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Climate Change and Dust Pollution Impact on Farmland Market: Evidence from California's Central Valley

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Summary:
Rising temperatures due to climate change can increase dust particulate concentrations leading to lower crop productivity and resulting in a decline in farmland values. Using pooled data with 9,300 observations representing 7,987 agricultural parcels that were sold in the Central Valley of California between 2010 and 2017, we estimate a Hedonic regression equation with month- and year-of-sale fixed effects. Ricardian estimates indicate that dust levels have a negative net effect on farmland values and highly significant with an inverted U-shaped response curve.

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Abstract

Rising temperatures due to climate change can increase dust particulate concentrations leading to lower crop productivity and resulting in a decline in farmland values. Using pooled data with 9,300 observations representing 7,987 agricultural parcels that were sold in the Central Valley of California between 2010 and 2017, we estimate a Hedonic regression equation with month- and year-of-sale fixed effects. Ricardian estimates indicate that dust levels have a negative net effect on farmland values and highly significant with an inverted U-shaped response curve.

Keywords: Agriculture, dust, particulate matter, climate change, Central Valley California

JEL Codes: Q12, Q53

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1. Introduction

Globally, exposure of plants to airborne pollutants has been shown to reduce crop health and yields significantly. Existing evidence comes from both high-income counties such as the United States, and low- and middle-income countries such as India, China, and Ghana, with a focus on crop health, yields, and agricultural productivity (Aragón & Rud, 2016; Lobell et al., 2022; Merfeld, 2023; Zhou et al., 2018). The negative effect of air pollution on agricultural productivity is exacerbated in the presence of heat stress in the United States (Liu & Desai, 2021), including in California, where the economic loss caused by such pollution in the agricultural sector is significant (Hill et al., 2024; Hong et al., 2020; McGrath, 2020; Chang et al., 2016).[1] This paper empirically assesses the impact of particulate matter on the value of farmland in the Central Valley of California. We use the Ricardian framework to demonstrate that the higher levels of particulate matter are linked to an economically significant decline in the value of farmland.

The presence of high levels of coarse particulate matter (PM), a measure of dust, in the atmosphere impairs the photosynthesis process necessary for plant growth by reducing solar radiation through absorption and scattering (Cánovas et al., 2017; Matyssek et al., 2008). The damaging impact of pollution (e.g., particulate matter and ozone) on crop health and yields is potentially due to the internal reaction of plant tissues and pollutants in response to higher levels of air pollutants. (Matyssek et al., 2008; Miller, 1988).[2] Furthermore, air pollutants

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[1] Hong et al. (2020), for example, found that high-value perennial crops in California were negatively affected by changes in local temperature and ozone concentrations, with yield losses of 5% to 15%, depending on the varying degree of pollutant exposure and the different crop types. According to that study, yield loss in high-value crops is translated into a loss in production value of roughly US$1 billion per year, suggesting that air pollution combined with the non-linear impact of precipitation and maximum temperature has a significant negative impact on the agricultural economy in California.

2 Simply put, chronic exposure to airborne pollutants causes damage to vegetation through lower stomatal conductance (ability to exchange gases and transpiration through leaf stomata, critical for plant growth).

association with low precipitation and high temperatures during severe drought periods can cause a decrease in farm income. Climate change causes more intense drought cycles, which increase airborne dust, and negatively impact agricultural productivity. For example, Achakulwisut et al. (2019) found a relationship between climate change-induced increased aridity and dust levels in the southwestern United States. This paper documents the relationship between dust levels and farmland values in California's Central Valley, a region that is dependent on agriculture and has high levels of pollution. Quantifying this relationship is important to inform the debate on environmental policies and negative externalities on agriculture. Specifically, in changing climates with uncertain irrigation and increased farmland abandonment, which potentially contribute to increased dust concentration.

Previous analytical work (e.g., Liu & Desai, 2021) in the United States supports the thesis that the rise in levels of air pollution and global climate warming are interconnected. While strong evidence exists of a relationship between changes in air pollutants and crop yields, their impact on farmland's value has not yet been empirically quantified. Our farmland hedonic model is based on the standard Ricardian framework (Mendelsohn et al., 1994; Mendelsohn & Dinar, 2003), but it is extended to include particulate matter in the production function along with climate variables that affect agricultural productivity and therefore the expected rent from farmland. We exploit the quasi-random variation in particulate matter attributable to the transportation of pollutants by wind to estimate the causal impact of dust levels on farmland values in agricultural-dependent regions of California.

By estimating the effects of dust levels on farmland values, this study provides empirical evidence on whether pollution-induced crop yield loss translates to decrease in farmland values. Ricardian estimates indicate that dust levels have a negative net effect on farmland values and highly significant with an inverse U-shaped response curve. The inverse U-shape's increasing portion captures preparatory agricultural activities (plowing, disking) on farmland necessary for increased productivity that also produce dust, but the farmland values decrease after a threshold of dust level (that may blow from neighboring locations by winds. This implies that coarse particulate matter is sufficient to cause pollution-induced crop losses after a threshold point, and a decrease in farmland sale price per acre. Air pollution can have varying effects on annual crops (e.g., wheat, rice, maize, and soybean), and perennial crops (e.g., fruits, nuts, and other tree crops). Moreover, pollution may affect buyers' expectations of land if they repurpose farmland for uses other than agriculture, such as solar development, housing development, recharge basins, and upland habitat restoration. Therefore, changing land use in our study region necessitates the quantified impact of pollution on farmland values. Our empirical strategy accounts for differences in agricultural land-use in the Central Valley.

In this paper, we present the first empirical evidence of the impact of parcel-specific dust levels on the sales prices of farmland in the California context. Our findings are relevant to policy issues about the farmland market in the Central Valley, particularly in the context of changing agricultural land use and its effects on possible climate-induced dust levels in a major (and more diverse crops) agricultural producing region of the United States.

2. Analytical Framework and Identification Strategy

This section summarizes the analytical framework of a pooled Ricardian model as applied to farmland exposed to varying degrees of dust particulate levels. To model the relationship between agricultural production, climate and dust levels, we follow a Ricardian model similar to Mendelsohn, Arellano-Gonzalez, and Christensen (2010), and a partial derivative framework similar to Tai and Val Martin (2017). The Ricardian model is represented by:

$$\pi = \sum P_j Q_j \left(\boldsymbol{X}_j, PM_j, \boldsymbol{E}_j\right) - \sum r\boldsymbol{X}_{\boldsymbol{j}},\ \ j = 1,2,3, \dots, n \tag{1}$$

where Q_j is the output of crop j, $\boldsymbol{X}_{\boldsymbol{j}}$ is a set of vectors of purchased inputs; PM_j represents exposure to coarse particulate matter (a measure of dust) and $\boldsymbol{E}_j$ is a set of vectors of local environmental conditions, including climate and soil quality, for crop production. P_j is the market price of crop j, and r is a vector of input prices. Assuming constant impact of other pollutants on crop productivity, we focus on a single pollutant, average coarse particulate matter (PM10) for 36-months prior to the sale of farmland, and the effect of coarse particulate matter on crop productivity and thus on the value of farmland. We acknowledge that dust is not always an independent component in crop production, and its level/concentration can be partially influenced by weather (Achakulwisut et al., 2019). We carried out a series of checks to address the confounding factors between dust particulate concentrations and weather variables. Specifically, to claim exogeneity in our main explanatory variable, dust levels, we explain the variation in coarse particulate matter with the number of days of wind associated with low polluting days (hereafter refer to as clean winds) and the number of days of wind associated with high polluting days (hereafter refer to as polluting winds). Then derive the predicted values of PM10 after controlling for weather variables and month- and year-of the sale. The weather variable (derived 36-months prior to the sale of land) includes wind speed, total precipitation, relative humidity (and their squared terms), five bins of maximum temperature, and their interaction with relative humidity.

Air pollution and weather have an interactive effect, and when pollution is included alongside weather variables in the same estimated equation, the estimates will be biased by confounding factors. Because pollution and weather (particularly, maximum temperature) covary, we believe that including predicted measures of pollution (PM_{10}) alongside the climate normal (29-year moving averages of degree-days during summer and winter, total precipitation, and chill hours in winter) may circumvent the issue of pollution-weather covariation.

Furthermore, dust is both a result of dryness of soil due to drought, with a negative impact, but also the result of the production processes (e.g., plowing, tillage, pollution from farm machinery, and from vehicle traffic on unpaved roads, etc.) that increase productivity but create dust (Lambert et al., 2020). This raises a concern about simultaneity, which could bias our estimates. The empirical section addresses concerns about simultaneity by using the parcel-specific predicted PM10.[3] Particulate matter also has an impact on agricultural productivity by affecting labor force health and participation, either through productivity loss or absenteeism due to sick days resulting from negative impacts of pollution. However, this study is unable to investigate the effect of dust on agricultural labor supply due to data limitations.

Following Eq. (1), the farmer is expected to choose a set of inputs **X**, such that the rent on the land is maximized. The farmland value is proportional to the net revenue from the land, meaning that $V = \frac{\pi}{r}$ where r is the interest rate. The reduced form of the Ricardian pooled

[3] In our robustness checks, we also utilize the inverse distance weighted interpolation technique to measure pollution at the parcel.

model that examines the relationship between farmland value (V_{it}) of parcel i, dust particulates ($PM_{i,y}$), and climate variables (E_{it}) is as follows:

$$ln\, V_i = \beta_0 + \beta_1 PM_{i,y} + \beta_2 PM_{i,y}^2 + \theta \boldsymbol{E}_{i,y} + \rho_{my} + \mu_i \quad (2)$$

where β is the estimated coefficient. $PM_{i,y}$ represents exposure to the coarse particulate concentrations (PM_{10}) at the parcel level, $i = 1, \dots, 7987$ in year $y = 2010, \dots, 2017$. We include quadratic terms of PM in the right-hand side of the model to account for the non-linear relationship between PM_{10} and agricultural production. We follow previous Ricardian literature and include a host of climate variables, $\boldsymbol{E}_{i,y}$, such as 29-year moving averages of degree-days during summer and winter, total precipitation, and chill hours in winter (and their squared terms and the interaction between degrees-days and precipitation). We also consider parcel-specific characteristics, which include land quality (an indicator of high- and low-quality land), topographical characteristics, such as elevation, slope, and coordinate latitude. Other covariates include the distance from the nearest city to capture partial development pressures, the number of wells serving a parcel to capture potential irrigation capacity, and an indicator for multiple parcel sales to control for possible discount sale price per unit of land. ρ_{my} is the month- and year-of-sale fixed effects to capture the time-varying changes on farmland values, such as a common technology trend impacting crop yields. The expression μ_i denotes disturbance term, representing the variations in farmland values that are not explained by our model. To account for spatial correlation in the error term, we cluster the standard errors at the parcel level. The marginal effect of pollution on farmland values is given by $\frac{\partial \ln V}{\partial PM_{i,y}} = \bar{V}(b_1 + 2b_2\overline{PM}_{i,y})$.

Any observed correlations between *V*, *PM*, and *E* could be confounded by the inherent covariation between dust particulate concentrations and climate variables. For example, it is expected that with higher wind speeds more dust is emitted. Also, with an increase in temperature and a decrease in relative humidity, the "stickiness" of the emitting surface might change, making these surfaces prone to more sources of dust. Furthermore, if the pollution and temperature both affect and are affected by current intensive farming in the local area, then this could bias our estimates. One approach to address this concern is to use the predicted value of PM_{10} instead of the observed value of PM_{10}. This assumes that the measurement of PM_{10} at the parcel level can be explained by wind speed and direction, daily maximum temperature, precipitation, and relative humidity. Then the predicted value of PM_{10} can be estimated by regressing daily PM_{10} on these predictors. By including the predicted value instead of the observed value in the hedonic regression of dust impact on land value, we minimize omitted variable bias. The estimated equation is:

$$ln\, V_i = \beta_0 + \beta_1 \widetilde{PM}_{i,y} + \beta_2 \widetilde{PM}^2_{i,y} + \theta \boldsymbol{E}_{i,y} + \rho_{my} + \mu_i \tag{3}$$

where $\widetilde{PM}_{i,y}$, is the predicted PM_{10} pollutant, explained by wind speed and direction, maximum temperature, precipitation, and relative humidity. We also include the land use share of annual crops, perennial crops, non-cultivated land (fallowed or idle land and natural vegetation) and developed land. Lastly, we include soil attributes such as erosion factor, saturated hydraulic conductivity, and organic matter.

Equation (3) eliminates the confounding effects of covariation between coarse particulate matter and omitted variables in the model. This model is similar to two-stage least squares; the first stage of which can be written as

(4) $$\widetilde{PM}_{i,y} = \tau_0 + \tau \boldsymbol{W}_{i,y} + \rho_{my} + \varepsilon_{i,y}$$

where $\boldsymbol{W}_{i,y}$is the 36-months averages of host of weather variables that explain the PM_{10} at the parcel level. $\varepsilon_{i,y}$ represents the residual terms $(PM - \widetilde{PM})$. Equation (3) represents the second stage. It is important to note that $\boldsymbol{W}_{i,y}$ in Eq. 4 is different from $\boldsymbol{E}_{i,y}$ in Eq. 3. The former is a set of 36-month averages of weather, while the latter is 29-year averages of climate variables, which is the climate normal.

Furthermore, to explore the estimate of endogeneity bias, we estimate a correlated coefficient model similar to Bento, Freedman, and Lang (2013), which can be written as

(5) $$ln\, V_i = \beta_0 + \beta_1 PM_{i,y} + \beta_2 PM_{i,y}^2 + \psi\widehat{\varepsilon_{i,y}} + \delta PM_{i,y} * \widehat{\varepsilon_{i,y}} + \theta \boldsymbol{E}_{i,y} + \rho_{my} + \mu_i$$

The coefficient on the PM is interpreted as the valuation of exogeneous changes in air quality. The coefficient on the residual term is interpreted as the bias resulting from the endogeneity of PM10. The coefficient on the interaction term is an indication of the direction of bias.

3. Data Sources and Summary Statistics

This article relies on datasets from multiple sources, including geo-referenced farmland parcel sales prices for California's Central Valley from private vendor, and publicly available air pollution, climate, soil quality, and general non-climatic variables. A detailed definition of the variables used in this article is provided in Appendix B. Summary statistics are reported at the parcel level.

3.1. Agricultural parcels

This study focuses on the dust exposure of sold parcels for agricultural purposes in 18 counties in the Central Valley of California between 2010 and 2017.[4] These parcels are associated with field crops, orchards, and vineyards. We explore Ricardian estimates based on two dependent variables: farmland sale prices per acre and the use (appraisal) value of the land for agricultural purposes. Parcel-level farmland sale price and the appraisal value of the land (separate use values for both the land component and any improvements made to the land is reported) is obtained from ATTOM Data Solutions, a private data vendor which aggregates data across the County Assessor Offices in California. Using the dependent variables mentioned earlier, we evaluate Ricardian estimates of the impact of dust exposure on the farmland market. To conduct an analysis, we utilize 9,300 observations representing 7,987 agricultural parcels sold in California's Central Valley between 2010 and 2017.

The Central Valley offers several advantages in investigating dust exposure in the agricultural sector. First, Central Valley grows hundreds of different types of crops due to its Mediterranean-like climate, and supports the food security of the United States (Jessoe et al., 2021). Importantly, for our purposes, the farmland values of the Central Valley are primarily determined by their ability to support agricultural production. Second, Central Valley is vulnerable to future climate change (Lee, De Gryze, and Six 2011), and air pollution (Hong et al., 2020).[5] Climate change causes more intense drought cycles, which increase airborne

[4] For our analysis, we combine the counties that make up the Sacramento and San Joaquín Valleys. Sacramento Valley comprises the counties of Tehama, Glenn, Butte, Colusa, Yolo, Solano, Sutter, Yuba, Placer, and Sacramento. The northern part of the San Joaquin Valley consists of the counties of San Joaquin, Stanislaus, and Merced. The central part of the San Joaquin Valley includes the counties of Madera, and Fresno. The southern part of the San Joaquin Valley includes the counties of Tulare, Kern, and Kings. Fresno and Tulare counties together account for 42% of land sales observations in the Valley.

[5] California's Central Valley is exposed to some of the highest levels of particulate and ozone pollution in the nation, which damages human health and economic output, including revenue from agricultural production (Hong et al., 2020; Huang & London, 2012; H. J. Lee et al., 2016).

dust that negatively impact agricultural productivity and, therefore, reduce the value of farmland. Third, for empirical purposes, Central Valley can plausibly assume to be as homogenous as possible with respect to the variables excluded from the explanatory relationship, such as input prices, prevailing agricultural practices, and sources of air pollution arising from agricultural operations (e.g., pollution from farm machinery, and from vehicle traffic on unpaved roads, etc.). Appendix Figure A1 presents the map of the study area.

Summary statistics for farmland sales values and appraisal values are provided in Panel A of Table 1. The average per-acre sale value of farmland in the study region and period (2010–2017) is $20,683, compared to the appraisal value of the land, which is $6,543. The dollar values are adjusted for inflation. The annual Gross Domestic Product (Chain-Type Price Index) obtained from the Federal Reserve Economic Database is used to convert nominal values to 2017 U.S. dollars (U.S. Bureau of Economic Analysis, 2024). Furthermore, we *winsorize* the farmland sale price and the appraisal values at the 1 and 99 percentiles to minimize the impact of outliers. In 2017, farmland sale prices in the Central Valley were slightly less than doubled, reaching $25,250 from $13,197 in 2010 (as shown in Appendix Table A1).

3.2. Air pollution data

We measure the exposure of agricultural parcels to air pollution based on their locations and the sale of farmland month-by-year. Using the parcels geo-coordinates, we obtain air pollution data (coarse particulate matter, PM10) from the CAMS-EAC4 satellite reanalysis project (Inness et al., 2019).[6] Air pollution data during our study period are reported as a 3-hour temporal data with a horizontal resolution of 0.75 x 0.75 degrees grid (approximately 80 Km).[7] We first construct the daily average measure of particulate matter and then aggregate it to obtain the monthly means at the parcel level. For the purposes of our analysis, we construct a 36-month rolling average of PM10 as a measure of dust exposure and map it to the farmland sales month-year.[8] Our main explanatory variable in the main results is coarse particulate matter, PM10. The average PM10 level during our study period is 21.56 $\mu g/m^3$, with a maximum value of 47 $\mu g/m^3$(as shown in Panel B of Table 1). Next, we obtained daily ozone O_3 and nitrogen dioxide NO_2 concentrations data from the Environmental Protection Agency's (EPA) Air Quality System monitoring site. [9]

Our identification strategy relies on the direction of wind. Particularly, for each parcel, the number of days when the wind direction is associated with high pollution (polluting winds) and the number of days when the wind direction is associated with low pollution (clean winds).[10] For information on clean and polluting winds, we obtain the magnitude of 10-meter wind vector from the CAMS-EAC4 satellite reanalysis project. We use pre-samples

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[6] Although not shown, we also use daily interpolation pollution data from the monitoring station under the Air Quality and Meteorological Information System of the California Air Resources Board (CARB) as a robustness check. The main results are robust when using interpolated pollution levels.

[7] Air pollution data is available at https://ads.atmosphere.copernicus.eu/cdsapp#!/dataset/cams-global-reanalysis-eac4?tab=form.

[8] We believe that a 36-month moving average is better suited to identify heterogeneous dust exposure, and for the purposes of computational efficiency, we limit ourselves to 36-month average pollution levels.

[9] Data is available at https://aqs.epa.gov/aqsweb/airdata/download_files.html

[10] Following Dechezleprêtre et al., (2019), we calculated the number of days that wind originates from each of eight octants in each year between 2007 and 2009. To establish the rank, we link daily pollution and wind direction. The direction of wind that is linked to the lowest pollution level is given the number 1, while the direction of wind that is linked to the most pollution is given the number 8. We combine rank 1, 2, and 3 to create clean winds, while rank 6, 7, and 8 to create polluting winds, relative to rank 4 and 5.

from 2007–2009 to construct the number of clean and polluting days associated with low- and high-levels of pollution, in the spirit of (Dechezleprêtre et al., 2019). Importantly for our identification, the variation in wind directions is high, both temporally and spatially.

3.3. Climate data

Following the literature (e.g., Jackson et al., (2012); H. Lee & Sumner, (2015)), we use daily minimum and maximum temperature and precipitation data for the years 1981–2017 from the PRISM (PRISM Climate Group, 2014) to derive 29-year moving averages of degrees-days for summer (April–August) and winter (November through May of the next year), total precipitation, and chill hours in winter.[11] Panel C of Table 1 provides summary statistics for all climate variables used in this study. The number of degree days in summer is more than twice as high as in winter. During our study period, on average, there were 2,079-degree days in summer and 977-degree days in winter. The long-term average total precipitation was 334 mm. In winter, the valley accumulates 983 long-term chill hours, on average. Although climate change is occurring in Central Valley, the cross-sectional variation in climate has remained stable over the study period (as shown in Appendix Table A1).

3.4. Land quality

We link the farm to the land capability class (LCC), a global land evaluation ranking that groups soils based on their potential for agricultural and other uses. The LCC is used to measure land quality. We obtained LCC data for California from the California Soil Resource Lab at UC Davis, which is available in grid cells of 800 meters (Walkinshaw et al., 2023).[12]

[11] Chill hours are calculated from November to February of the next year. Appendix B provides more details about how we calculated the climate variables used in our analysis.
[12] LCC data is available at https://casoilresource.lawr.ucdavis.edu/soil-properties/.

LCC has eight classes. As we move along the land capability classes, from class I through VIII, the constraints on soil suitability for crop cultivation also increase. The constraints in LCC are characterized by soil erosion and runoff, excess water, root zone depth, climate limitations, and limitations on mechanized farming activity. Class I soil has a few limitations that do not restrict its use for crop cultivation, while class VIII soil has severe limitations that reduce the choice of plants and increase the need for special conservation practices.

To assess a parcel's suitability for agricultural production, we construct one indicator for high-quality land (LCC12: combined classes 1 and 2) and two indicators for lower-quality land: LCC34: combined classes 3 and 4 for low-quality land, and LCC5678: combined classes 5 through 8 for poor-quality land). On average, more than half of the sample is on high-quality land (53.08%), 43.85% of the sample is on low-quality land, and only 3.07% of the sample is on the poor-quality land.

3.5. Topographical characteristics and other covariates

We obtain the elevation and slope of parcels at a 30-meter grid cell using the U.S. Geological Survey (USGS) National Elevation Data. Following the literature, the analysis also includes the number of wells serving a parcel and an indicator of whether parcels are within an irrigation district service area, which are sourced from the California Department of Water

Resources to capture parcel-specific irrigation capacities. About 40% of parcels in our sample have at least access to one well, and 25% of parcels are not served by any irrigation districts. In addition, we include the parcel-specific distance from the nearest city center to partially control for urban pressures on farmland.

4. Methodology

We use publicly available pollution data, and farmland sale values data from private vendors in California to quantify the net impact of particulate matter on California agriculture. We create a 36-month average coarse particulate variable prior to the sale of farmland as a measure of dust exposure. We use a pooled hedonic regression analysis of farmland in the Central Valley, and dust levels (PM_{10}, coarse particles) from 2010 to 2017 to estimate the economic impacts of climate change and dust particulate exposure on land value. Our analysis controls for other pollutants, such as ozone O_3 and nitrogen dioxide NO_2, that could impact crop productivity (Liu & Desai, 2021; Lobell et al., 2022) and, therefore, on farmland values. In doing so, we are able to identify the impact on farmland values from dust particulates only. We find evidence of a significant reduction in the value of farmland in our study region attributed to higher levels of dust.

A main empirical challenge is the endogeneity of dust levels in the Ricardian framework along with climate variables, as dust levels are also affected by climate. To overcome this concern, we conduct a series of checks to address the confounding factors between parcel-specific dust particulate exposure and climatic factors. Specifically, our empirical strategy employs a two-stage approach, similar to Dechezleprêtre et al., (2019). In the first stage, we explain the variation in pollution level using the number of days of clean and polluting winds as an instrument, and then derive the predicted level of pollution, controlling for a host of weather variables. In the second stage, we use this predicted pollution level as our main explanatory variable in the Ricardian model to estimate the effect of dust levels on farmland market in our study region. This approach enables us to account for pollution-weather covariation and we also take advantage of the residuals from the first stage to reduce omitted variable bias.

Our specification includes month- and year-of-sale fixed effects that control for parcel-specific time-varying factors, climate, and non-climate variables. Climate variables include 29-year moving averages of degree-days during summer and winter, total precipitation, and chill hours during winter. Non-climate variables include parcel-specific characteristics, such as land quality, topographic characteristics, and other covariates standard in the Ricardian literature. We estimate the interaction effect between PM and climate factors and explore the non-linear impact of PM level and climate factors on the sale price of farmland. Furthermore, our results are robust to nonfarm omitted variable bias. We utilize the appraisal value of the farmland, a hypothetical value that does not capitalize returns from expected nonfarm land use conversion (Bigelow & Kuethe, 2023), as an alternative dependent variable in the hedonic model (Ma & Swinton, 2012). The appraisal value of the land is based on potential returns from crop production in a given year and does not capitalize future returns from land use conversion for nonfarm purposes. The difference between the farmland sale price and the appraisal value of the land in the sale year may be considered as the expected value arising from conversion to nonfarm land use. We exploit the value obtained from this difference in our analysis to detect the presence of nonfarm influences on the farmland market in our study region.

5. Empirical Results

This section demonstrates the relationship between dust levels and farmland values. First, we present the correlation between farmland price and land appraisal value with pollution levels. Second, we present our main empirical results. Finally, we perform robustness checks.

Figure 1 presents the correlation between farmland values and appraisal values within the eighteen counties in California that make up the Central Valley over time. Pollution levels had a positive correlation with both farmland sale prices and appraisal values in the study region during the study period. Although the magnitude of correlation coefficient for the farmland sale price compared to the appraisal value is lower until 2013, it then becomes higher and remains higher throughout the remaining period. The variation in pollution levels in the study region coincides with the variations in the appraisal values and in the farmland sale price. Initially, PM10 declined during the early study period, then increased in 2014, and is continuing to rise.

Farmland prices experienced a gradual increase over time, but in 2015, they saw a spike of almost $6,000 to $27,876 from $21,774 in 2014, then declined to $24,033 in 2015 (as shown in Appendix Table A1). The appraisal value of land has been increasing, except for a slight decline in 2014 and 2015. The spatial variation in average farmland value per acre and pollution levels in the study region during the study period is shown in Appendix Figure 1. The average pollution levels in the valley have a similar spatial distribution to the average farmland value per acre. In particular, in the central and southern regions of the San Joaquin Valley, where high concentrations of pollution are prevalent, high farmland value per acre is also present.

Next, to estimate the impact of dust levels on farmland values, we employ a pooled Ricardian model that takes into account both climatic and non-climatic variables. Note that the unit of observation is the parcel that was sold in the Central Valley from 2010 to 2017. The dependent variable is the log of land value per acre. The primary explanatory variable is the daily PM10 concentration at the parcel level. Table 2 presents our main results. In column 1, we employ Eq. (2) to explore the relationship between farmland value and coarse particulate matter, PM10, as our measure of dust level. We note that PM10 exhibits an inverse U-shaped relationship with farmland values. This result is evident from the coefficient of the quadratic term of coarse dust levels, which is statistically significant and negative, suggesting an inverse U-shaped relationship between farmland sale price and coarse particulate matter. Column 2 includes other pollutants in Eq. (2) to distinguish the effect of particulate matter from those that have been shown to impact crop health and yields. The sign and significance of the outcome of interest are the same as in column 1, though the effect size is slightly smaller than in column 1.

Columns 3 and 4 are obtained by employing residuals (an additional regressor) and predicted values (the main explanatory variable) from the first stage regression, respectively. The estimated coefficient on residuals (Column 3 of Table 2 obtain from the Eq. (5)) from the first stage indicates that the endogeneity bias is small and in the downward direction, although the estimated coefficient is statistically insignificant at conventional level of significance. The interaction term between residuals and observed dust exposure is indistinguishable from zero and does not have any significance in our analysis.

Column 4 presents our preferred specification obtained from Eq. (3). We first calculate predicted PM10 by regressing observed PM10 on our instrument—the number of days that wind originates from any of the three cleanest (dirtiest) octants, using pre-sample data from 2007–2009, which we refer to as clean (polluting) winds. Table 3 presents the first stage results obtained from Eq. (4). We explain the variation in PM10 levels by clean and polluting winds, controlling for wind speed, precipitation, maximum temperature, relative humidity, their interactions, and soil attributes. In addition, we include the land-use share, which includes perennial and annual crops, as well as non-cultivated and developed land. As expected, the estimated coefficient for clean winds is negative in the first stage while it is positive for polluting winds. Results are similar to the OLS estimates, but with a larger effects size.

The average marginal effect of PM10 on farmland values becomes negative at the threshold of 30 $\mu g/m^3$, and remains negative and statistically significant with higher levels of PM10 (as shown in Figure 2). To explore these results further, we calculate the total number of days during which the dust level was above 30 $\mu g/m^3$ in the last 36 months prior to the sale of farmland as a measure of extreme dust level exposure. We include this variable as an additional regressor in Eq. (3). Column 5 of Table 2 provides estimates of total days with higher levels of PM10 concentration. The estimated coefficient is positive and significant, but the magnitude is very small and close to zero.

6. Robustness Checks

We interpret the previous findings as evidence that higher levels of dust have a negative net effect on farmland values. In this section, we address additional concerns about whether changes in farmland values in our study region can be attributed to variations in pollution levels during our study period. First, we check whether farmland market in our study region is vulnerable to potential nonfarm omitted variable bias and second, we cluster standard errors at a regional level, such as irrigation districts, to address spatial dependence in farmland values.

6.1. Ricardian model with an alternative dependent variable: Appraisal value of the land

First, there may be a concern that nonfarm factors, such as economic development pressures, may influence farmland markets in our study region. In that case, the dependent variable with farmland sales prices may not be primarily driven by returns to farming. Therefore, the Ricardian estimate of dust levels may be biased in a direction that is not known. The Central Valley's primary agricultural land-use may provide assurance that our results are not primarily driven by nonfarm influences on the farmland market. In addition, empirically, we utilize the appraisal value of agricultural land, which is a hypothetical value that reflects the expected near-term agricultural profits and excludes future benefits of nonfarm use, to empirically address this concern. This strategy may minimize bias in the presence of nonfarm omitted variables.

In theory, the appraisal value of land should exclude nonfarm pressures. Therefore, the Ricardian model should avoid potential nonfarm omitted variable bias by utilizing the appraisal value of land per acre as the dependent variable. We first test the potential presence of nonfarm omitted variables in our Ricardian model by regressing the difference between the farmland sale prices and the appraisal value of land on pollution levels, controlling for climatic and non-climatic variables. Second, we replace farmland sales price per acre with the appraisal value of agricultural land per acre as a dependent variable in Ricardian estimates to measure the effect of dust levels on the farmland market without reflecting nonfarm influences caused by expected land use changes. Table 4 presents the result of the alternative Ricardian model. In addition to the month and year-of-sale, we include county-level fixed effects to account for any county-specific common shocks that may influence the assessment of farmland. The estimated coefficient on Column 1 of Table 4 is statistically insignificant and suggests that nonfarm omitted variables are not a concern in our study region. Columns 2 and 3 of Table 4 show that Ricardian estimates using per-acre appraisal value of land as a dependent variable are qualitatively similar to our main results. Column 3 utilizes the land's appraisal value without any improvements to only include the land component. The estimated coefficient for predicted PM10 remains the same, although the order of magnitude has slightly reduced.

6.2. Standard errors cluster at the regional level: Irrigation districts

Second, in the main specification, the standard errors are clustered at the parcel level. There may be a concern that farmland values and covariates on the right hand side of the main specification are spatially dependent. As a result, the standard errors are likely biased downward. To address this concern, we cluster the standard errors at the irrigation district level to allow for correlation among parcels within the irrigation districts. We associate each georeferenced parcel with irrigation districts to achieve this. 2,033 parcels that are not within any irrigation districts are not included in this analysis. Column 4 of Table 3 reports the results. The estimated coefficients for predicted dust levels are similar to the main results.

The findings discussed above support our finding that higher levels of dust have a negative impact on farmland values through a negative impact on agriculture in our study region. With the data at hand, we are unable to directly examine the observable pathways within the agricultural sector, for instance, agricultural labor productivity and crop health and yields, through which pollution affects the farmland market in our study region.

7. Conclusion and Policy Implications

Air pollution has been shown in recent studies to significantly decrease crop yields, resulting in significant economic losses for perennial crops in California. Due to changing climate conditions and the link between increased aridity and increased dust levels, the loss caused by air pollution may increase further in the future. Using this new knowledge, we incorporate coarse particulate matter, as a dust level indicator, and climate variables in the Ricardian framework to estimate the reduced-form effect of dust levels on farmland values in the Central Valley of California.

This paper extends the Ricardian model to include dust particles to estimate the economic impacts of climate change-induced dust levels on agricultural land value. We provided causal estimates of the effects of coarse dust particulate on farmland values in the Central Valley from 2010 to 2017. Using pooled hedonic regression analysis, our results indicate that dust levels have a negative net effect (negative effects are larger at higher levels of pollution) on farmland values and highly significant with an inverted U-shaped response curve. This finding is robust to the use of an alternative Ricardian model that minimizes nonfarm omitted variable bias. These findings have important implications for environmental policies. In particular, they suggest that environmental assessments should consider the possible impact of dust levels on the farmland market.

Dust levels rise with drought, either due to transported dust (windblown dust mobilization) or dust from agricultural operations on less-irrigated farmland that increases as a result of drier soil, or dust from poorly managed fallow land. The Central Valley growers may have limited options for minimizing dust levels on plants, which could potentially inhibit plant growth through their reduced ability to respire and process photosynthesis. Future climate mitigation policies in agriculture should consider ways to suppress dust (e.g., conservation tillage, mulch cover or surface roughening), and avoid dust at the local and regional levels, including on-farm dust mitigation measures (e.g., maintenance of stubble and vegetative cover on idle land).

Particulate matter is complexly interrelated with climate change through warmer temperatures and changes in agricultural operations, such as the increase in fallow land. Howitt et al. (2015) estimated that large areas of irrigated land in the Central Valley of California may be out of production due to prolonged drought, leading to more fallow land in the future, which will intensify the problem of dust in agriculture. In addition, recent research in the US highlights the negative impact of pollutants on agricultural productivity and global food security. In this context, our paper attempts to characterize the effects of windblown dust particle exposure on California agriculture and provide policymakers with quantifiable estimates of potential loss in farmland values. This study contributes, in such respect, to the environmental economics and hedonic literature. A main limitation of this study is that we are unable to independently assess several mechanisms through which pollution could affect the farmland market, which warrants further research.

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Table 1. Summary Statistics (N = 9,300)

Variable	Mean	Std. Dev.	Min.	Max.
Panel A: Agricultural parcels				
Farmland sale price per acre	20,683	30,003	122	210,555
Appraisal value of the land per acre	6,543	6,948	42	37,454
Parcel size (in acre)	104.66	287.25	1.00	14972.82
Panel B: Air pollution from 36-month moving average				
Coarse particulate matter (PM_{10}, $\mu g/m^3$)	21.56	5.08	10.66	46.93
Panel C: Other pollutants				
Ozone (parts per million)	0.03	0.004	0.01	0.04
Nitrogen dioxide (parts per billion)	10.22	1.16	5.78	14.80
Panel D: Long-term climate normal from 29-year moving averages				
Growing degree days (thousands, summer)	2.08	0.13	0.90	2.32
Growing degree days (thousands, winter)	0.98	0.08	0.13	1.27
Annual precipitation (100 mm)	3.34	1.39	1.06	18.40
Chill hours (100 hours, winter)	9.83	0.95	6.34	24.00
Panel E: Land capability class				
Land capability class (class 1 or 2)	0.53	0.50	0	1
Land capability class (class 3 or 4)	0.44	0.50	0	1
Land capability class (class 5 through 8)	0.03	0.17	0	1
Panel F: Topographical characteristics				
Elevation (m)	93.19	130.91	-5.18	2067.35
Slope (degree)	0.84	2.19	0.00	32.24

Coordinate latitude	37.17	1.19	34.82	40.43
Panel G: Other covariates				
Distance from nearest city (m)	5714.26	4279.57	52.71	32283.18
Indicator for access to well water	0.51	0.79	0	21
Indicator for multi-parcel sale	0.27	0.45	0	1

Notes:

[1] All variables are averages at the parcel level over the period 2010–2017. Appendix Table A1 presents the mean values for each year.
[2] Climate variables are computed as the twenty-nine-year average of yearly weather variables.

Table 2. Impact of dust levels on farmland values: Hedonic estimates

	Dependent variable: Log (value per acre)				
	[1]	[2]	[3]	[4]	[5]
Coarse particulate matter (PM10, $\mu g/m^3$)	0.157***	0.144***	0.148***		
	(0.023)	(0.023)	(0.043)		
Coarse particulate matter square	-0.003***	-0.002***	-0.002***		
	(0.0004)	(0.0005)	(0.001)		
Residual			-0.009		
			(0.025)		
PM10 x residual			-0.0003		
			(0.001)		
Predicted PM10				0.222***	0.221***
				(0.051)	(0.051)
Predicted PM10 square				-0.004***	-0.004***
				(0.001)	(0.001)
Number of days when PM10 > 30 $\mu g/m^3$					0.001
					(0.0004)
Other pollutants					
Ozone (parts per million)		18.476	15.998	37.039	39.387
		(51.531)	(51.693)	(51.834)	(51.887)
Ozone square		4.017	40.716	-686.567	-660.073
		(860.489)	(862.324)	(863.850)	(864.108)
Nitrogen dioxide (parts per billion)		-0.073	-0.062	-0.135	-0.125
		(0.129)	(0.129)	(0.130)	(0.129)
Nitrogen dioxide square		0.008	0.008	0.011*	0.010
		(0.006)	(0.006)	(0.006)	(0.006)
Long-term climate normal from 29-year moving averages					
Growing degree days (thousands, summer)	-4.522	2.384	3.554	-2.362	-0.390
	(6.246)	(6.492)	(6.577)	(6.360)	(6.557)
Growing degree days square	0.216	-1.401	-1.704	-0.337	-0.819
	(1.462)	(1.521)	(1.548)	(1.493)	(1.542)
Growing degree days (thousands, winter)	13.958*	10.791	10.308	14.948*	14.495*
	(7.765)	(7.784)	(7.855)	(7.728)	(7.766)
Growing degree days square	-5.390	-4.057	-3.799	-6.356*	-6.004*
	(3.513)	(3.525)	(3.575)	(3.483)	(3.506)
Annual precipitation (100 mm)	-0.117	0.064	0.007	-0.126	-0.105
	(0.306)	(0.317)	(0.321)	(0.312)	(0.314)
Annual precipitation square	-0.046***	-0.045***	-0.044***	-0.045***	-0.046***
	(0.255)	(0.007)	(0.007)	(0.007)	(0.007)
Chill hours (100 hours, winter)	-0.620**	-0.637**	-0.665**	-0.846***	-0.847**
	(0.291)	(0.292)	(0.298)	(0.288)	(0.290)
Chill hours square	0.030**	0.031**	0.032**	0.040***	0.041***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
Growing degree days summer x annual precipitation	1.421***	1.240***	1.262***	1.444***	1.438***
	(0.255)	(0.262)	(0.263)	(0.260)	(0.261)

Growing degree days winter x annual precipitation	-2.225***	-2.065***	-2.074***	-2.256***	-2.273***
	(0.343)	(0.345)	(0.345)	(0.346)	(0.348)
Land capability class (class 1 or 2, base case)					
Land capability class (class 3 or 4)	-0.154***	-0.162***	-0.162***	-0.146***	-0.146***
	(0.026)	(0.026)	(0.026)	(0.026)	(0.026)
Land capability class (class 5 through 8)	-0.675***	-0.699***	-0.692***	-0.681***	-0.677***
	(0.103)	(0.104)	(0.104)	(0.104)	(0.104)
Topographical characteristics					
Elevation (m)	-0.002***	-0.002***	-0.002***	-0.003***	-0.003***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Slope (degree)	-0.068***	-0.066***	-0.066***	-0.062***	-0.062***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Coordinate latitude	-0.441***	-0.396***	-0.373***	-0.453***	-0.440***
	(0.047)	(0.049)	(0.049)	(0.048)	(0.049)
Other covariates					
Distance from nearest city (m)	-0.0001***	-0.0001***	-0.0001***	-0.0001***	-0.0001***
	(4.09e-06)	(4.09e-06)	(4.10e-06)	(4.14e-06)	(4.12e-06)
Indicator for access to well water	-0.119***	-0.120***	-0.120***	-0.116***	-0.116***
	(0.021)	(0.021)	(0.021)	(0.021)	(0.021)
Indicator for multi-parcel sale	0.097***	0.103***	0.103***	0.097***	0.097***
	(0.033)	(0.033)	(0.033)	(0.033)	(0.033)
Month of sale FEs	Yes	Yes	Yes	Yes	Yes
Year of sale FEs	Yes	Yes	Yes	Yes	Yes
Observations	9,300	9,300	9,300	9,300	9,300
Adjusted R-squared	0.243	0.246	0.247	0.241	0.241

Notes:

[1] Columns 3 and 4 are obtained by employing residuals (an additional regressor) and predicted values (the main explanatory variable) from the first stage regression. Column 4 presents our preferred specification. In column 5, the number of days during the 36-month period before farmland is sold where PM10 exceeds 30 units in our study area. The average number of days is 137.

[2] Standard errors in parentheses are clustered at the parcel-level.

[3] Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3. First stage regression

Dependent variable: PM10	Coef.	SE
Clean winds	-0.002**	(0.001)
Polluting winds	0.010***	(0.001)
Max. temperature bin: Bin 1 [< 15-degrees Celsius, base case]		
Bin 2: [15,20)	-9.724***	(2.560)
Bin 3: [20, 25)	4.567**	(1.813)
Bin 4: [25, 30)	-10.571***	(2.010)
Bin 5: [30+]	-0.538	(1.173)
Other weather controls		
Precipitation (mm)	0.026*	(0.014)
Precipitation square	-0.0004**	(0.0002)
Wind speed (mph)	12.522***	(1.015)
Wind speed square	-2.198***	(0.159)
Relative humidity (%)	0.475	(0.829)
Relative humidity square	-0.011***	(0.003)
Temp. bin 2 x relative humidity	0.164***	(0.044)
Temp. bin 3 x relative humidity	-0.119***	(0.031)
Temp. bin 4 x relative humidity	0.196***	(0.034)
Temp. bin 5 x relative humidity	-0.008	(0.021)
Land-use share		
Perennial crops share	1.635***	(0.204)
Annual crops share	0.420**	(0.201)
Non-cultivated crops share	-0.809***	(0.261)
Developed share	1.968***	(0.627)
Soil attributes		
Soil erosion K factor	-376.704**	(156.448)
Saturated hydraulic conductivity (mm/s)	8.943**	(4.222)
Water storage capacity (cm)	-0.537**	(0.264)
Soil organic matter (Kg/m2)	3.440	(1.156)
Month of sale FEs	Yes	
Year of sale FEs	Yes	
Observations	9,300	
Adjusted R-squared	0.333	

Notes:

[1] Clean (polluting) winds are the number of days that wind originates from any of the three cleanest (dirtiest) octants, using pre-sample data from 2007–2009.

[2] We construct land-use shares by dividing the shares of each crop within a parcel by the total parcel size. The cropland data is obtained by Cropland Data Layer (CDL). Non-cultivated crop share includes fallow and idle land, as well as natural vegetation.

[3] Standard errors in parentheses are clustered at the parcel-level.

[4] Level of significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4. Robustness Checks

	Difference between sales price and the appraisal value	Log (per-acre appraisal value of the land)	Log (per-acre appraisal value of the land without improvement)	Log (value per acre)
	[1]	[2]	[3]	[4]
Predicted PM10	-56269.184	0.295***	0.188***	0.255***
	(170945.195)	(0.045)	(0.043)	(0.076)
Predicted PM10 square	1054.054	-0.005***	-0.004***	-0.005***
	(3656.384)	(0.001)	(0.001)	(0.002)
Climate Controls	Yes	Yes	Yes	Yes
Non-climate Controls	Yes	Yes	Yes	Yes
County FEs	Yes	Yes	Yes	No
Month of sale FEs	Yes	Yes	Yes	Yes
Year of sale FEs	Yes	Yes	Yes	Yes
Observations	9300	9300	9300	6957
Adjusted R-squared	0.192	0.414	0.411	0.269
Mean dependent variable	980,296	8.196	7.741	9.276

Notes:

[1] The appraised value of the land, adjusted for inflation in 2017 dollars, includes the value of improvements made to the land.

[2] In Column 4, the sample size is restricted to parcels that are associated with irrigation districts.

[2] Climate variables include degree days during summer and winter, precipitation, chill hours in winter (and their squared terms), and the interaction between degree days and precipitation. The list of non-climatic variables includes soil quality, topographical characteristics, and other covariates. See Table 1 for more specifics.

[3] Standard errors in parentheses are clustered at the parcel-level in columns 1-3 and at the irrigation district in column 4.

[4] Level of significance: *** $p < 0.01$.

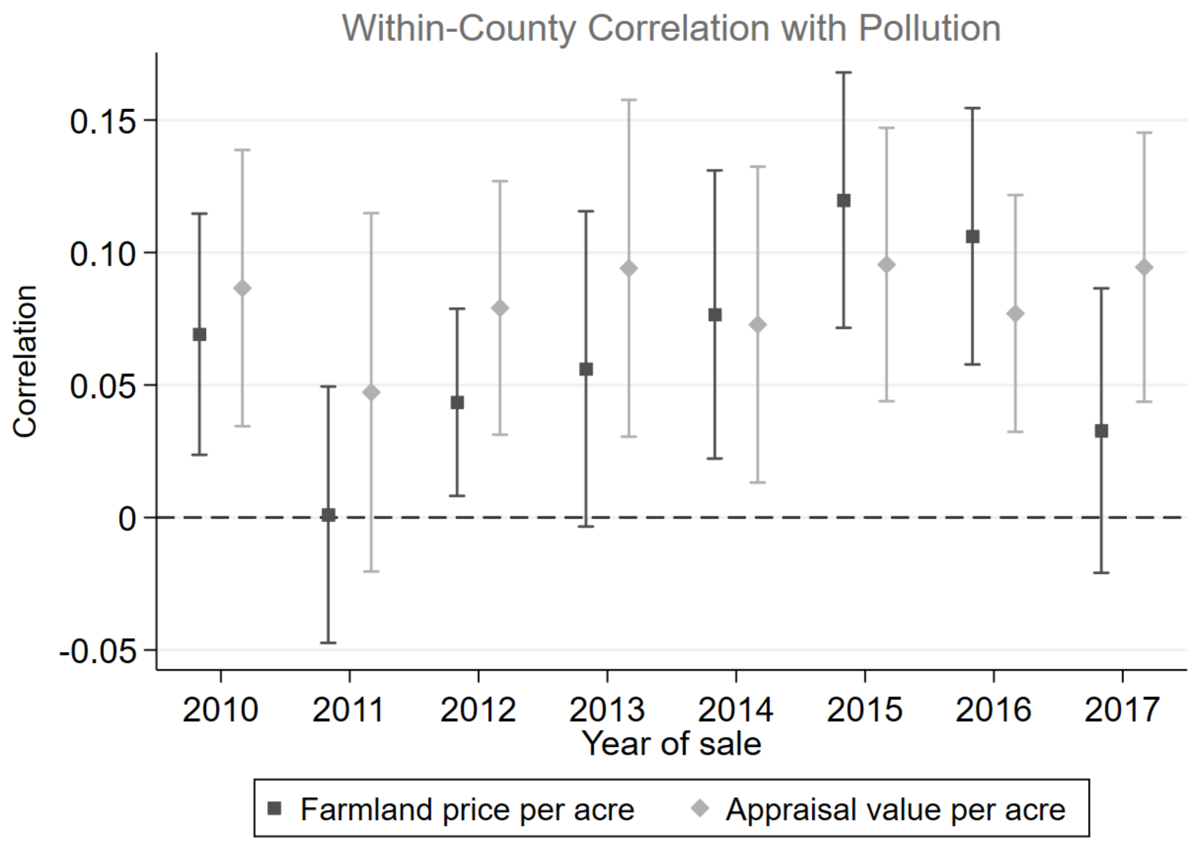

Figure 1. The correlation between pollution levels within the eighteen counties of the Central Valley of California

Note: The within-county Pearson correlation is computed from parcel-level deviations from the county mean of farmland sale price and land appraisal value. The 95% confidence interval is obtained from 1,000 bootstraps.

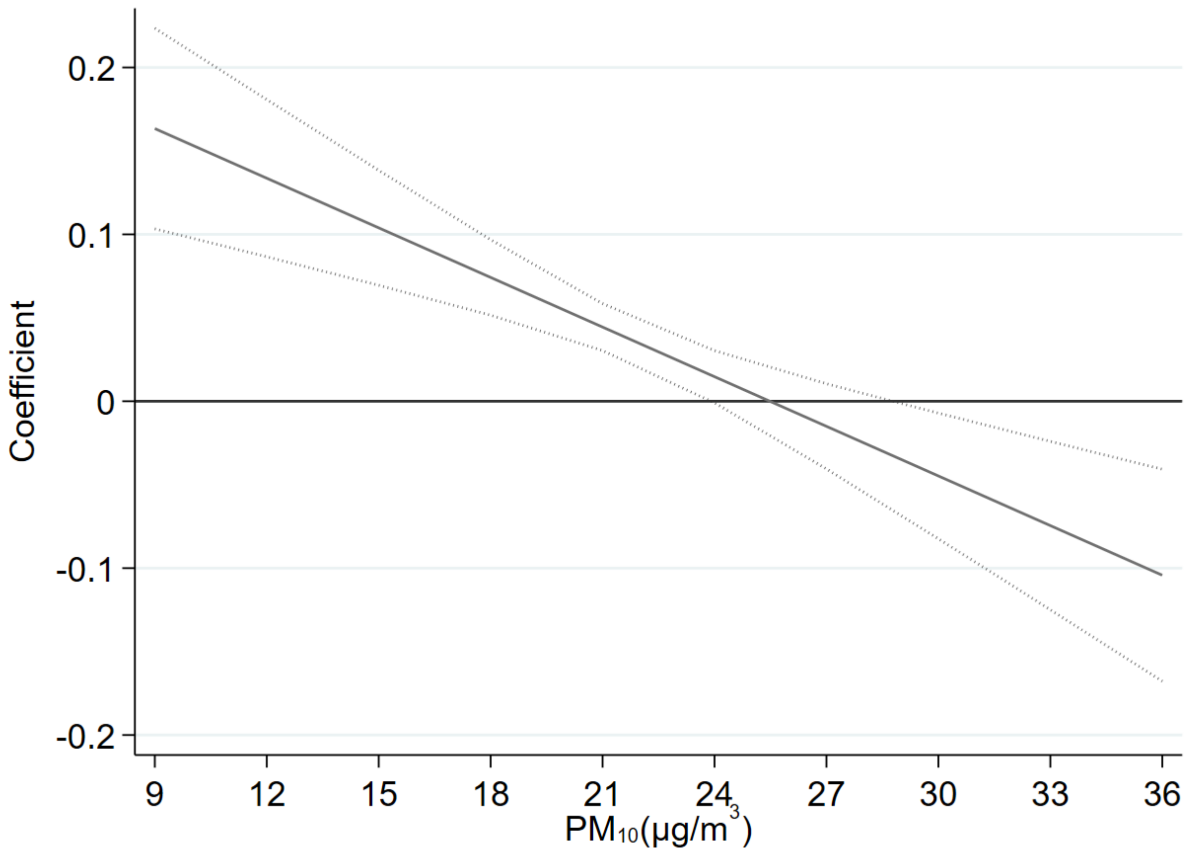

Figure 2. Average marginal effects of PM10 on farmland values.

Note: The downward slope of the estimated effect of PM10 on farmland values becomes negative and significant at the threshold of 30 $\mu g/m^3$, and remains negative and statistically significant with higher levels of PM10. The dots represent the 95% confidence interval.