{–}32°C}$, $DD_{8\text{–}32°C}$ squared, the square root of $DD_{34+°C}$, precipitation, and precipitation squared. Fixed effects include county FE and year FE. Standard errors are clustered at the year level ($^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$).

crops in a region. For instance, grain infrastructure might have already been optimized for corn and soybeans in regions where they are the dominant crop types (Cui 2020b), yielding higher switching costs from corn and soybeans to other crop types. In this case, the corn and soybean acreage are arguably less affected by ambient ozone for regions where these two crop types are dominant. By contrast, crop growers might be more sensitive to the corn and soybean production losses in regions where these two crops are dominant, as the growers' livelihood and income are highly dependent on these two crop types. If this is the case, the corn and soybean acreage should then be more responsive to elevated ambient ozone for regions where these two crop types are dominant.

This section tries to test for such a spatial heterogeneity. Specifically, I modify the baseline 2SLS model by interacting ambient ozone with an indicator variable for the Corn Belt ($\mathbb{I}_c^{Belt}$). The Corn Belt states, including Illinois, Indiana, Iowa, Michigan, Minnesota, Missouri, Ohio, and Wisconsin, are where most corn and soybeans are produced in the US (USDA n.d.; Schnitkey 2013); three quarters of the agricultural land in the Corn Belt is devoted to corn and soybeans, the two dominant crop types in the Corn Belt (Goodwin et al. 2004; USDA n.d.). The indicator variable equals to one if county c belongs to one of the Corn Belt states. The following model is used to explore the potential heterogeneity of the estimated effect of ambient ozone on the total acreage of corn and soybeans combined across the Corn Belt states and non-Corn Belt states:

$$A_{ct} = \beta_0 + \beta_1 \hat{O}_{ct_{pre}} + \beta_2 \hat{O}_{ct_{pre}} \cdot \mathbb{I}_c^{Belt} + \beta_3 \mathbb{I}_c^{Belt} + \boldsymbol{W}_{ct_{pre}} \gamma + \hat{\boldsymbol{P}}_{ct_{pre}} \eta + \sigma_c + \tau_t + \varepsilon_{ct}. \tag{17}$$

Table 6 reports estimates from the above specification. As indicated by the results, the acreage within the Corn Belt region is more sensitive to ambient ozone. Specifically, a one-additional ppb of average ambient ozone during the past one to three growing seasons decreases corn and soybean acreage within the non-Corn Belt region by 1.39%–1.71%; for the Corn Belt region, this ozone-induced acreage shrinkage is exacerbated by 0.66–1.60 percentage points. This heterogeneity across the Corn Belt and the non-Corn Belt states suggests that crop growers within the Corn Belt are more responsive to the ozone-induced corn and soybean production losses, which might be attributable to the aforementioned disparity across the Corn Belt and the non-Corn Belt regions in terms of the importance of corn and soybeans to the crop growers.

7 | Discussion and Conclusions

Building upon the literature on crop yield and the biological mechanism through which ozone influences crop production (Avnery et al. 2011; Boone et al. 2019; Carter et al. 2017; Da et al. 2022; McGrath et al. 2015; Yi et al. 2018), this study shows that, in additional to such a biological mechanism, ozone may also impact crop production through another channel that has been disregarded. Specifically, this study emphasizes the importance of behavioral responses to ozone-induced crop damage and provides the first empirical analysis of how exposure to ambient ozone affects the total acreage of corn and soybeans combined. To address the empirical challenges raised by endogeneity concerns and measurement errors, this study leverages the variation in ambient ozone transmitted from upwind neighbor counties as an arguably exogenous shock for identification. The empirical results show that a one-additional ppb of average ambient ozone reduces subsequent plantings of corn and soybean acreage by 1.59%–1.97%. Such findings exhibit spatial heterogeneity, with corn and soybean acreage within the Corn Belt being more sensitive to elevated ambient ozone. Further analysis suggests that such ozone-induced acreage shrinkage is partially achieved through acreage shifts to less-ozone-sensitive crops. Underlining the importance of behavioral responses, my simulated prediction results indicate that, when ozone concentrations are projected to fall, the expected rise in corn and soybean production by 2050 would be underestimated by 43.41%–49.72% without considering acreage adjustment.

This study's empirical setting focuses on the US, where ambient ozone concentrations have been declining in recent decades and are expected to decrease further in the future under a number of emission scenarios. As projected in the Predictions section, crop production in the US is expected to benefit from lower ozone levels under multiple emission scenarios. Similarly, ambient ozone levels in Europe are predicted to follow a similar declining trajectory as in the US (Wild et al. 2012), implying possibly comparable benefits for crop output.[14] Nonetheless, in other parts of the world, such as South Asia, ambient ozone levels are predicted to rise in the near future (Tai et al. 2014). This implies that ambient ozone may endanger crop production in these areas, suggesting the need for further research.

This study has several policy implications. First, my findings indicate that the saved corn and soybean production from ozone management, after taking the acreage adjustment into account, is greater than previously believed. This expanded production benefit may encourage policymakers to implement more stringent standards to reduce ambient ozone pollution. Given that ambient ozone is a secondary pollutant formed by its chemical precursors (Sillman 1999), efforts in reducing ambient ozone concentrations primarily target at its precursors, especially NO_X. The relevant policy discussions, with an emphasis on NO_X, include the Clean Air Act (Aldy et al. 2022; Greenstone 2003; Schmalensee and Stavins 2019), the REgional CLean Air Incentives Market program (Fowlie et al. 2012), and the NOx Budget program (Deschênes et al. 2017). Future ozone reduction policy could target at those precursors that receive less attention, such as VOCs.

Second, specific attention should be paid to cultivar differences in sensitivity to ambient ozone exposure (Mills et al. 2018). For example, Loda and Pana, two soybean cultivars, are more tolerant of elevated ozone concentrations than the others (Betzelberger et al. 2010). Two corn inbred lines, M37W and CML333, are resistant to elevated ozone concentrations in terms of photosynthesis and stomatal conductance, which are two important traits for crop productivity (Sitch et al. 2007; Yendrek et al. 2017). The corn and soybean production losses caused by ozone, from both the biological and behavioral channels, point to the need for raising the adoption rates of corn and soybean cultivars that are more tolerant to ambient ozone.

Third, the Corn Belt region deserves particular attention. As suggested by the spatial heterogeneity analysis, the corn and soybean acreage within the Corn Belt states is more sensitive to ambient ozone exposure. Given that the Corn Belt states account for around one-third of the corn and soybean production across the world (Zhou et al. 2020), this spatial heterogeneity highlights the value of subsidizing protection expenses against ozone damage within the Corn Belt region. For instance, ethylenediurea, often applied as a foliar spray, could potentially be used against ambient ozone injury on plant growth (Gupta et al. 2020; Mills et al. 2018), though the negative spillovers of such chemical agents to the environment must be closely watched. Prioritizing such subsidies to the-Corn-Belt crop growers could strike a balance between a limited budget and an effective protection against ozone damage.

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Conflicts of Interest

The author declares no conflicts of interest.

Endnotes

[1] This conceptual model builds upon the models in Cui (2020b), Liu (2025b), and Liu and Lu (2024).

[2] I thank an anonymous referee for suggesting a detailed discussion on the temporal and spatial variations, as well as the sources of variations, of ambient ozone.

[3] The NASS planted acreage data is accessible at https://www.nass.usda.gov/Quick_Stats/.

[4] The ECMWF ozone data is accessible at https://ads.atmosphere.copernicus.eu/cdsapp#!/dataset/cams-global-reanalysis-eac4.

[5] The ECMWF weather data is accessible at https://doi.org/10.24381/cds.adbb2d47 and https://doi.org/10.24381/cds.bd0915c6.

[6] The standard errors of ambient ozone over one, two, and three growing seasons are 3.49, 3.32, and 3.19 ppb, respectively.

[7] I appreciate an anonymous referee's suggestion on drawing inferences about historical variation that has been caused by ozone.

[8] Yu et al. (2018) finds that the own-subsidy acreage elasticity is 1.29 for corn and soybeans.

[9] That is, only counties located in states west of the Rocky mountains are excluded.

[10] Non-growing seasons are the gap between growing seasons. Given that growing seasons are specified as March to August, non-growing seasons are hence specified from September to next February.

[11] The ratio of the harvested acreage to the planted acreage.

[12] I appreciate an anonymous referee's comments regarding the nonlinearity of the ozone effects on crop production.

[13] This figure follows the Schlenker and Roberts style (2009).

[14] I appreciate an anonymous referee's suggestion on discussing implications for other regions of the world.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.