China Economic Review 82 (2023) 102075

Contents lists available at ScienceDirect

China Economic Review

journal homepage: www.elsevier.com/locate/chieco

Air pollution and agricultural labor supply: Evidence from China

Hai-Jian Ye [b], Zuhui Huang [b], Shuai Chen [a,b,*]

[a] Academy Of Social Governance, Zhejiang University, China
[b] China Academy for Rural Development (CARD) and School of Public Affairs, Zhejiang University, China

ARTICLE INFO

JEL codes:
Q15
Q51
Q53

Keywords:
Air pollution
Avoidance behaviors
Low-income group
Labor supply
Labor relocation

ABSTRACT

Research on avoidance behaviors related to air pollution, particularly among low-income groups in developing countries, is relatively limited. This study aims to analyze the connection between air pollution and farmer labor supply in China, while also examining the labor relocation effect. The identification strategy relies on a widely used instrument variable, namely that thermal inversion exerts a plausibly exogenous shock on air quality. Two-stage least squares regression results indicate that at the intensive margin, farmer working hours in agricultural work during their busy farming seasons are reduced by 0.4 h/day for a 10 μg/m3 increment in $PM_{2.5}$, whereas at the extensive margin, their working days in agricultural work throughout the year are reduced by 2.7 days for a 1 μg/m3 increase in the yearly average $PM_{2.5}$ concentration. We also consider the labor relocation effect, as farmers are likely to shift their labor supply from agriculture to indoor off-farm work to avoid pollution damage. These findings add to the negative social externality of air pollution and expand the determinants of the agricultural labor supply.

1. Introduction

Air pollution has emerged as one of the most critical public health challenges worldwide and has been demonstrated to have a series of impacts on health and economic dimensions (Arceo, Hanna, & Oliva, 2016; Chay & Greenstone, 2003; Deryugina, Heutel, Miller, Molitor, & Reif, 2019; Zivin & Neidell, 2012; Hanna & Oliva, 2015; He, Liu, & Salvo, 2019; Schlenker & Walker, 2016; Zhang & Mu, 2018). From an individual perspective, there is abundant evidence that residents adopt various types of avoidance behaviors to mitigate pollution damage, including purchasing health insurance and protective items (Ito & Zhang, 2020; Zhang & Mu, 2018), investing in medical resources such as medical insurance and medical expenditures (Chang, Huang, & Wang, 2018; Chay & Greenstone, 2003; Deryugina et al., 2019), and "voting with their feet" by moving to locations with better air quality (Bayer, Keohane, & Timmins, 2009; Chen, Chen, Lei, & Tan-Soo, 2021; Chen, Oliva, & Zhang, 2017; Freeman, Liang, Song, & Timmins, 2017; Khanna, Liang, Mobarak, & Song, 2021; Tiebout, 1956). Most of these studies indicate that people with higher educational levels and better economic conditions are more sensitive to air pollution (Chen et al., 2017; Freeman et al., 2017; Ito & Zhang, 2020). Excluding a few exceptions,[1] there is still a significant lack of research attention on the avoidance behaviors of groups with relatively low income class and a high risk of air pollution exposure, particularly farmers in the developing world.

This study examined farmer labor responses to air pollution in China by establishing a causal link between air pollution and labor

* Corresponding author.
E-mail addresses: haijianye@zju.edu.cn (H.-J. Ye), zhhuang@zju.edu.cn (Z. Huang), shuaichen@zju.edu.cn (S. Chen).

[1] Zivin and Neidell (2012) is one of the few existing studies that specifically examines the impact of air pollution on low- and middle-income groups such as farmers.

https://doi.org/10.1016/j.chieco.2023.102075
Received 13 June 2022; Received in revised form 15 September 2023; Accepted 31 October 2023
Available online 4 November 2023
1043-951X/

supply. By exploring a two-period individual-level panel survey across China, we recovered the average $PM_{2.5}$ concentrations during the busy farming season (BFS) for each farmer and the average $PM_{2.5}$ concentrations during the entire year for each county so that both the intensive margin (number of hours worked in agricultural work during the BFS) and extensive margin (number of days worked in agricultural work during the entire year) of farmer labor supply in response to air pollution could be empirically examined.

The critical empirical challenge is the omitted variable bias introduced by the so-called self-selection behaviors of farmers in the presence of air pollution (Hanna & Oliva, 2015; Lazear, 2000; Viard & Fu, 2015), such as working less efficiently and being selective with work timing to avoid the adverse impacts of severe air pollution. Additionally, unobservable variables, such as socioeconomic conditions, can lead to bias in ordinary least squares (OLS) estimates. This challenge is particularly relevant in China due to variations in industrial organizations and economic policies across different regions and time periods. To address endogeneity, our identification strategy relies on a widely used instrument variable (IV), namely weather phenomena called thermal inversions, which 1) exert a plausibly exogenous shock on air quality levels and 2) are not likely to be correlated with other socioeconomic factors on a daily basis (Arceo et al., 2016; Chen, Oliva, & Zhang, 2018; Hicks, Marsh, & Oliva, 2016; Yi, Ye, Wu, Zhang, & Jiang, 2020). Therefore, we can identify the causal effects of air pollution on farmer labor responses by performed generalized two-stage least squares (2SLS) estimation.

Our baseline results indicate a significant negative relationship between the agricultural labor supply and air pollution. Specifically, at the intensive margin, the labor hours of Chinese farmers in agricultural work during their BFS are reduced by 0.4 h/day for a 10 $\mu g/m^3$ increment in $PM_{2.5}$, whereas at the extensive margin, the number of days of agricultural work during the entire year is reduced by 2.7 days for a 1 $\mu g/m^3$ increase in the average $PM_{2.5}$ concentration. These findings are consistent across various robustness checks, including alternative IVs, flexible weather controls, and different air pollution measurements. Furthermore, farmers are likely to shift their labor from the agricultural sector to off-farm employment, particularly indoor work, to avoid pollution damage. As a result, the farmer income structure changes according to their labor relocation.

This paper addresses three trends in the literature. First, we extend studies on the avoidance behaviors of low-income groups. Most studies have pointed out that people with higher education and better economic statuses are more sensitive to pollution damage (Ito & Zhang, 2020; Khanna et al., 2021; Zhang & Mu, 2018), but direct empirical evidence for low-income groups is still inadequate. Our findings reveal the negative externality of air pollution, even for low-income groups in developing countries, and marginally highlight the potential policy benefits of air pollution control.

Second, to complement avoidance behaviors in environmental economics, we further examined the labor relocation effect under air pollution. Previous studies focusing on farmer responses to air pollution have generally paid little attention to its significant consequences on labor allocation (Aragón, Miranda, & Oliva, 2017; Chang, Graff Zivin, Gross, & Neidell, 2016; Chang, Graff Zivin, Gross, & Neidell, 2019; Zivin & Neidell, 2012; Hanna & Oliva, 2015; Kim, Manley, & Radoias, 2017). Additionally, studies considering the environmental determinants of labor supply tend to focus on either weather shocks or man-made disasters[2] (Colmer, 2021; Hoang, Le, Nguyen, & Vuong, 2020; Huang, Zhao, Huang, Wang, & Findlay, 2020; Karadja & Prawitz, 2019; Minale, 2018; Munshi, 2003). In this study, we determined that farmer labor supply shifts across sectors and within sectors, and shed light on a new external determinant that induces farmer labor relocation.

Third, this study examined both intensive and extensive margins in a unified empirical framework. Most existing studies examining how air pollution affects agricultural labor supply focus only on one of the following two aspects: 1) labor intensity (e.g., labor productivity and piece-rate-wage) at the intensive margin (Aragón & Rud, 2016; Chang et al., 2016; Chang et al., 2019; Zivin & Neidell, 2012), or 2) labor participation or working times at the extensive margin (Aragón et al., 2017; Hanna & Oliva, 2015; Kim et al., 2017). Few studies have combined these two aspects into a single framework based on data limitations and endogeneity restrictions. In this study, rich information from individual-level surveys allowed us to not only examine farmer labor intensity and labor participation, but also explore the labor relocation effect across sectors and within sectors.

The remainder of this paper is organized as follows. Section 2 introduces our theoretical motivation and empirical identification strategy. Section 3 provides summary statistics for the data and variables used in this study. The estimation results are discussed in detail in Section 4. Finally, in Section 5, we summarize our findings, discuss policy implications, and conclude this paper.

2. Theoretical and empirical strategy

2.1. Theoretical model

We adopted the standard farmer labor allocation model (Carter & Yao, 2002; Chen, Chen, Lei, & Tan-Soo, 2020; Ward & Shively, 2011). We assumed that air pollution P affects farmers' labor endowment L by influencing their health S. Finally, $L(S(P))$ is incorporated into the objective function of the farmers' utility maximization and the labor time constraint. By solving for the optimal labor allocation under air pollution, we found that air pollution has a negative effect on agricultural labor supply but a positive effect on farmers' participation in non-agricultural work.[3] Based on this theoretical finding, we further derived two hypotheses.

Hypothesis 1. Given the wage gap between the agricultural sector and the non-agricultural sector, worsening air pollution will encourage additional agricultural labor to shift towards non-agricultural sectors.

[2] Man-made disasters include marine environmental crises, gas leaks, oil spills, and chemical contamination.

[3] For detailed theoretical model specification and optimization deduction, please refer to Online Appendix 1.

Intuitively, if Hypothesis 1 is valid and air pollution indeed triggers avoidance behavior among rural residents, resulting in reduced outdoor exposure in the agricultural sector, it will also lead to a decline in their income from agricultural activities. In such case, rational farmers may opt to transfer their labor to the non-agricultural sector, where outdoor exposure is limited. This not only enables them to mitigate the damages of air pollution but also offsets the reduction in their overall household income. Testing this hypothesis necessitates distinguishing between the distinct impacts of air pollution on labor supply in both the agricultural and non-agricultural sectors.

Hypothesis 2. Despite the possibility of labor relocation by farmers from the agricultural sector to the off-farm sector in response to air pollution, both agricultural income and off-farm income are expected to decline simultaneously.

In theory, assuming no impact from air pollution, rational farmers allocate their labor between agricultural production and non-farm employment in an equilibrium state. They continually adjust this labor allocation until the marginal returns of labor in both the agricultural and non-farm sectors are equal (Colmer, 2021; Huang et al., 2020). Under this premise, if air pollution prompts farmers to transfer more labor from the agricultural sector to the non-farm sector, the marginal income in the non-farm sector decreases. In fact, previous studies have confirmed that air pollution reduces labor productivity (or piece-rate wages) in the manufacturing and some service sectors (T. Chang et al., 2016; T. Y. Chang et al., 2019; He et al., 2019). Nonetheless, even with the lower marginal income in the non-farm sector, if Hypothesis 1 is valid, farmers increase their labor input in non-farm employment. Therefore, empirically examining the ultimate changes in farmers' income under air pollution requires establishing an empirical relationship between air pollution, farmer income, and income structure.

2.2. *Statistical challenges and identification strategy*

2.2.1. *Statistical challenges*

To empirically test the two theoretical hypotheses, establishing a causal relationship between air pollution, as measured by $PM_{2.5}$, and farmer labor supply is a necessary step. However, there are several empirical challenges that need to be addressed to ensure consistent results.

The first challenge is to measure pollution exposure at different times of the year for farmers. To address this, we utilized the BFS information from the survey, which allowed us to construct two measurements for air pollution exposure during different periods. At the individual level, we extracted the average $PM_{2.5}$ during each farmer's BFS in a year, while at the county level, we calculated the average $PM_{2.5}$ concentration throughout the year. These two measurements support our empirical goals by allowing us to detect the intensive margin and extensive margin of air pollution on labor supply.

The second challenge involves the potential for omitted variable bias. Air pollution may be linked to various socioeconomic factors that simultaneously influence farmer labor supply. To illustrate this, consider the example of "straw burning". If we exclude this variable, it has a dual impact: firstly, it significantly raises local air pollution levels (He, Liu, & Zhou, 2020). Secondly, after burning, the residue enhances soil fertility, leading to increased agricultural yields and motivating farmers to invest more in agricultural labor. Therefore, excluding "straw burning" may introduce an upward bias.[4] If our baseline finding indicates that air pollution reduces agricultural labor supply, this upward bias ultimately results in underestimating the decrease in agricultural labor supply. Of course, whether OLS ultimately overestimates or underestimates is a matter for empirical testing.

Finally, reverse causality and measurement error may also bias OLS estimates. Agricultural production exerts its own influence on the environment, and one vital aspect of air pollution is straw burning (He et al., 2020). Additionally, varying distances between the CLDS survey counties and monitoring stations introduce measurement errors in air pollution data, which cannot be completely eliminated.

Therefore, it is essential to account for these factors when examining the causal relationship between air pollution and farmer labor supply.

2.2.2. *Identification strategy*

To address endogeneity issues related to air pollution, we employed thermal inversions as an instrumental variable (IV). Thermal inversions are meteorological phenomena that occur under specific conditions where temperature inversion takes place, with temperature increasing with altitude. This leads to cold air being trapped near the ground due to the higher density of cold air, preventing the upward dispersion of air pollutants and worsening air quality (Schwartz, 1994). As thermal inversions are relatively random and short-term, they are unlikely to be correlated with socioeconomic activities in the same space-time dimension, satisfying the exclusion restriction conditions for an IV (Angrist, Imbens, & Rubin, 1996; Conley, Hansen, & Rossi, 2012). Thus, thermal inversions have been widely used as an IV for air pollution in previous studies (Arceo et al., 2016; Chen et al., 2018; Hicks et al., 2016; Yi et al., 2020). By the same principle, we argue that, in our research case, thermal inversions affect farmer labor supply solely through the channel of changing air quality levels.

To ensure that our argument holds, we need to strengthen several conditions for the exclusion restriction of thermal inversions in our research case. Specifically, we need to minimize the possibility of thermal inversions affecting farmer labor supply through

[4] Statistically, the direction of omitted variable bias hinges on the correlation between the omitted variable ("straw burning") and the dependent variable (agricultural labor supply), which is expected to be positively correlated. It also depends on the correlation between the omitted variable ("straw burning") and the key explanatory variable (air pollution), which is also expected to be positively correlated.

channels other than air pollution.

One possible scenario is that thermal inversions are the result of specific combinations of meteorological conditions and, therefore, are highly correlated with meteorological variables. In this case, thermal inversions may affect labor supply by influencing meteorological factors. To address this, previous studies have recommended controlling for flexible weather variables (Arceo et al., 2016; Hicks et al., 2016) to ensure that meteorological channels are excluded.

Another possible scenario is that thermal inversions may affect farmer labor supply by influencing other socioeconomic factors. We observe a clear spatial pattern of thermal inversions, where places with severe air pollution, such as the North China and Northeast regions, experience frequent thermal inversions (Panel A of Fig. A1). The spatial variability of thermal inversions might be related to the inherent socioeconomic disparities among regions, which could impact labor supply through various channels. Therefore, using prolonged periods of thermal inversion as IVs for long-term air pollution may not fully exclude socioeconomic factors.

In our research, we use the number of thermal inversion events during the BFS at the county level and the cumulative number of thermal inversions over the year as IVs. We further strengthen the effectiveness of prolonged periods of thermal inversion as an IV for air pollution from two aspects.

First, after removing county fixed effects to exclude inherent spatial differences, the remaining variation in thermal inversion within the county is relatively random (Panel B of Fig. A1), which better ensures the exogeneity of IV. This indicates that the prolonged period of thermal inversion as an effective IV for air pollution is conditional on controlling for regional fixed effects. Recent literature also supports this point (Arceo et al., 2016; Chen et al., 2021).

Second, we use annual data to further analyze the time trend of thermal inversion and its relationship with economic activities. The time trend graph shows that although GDP has an obvious increasing trend over the years, the level of thermal inversion remains stable and fluctuates smoothly. This provides evidence that thermal inversions there are unlikely to be correlated with socioeconomic activities (Fig. A2).

2.3. Empirical model

To test the two theoretical hypotheses, we need to establish three types of empirical relationships: 1) the linkage between air pollution and agricultural labor supply; 2) the linkage between air pollution and non-agricultural labor supply; 3) the linkage between air pollution and either labor income or income structure. Among these, the empirical results of 1) and 2) support Hypothesis 1, while the empirical results of 3) support Hypothesis 2.

Considering that we need to base our empirical models on consistent settings to compare the differential impacts of air pollution on different outcomes, as variations in estimation results could arise from different model specifications, we will describe the empirical model using 1) the empirical setting of air pollution's impact on agricultural labor supply as an example.

We adopted a standard Two-stage least squares (2SLS) procedure for implementing the instrumental variables (IV) estimation. Specifically, we firstly investigated the marginal impact of air pollution on farmer labor supply at the intensive margin by considering the busy farming season (BFS) of each farmer and examining the impact of air pollution during those periods. We constructed the following models:

$$\boldsymbol{WH_{it}} = \boldsymbol{\beta_0} + \boldsymbol{\beta_1}\widehat{\boldsymbol{P}}_{ct(i)} + \boldsymbol{W_{ct(i)}}\boldsymbol{\theta} + \boldsymbol{\varphi_i} + \boldsymbol{\gamma_{pt}} + \boldsymbol{\epsilon_{it}} \tag{1}$$

$$P_{ct(i)} = \alpha_0 + \alpha_1 I_{ct(i)} + W_{ct(i)}\vartheta + \varphi_i + \gamma_{pt} + \mu_{it} \tag{2}$$

The dependent variable $\boldsymbol{WH_{it}}$ in Eq. (1) denotes the working hours per day of farmer i applied to agriculture during his/her BFS in year t. Even in the same year (t), the BFS for different farmers (i) may correspond to different months. Therefore, in Eqs. (1) and (2), we use $t(i)$ to indicate the different periods corresponding to the BFS for different farmers in the same year. The key explanatory variable $\boldsymbol{P_{ct(i)}}$ represents the county (c)-average $PM_{2.5}$ during farmer i's BFS in year t.

$\boldsymbol{W_{ct(i)}}$ denotes a set of weather variables that are constructed in the same manner to $\boldsymbol{P_{ct(i)}}$, including temperature, precipitation, relative humidity, sunshine duration, wind speed, and air pressure. To better capture the arbitrary nonlinear effects of weather variables, we have constructed flexible bins for each 3 °C temperature, each 1 m/s wind speed, and every 10% relative humidity. Other climatic variables were modeled using both their linear and quadratic terms. As discussion above, flexible weather controls are important for ensuring the IV's exclusion restriction.

We use the accumulated number of thermal inversion occurrences during each farmer's BFS to instrument the endogenous variable $\boldsymbol{P_{ct(i)}}$. Thermal inversions are defined as occurring in either a 24-h interval (as a baseline) or a 6-h interval (as a robustness check). Since the BFS duration differs among farmers, a higher number of thermal inversions occurring during this period may be due to some farmers having longer BFS durations. To accurately reflect the intensity of inversions during the BFS period while controlling for the effect of the BFS duration, we use the monthly average accumulated number of inversions during the BFS period to construct the variable $\boldsymbol{I_{ct(i)}}$.

In Eqs. (1) and (2), the individual fixed effect $\boldsymbol{\varphi_i}$ removes all time-invariant unobservable factors. Furthermore, the province-by-year fixed effects are incorporated to account for socioeconomic factors that change with both province and time. While the county-by-year FE is advantageous in excluding other socioeconomic variables, it also removes the effective variation of BFS at the county-year level, resulting in estimation results that only explain the BFS changes of a small number of remaining farmers in each county.[5] Therefore, in our methodology, we chose province-by-year FE instead of county-by-year FE as baseline results, although the latter is typically used to control for unobserved confounding factors. However, we employed an identification strategy (IV strategy) to ensure that potential omitted variables do not bias our estimated coefficients.

Next, we investigated the impact of air pollution on farmer labor supply at the extensive margin by taking into account the total number of days that farmers work in agriculture throughout the entire year and examining how air pollution affects this measure over the entire year. We constructed the following models:

$$WD_{it} = \beta_0' + \beta_1' \widehat{P}_{ct} + W_{ct}\theta' + \varphi_i + \gamma_{pt} + \epsilon_{ict} \tag{3}$$

$$\boldsymbol{P_{ct} = \alpha_0' + \alpha_1' I_{ct} + W_{ct}\vartheta' + \varphi_i + \gamma_{pt} + \mu_{ict}} \tag{4}$$

The dependent variable WD_{it} in Eq. (3) denotes the total number of days that farmer *i* spent on agricultural work in year *t*. The key explanatory variable, namely P_{ct}, measures the county (*c*)-year(*t*) averaged $PM_{2.5}$. The individual fixed effect φ_i and the province-by-year fixed effects γ_{pt} are in line with Eqs. (1) and (2) Weather controls W_{ct} and thermal inversions I_{ct} in Eqs. (3) and (4) were constructed in the same manner as P_{ct} at the county-year level.

We are interested in the estimated coefficients of β_1 and β_1'. The economic interpretation of β_1 is the marginal effect of air pollution on the intensive margin (measured by the number of hours per day farmers performed agricultural work during their BFS) of farmer labor supply, whereas β_1' is the extensive margin (measured by the number of days farmers performed agricultural work during the entire year) of farmer labor supply in response to air pollution.

Based on the model specifications derived from Eqs. (3) and (4), replacing the dependent variable WD_{it} with the number of days farmers engage in non-agricultural employment allows for an empirical examination of the causal impact of air pollution on farmers' non-agricultural employment. Similarly, by further replacing the dependent variables with farmers' income and income structure, we can also investigate the differential effects of air pollution on farmers' income and income structure.

3. Data

3.1. Data sources and variable construction

3.1.1. CLDS data and sample selection

- *Introduction to the CLDS data*

The China Labor-Force Dynamic Survey (CLDS)[6] is a national labor force tracking survey conducted by the Sun Yat-sen University Social Survey Center. It monitors the social structure of villages/communities and tracks changes in households and labor individuals, generating tracking databases at three levels: labor force, household, and community.

Using a stratified random sampling principle, the survey samples are selected by first choosing a sample county, followed by a sample village within the county, and finally selecting 30 households at random in the selected village. The baseline survey of CLDS covers 29 provinces, 256 counties, and 10,612 households, with a questionnaire survey conducted for household members aged 15–64 in the sample households. To ensure the sample distribution of the data is consistent with China's population distribution, the weighting used in the sampling is matched to individual information from the 2010 sixth national population census (Fig. 1).

The survey has been conducted every two years since 2012, and as of now, four rounds of data collection have been completed (2012, 2014, 2016, and 2018). Data for the first three rounds have been made public, while data for 2018 has not been released due to issues with the data. The 2012 survey collected 16,253 samples, and each subsequent survey produced three types of samples: successfully tracked, new, and lost. The sample loss situation for each survey period is summarized in Table A1, with follow-up rates of 61% for 2012 and 2014, and 42% for 2014 and 2016. The follow-up rate for all three surveys[7] conducted in 2012, 2014, and 2016 was 27%.

For this study, only the data from 2014 and 2016 were used, as the 2012 survey did not include questions about BFS and agricultural labor hours, which are crucial for the research purposes. Although the latest CLDS survey data from 2018 has been completed, it is not publicly available and thus currently unavailable to us.

[5] This could potentially result in the local average treatment effect (LATE) problem, as discussed by Imbens and Angrist (1994). For a more detailed examination of the decision between county-by-year FE and province-by-year FE, please see Online Appendix 2.

[6] The questionnaire and data can be downloaded online https://ssa.sysu.edu.cn/article/1994.

[7] In the context of the CLDS as a household survey, interviews with various respondents occur throughout the year. The majority of interviews happen in July and August, coinciding with the summer vacation period, facilitating large-scale surveys involving students (see Figure A9 for interview distribution).

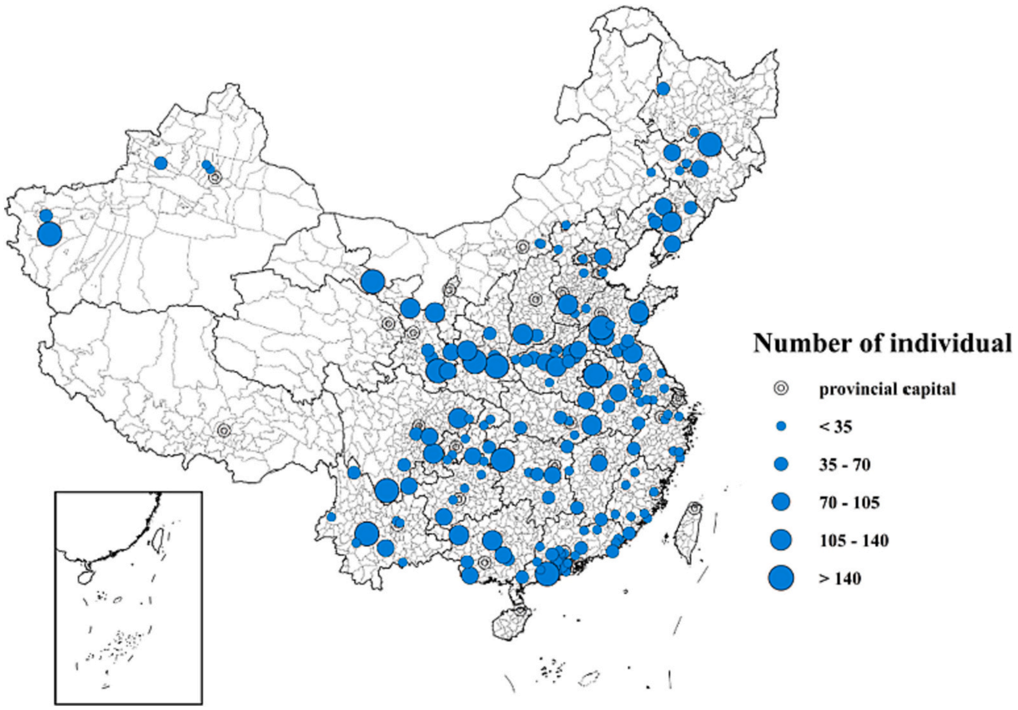


Fig. 1. Distribution of farmer sample in CLDS.
Notes: CLDS includes 10,516 observations from farmers in 256 sample counties, with the size of the bubble corresponding to the number of observations in each county.

- *Farmer selection*

Our definition of “farmers” in the sample encompasses anyone who has engaged in agricultural production activities in any period of the CLDS surveys. Specifically, the 2014 and 2016 CLDS sample included approximately 44,680 respondents.

We first categorized the respondents into “employed” and “unemployed” based on their employment status. “Employed” refers to those who engage in income-generating activities, including farming, part-time work, helping family businesses, but not including volunteering, student work, volunteering, and household chores. A total of 30,653 individuals answered this question, with 92.7% classified as “employed” and 7.3% as “unemployed”.

Then, we classified the employed respondents into “1 employees; 2 employers; 3 self-employed; 4 farmers”. The proportions of the four types of employment among the employed respondents are 42.6%, 1.9%, 12.8%, and 42.6%, respectively. Only those respondents who answered “4 farming” (referring to those engaged in agricultural production activities) were included in our research sample. This group comprises approximately 12,802 individuals.

Only respondents who answered “4 farming” were further asked about “the number of days spent on agricultural production in the past year”, “the busy farming season (months) in the year”, and “the number of hours spent doing agricultural work per day during the BFS in the past year”. These are the key issues that this study focuses on. We define this group of respondents as the “farmer” sample. Due to farmers’ tendency to omit answers to different questions, we were able to extract a total of 11,656 research samples that provided complete responses to all key questions.

Finally, based on the 11,656 “farmer” sample, we identified logical inconsistencies between variables.[8] We further removed these problematic samples, resulting in a final sample of 10,516 valid samples.[9] Ultimately, our research sample comprises approximately 34.9% of the entire sample.

3.1.2. Busy farming seasons and agricultural labor supply

- *Busy Farming season*

[8] For instance, individuals who reported working on the farm for several hours every day during the BFS answered that they spent zero days engaged in agricultural production in the past year.

[9] Our regression analysis can be divided into two types: intensive margin regression (e.g., Table 2) and extensive margin regression (e.g., Table 3). These two categories involve different sample selections. The primary distinction is that intensive margin regression excludes observations of individuals without employment in a given year (Obs. = 9926), whereas extensive margin regression includes such observations (Obs. = 10,516).

Respondents who reported their work status as “4 farming” were asked to answer the “busy farming season” (BFS) question. The original question in the questionnaire was “In the past year, which months were busy farming season for you?” The options provided were for the respondents to check the months during which their BFS occurred, from January to December. The BFS could be a continuous period or a single month, and farmers could have one or more BFS periods in a year.

In the CLDS sample of farmers, the average BFS lasted for 3.5 months per year. As depicted in Fig. 2, the agricultural BFS in southern China typically lasts longer than that in the north due to China’s climatic conditions. Generally, the agricultural BFS in South China appears from March to October, while the agricultural BFS in North China is concentrated around April to September.

However, even within the same county, different farmers have different BFSs throughout the year due to variations in planting types, planting structures, and available labor conditions among households. To visually demonstrate the distribution of BFS in the sample, we have presented a figure representation of the top 15 month-combinations of BFS answered by farmers (Panel A of Fig. A3). It is evident from the graph that the month-combinations of the top four BFS answered are extremely similar, with a difference of less than a month. For instance, for rice cultivation in China, March is typically the BFS for early rice sowing, May and June for mid-season rice sowing, and July and August are known as the “double busy season” for early rice harvesting and late rice sowing. Additionally, we have plotted the frequency of each month appearing in the BFS throughout the year (Panel B of Fig. A3). The BFS in China is spread across the entire year but is mainly concentrated around spring and autumn, which once again confirms the distribution of China’s major BFS.

- *Agricultural Labor Supply*

The CLDS is a suitable tool for our research objectives since it surveys two different measurements of farmer agricultural labor supply. The original questions were formulated as follows:

- “How many hours per day did you spend on farm work during your busy farming season in the past year?”
- “How many days did you spend on agricultural work in the past year?”

The response to the first question measures farmer agricultural labor intensity during the busy farming season (at the intensive margin), while the answer to the second question captures farmer agricultural labor participation throughout the entire year (at the extensive margin). Thus, these data enable us to separately examine labor intensity and participation in response to air pollution under the same empirical framework.

It should be noted that the effective sample selected in this study was from the two CLDS surveys conducted in 2014 and 2016, comprising those who answered the “farming” group in any of the survey periods. In multi-period tracking data, “the minimum working days in agriculture is 0” can occur in two cases:

- The respondent was engaged in agricultural work in the current period but not in the previous or following period.
- The respondent was not engaged in agricultural work in the current period but was engaged in agricultural work in the previous or following period.

In this case, the number of agricultural labor days for the year when the respondent was not engaged in agricultural work will be assigned a value of “0”. In this study, “working days” are used to measure the extensive margin, meaning that working days need to include whether the respondents who once answered “4 farming” participated in “agricultural production activities” in the current year.

3.1.3. Pollution data

The $PM_{2.5}$ concentration was collected from the China National Environmental Center (CNEMC).[10] Starting in January 2013, the CNEMC began reporting real-time $PM_{2.5}$ concentrations hourly for approximately 1400 monitoring stations across China. Because the finest granularity available in CLDS is the county level, we translated weather records from the station level to the county level using the inverse distance weighting (IDW) method. This method has been widely used in previous studies (Deschênes & Greenstone, 2007; Schlenker & Roberts, 2009) to interpolate data from pollution stations within a certain radius of the centroid of each county (50 km as a baseline) to the county level[11] based the inverse distance between the pollution station and county centroid.

In this study, we developed two measures of $PM_{2.5}$ based on the timeframe of the dependent variables. For the intensive margin, we used information on the farmers’ BFS and merged the air pollution data for each farmer during their respective BFS. For the extensive margin, we used the annual average $PM_{2.5}$ concentration of the county corresponding to the farmer’s working days in agriculture throughout the year.

[10] Pollution data can be obtained from http://www.cnemc.cn/.

[11] Our findings are also robust to alternative choices of radius. Results are available upon reasonable request.

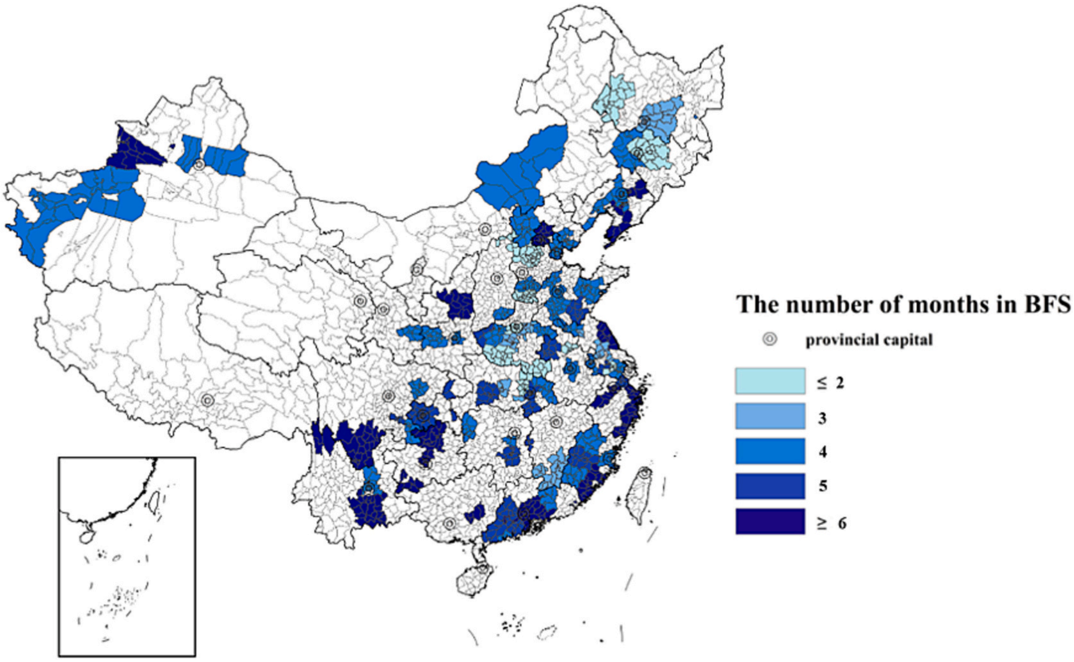


Fig. 2. The number of months in BFS in a year by city.
Notes: The county-level BFS is represented by the median value of BFS at the farmer level. Given the small and dispersed nature of county-level spatial displays, we averaged the county-level BFS to the prefecture level to create a local map for better visualization.

3.1.4. Temperature inversion data

Thermal inversion data were originally collected from Modern-Era Retrospective Analysis for Research and Applications version 2 (MERRA-2, version 5.12.4) which was released by the National Aeronautics and Space Administration.[12] MERRA-2 spatially divides the earth into 50 × 60 km grids and reports the air temperature for each of the 42 sea-level pressure layers in six hour intervals.

After averaging the air temperatures across grids within each county for each layer, the occurrence of thermal inversion was identified when the air temperature in the first layer (110 m) was lower than that in the third layer (540 m). We define thermal inversions in 24 h intervals (on a daily basis) by county as a baseline and all results are robust to the six hour interval definition.

3.1.5. Weather data

Daily weather data were downloaded from the China Meteorological Data Service Center,[13] where the average temperature, wind speed, relative humidity, precipitation, and solar duration data recorded by 820 weather stations across China are publicly available. Based on the location coordinates of the weather stations and county centroids, the IDW method was adopted to convert weather data from the station level to the survey county level.

We handled all meteorological variables in a manner consistent with thermal inversions (see detail in Section 2.3). To account for variations in the BFS among different farmers, we calculated monthly averages for all climate variables during these periods. Even though the duration of BFS differed among farmers, the monthly climate averages during these periods remained comparable.

3.2. Descriptive statistics

The descriptive statistics for the main variables used in our empirical analyses are presented in Table 1.

In our research sample, farmers worked an average of 8.84 h per day on agricultural work during their BFS (with a standard deviation of 3.47 h) and the total number of days they spent on agriculture was 198.3 per year (with a standard deviation of 103.8 days). To measure farmer labor allocation between agriculture and off-farm employment, we also report the number of days per year that farmers participated in off-farm work (indoor off-farm work) which was 256.35 (101.4) days per year. The changes in income structure corresponding to labor relocation are also a research topic worthy of follow-up empirical attention. In the CLDS survey, the average farmer total income 25.37 thousand yuan per year, of which agricultural income accounted for 16.01 thousand yuan per year.

The $PM_{2.5}$ concentrations at three different time intervals, namely the average $PM_{2.5}$ concentration during the farmer $PM_{2.5}$-BFS (denoted as busy farming seasons), average $PM_{2.5}$ concentration during the $PM_{2.5}$-SFS (denoted as slack farming season), and annual

[12] The data can be downloaded at https://disc.gsfc.nasa.gov/datasets/M2I3NPASM_5.12.4/summary?keyw ords = MERRA-2.
[13] Weather data can be obtained from http://data.cma.cn/.

Table 1
Summary statistics.

Variable	Definition (Unit)	Mean	SD	Min	Max	Obs.
Individual employment and income						
Working hours-BFS	The number of hours in agricultural work during BFS (hours/day)	8.84	3.47	1	19	9926
Working days	The number of days in agricultural work in the year (days/year)	198.3	103.8	0	365	10,516
Total income	Total income (Agricultural + Wage + Self-employment) (1000 yuan/year)	25.37	44.94	0	1020	10,516
Agricultural income	Total agricultural income (1000 yuan/year)	16.01	30.47	0	800	10,516
Air pollution						
$PM_{2.5}$-BFS	Average $PM_{2.5}$ concentration during busy farming seasons (μg/m^3)	52.55	24.06	13.7	115.9	9926
$PM_{2.5}$-SFS	Average $PM_{2.5}$ concentration during slack farming seasons (μg/m^3)	75.41	41.47	11.3	221.8	9926
$PM_{2.5}$	Annual average $PM_{2.5}$ concentration in the whole year (μg/m^3)	64.10	23.44	25.32	129.6	10,516
Thermal inversion (daily measurement)						
Inversions-BFS	The number of inversions during busy farming seasons (number/month)	7.75	5.74	0	29.25	9926
Inversions-SFS	The number of inversions during slack farming seasons (number/month)	10.34	6.59	0	30	9926
Inversions	The number of inversions in the whole year (number/month)	9.23	5.09	0.42	22.58	10,516

Notes: Summary statistics is based on farmer respondents in CLDS 2014 and 2016. Descriptive statistics for weather variables and date characters are reported in details in Table A1. Descriptive statistics for weather and socioeconomic variables are reported in details in Table A2 and Table A3.

average $PM_{2.5}$ concentration, are also reported in Table 1. Air pollution levels during the BFS (52.55 μg/m3) are lower than during the SFS (75.41 μg/m3), which is unsurprising in China, where heavy air pollution tends to occur in winter, particularly during heating season (Chen, Ebenstein, Greenstone, & Li, 2013). Overall, the $PM_{2.5}$-BFS value of 52.55 μg/m3 is five times higher than the threshold recommended by the World Health Organization (10 μg/m3).

To evaluate air pollution further, thermal inversion variables were constructed in the same manner as the $PM_{2.5}$ concentration variables, namely the total number of thermal inversions during the BFS (denoted as Inversions-BFS), SFS (denoted as Inversions-SFS), and the entire year for each farmer. In this study, the number of thermal inversions was calculated daily. At the baseline, thermal inversions were judged every 24 h, whereas in the robustness test, inversions were judged every 6 h. There were approximately 9.23 thermal inversions every month (24 h samples) in the sample counties, with a slightly higher number in the SFS (mainly in winter) than in the BFS. This relationship is consistent with the air pollution levels in the SFS and BFS, indicating a positive correlation between inversion and air pollution.

4. Results

4.1. Baseline results

Table 2 presents the baseline 2SLS estimation results for the intensive margin of farmer labor supply in response to air pollution. We gradually add weather controls, province-by-year fixed, and individual fixed effects in Column (1) to (3). Panel A reports the first-stage estimates of the 2SLS method, which establish the link between thermal inversion and air pollution levels. The results indicate that the occurrence of thermal inversion significantly aggravates air pollution and the KP *F*-statistics are much greater than the critical value of 16.38 in the case of a single IV with a single endogenous variable (Angrist et al., 1996), indicating that thermal inversion is a valid and strong IV for air pollution.

In Panel B, one can see that air pollution during the BFS induces a decrease in farmer working hours spent on agriculture. The significance and direction of the estimated coefficients are stable across the model specifications in Column (1) to (3). We favor the magnitude of the estimated coefficients in Column (3) because the covariates of this model are the most complete. Specifically, farmer working hours on agricultural work during their BFS decrease by 0.04 h per day for a 1 μg/m^3 increment in $PM_{2.5}$ concentration. These effects can be interoperated as intensive margins (Hanna & Oliva, 2015) because they measure changes in labor intensity (rather than labor participation) during the BFS. The magnitude of this marginal effect is comparable to previous literature. As shown in Table A4, our estimation results are very close to the conclusions of past studies on China. Even compared with the conclusions of studies on other countries and regions, the results are in the same order of magnitude.

For comparison, we also report the OLS estimates in Column (4). Without considering endogeneity, we cannot identify a significant link between air pollution and farmer labor supply. This also indicates that endogeneity leads to an upward bias in estimation, which is consistent with our previous logical analysis in Section 2.2.

We then estimated the extensive margin of farmer agricultural labor supply in response to air pollution in the same manner shown in Table 2. Because farmer working days spent on agriculture during the entire year represent their labor participation in the agricultural sector, this can be considered as the extensive margin of labor supply in agriculture. Column (3) in Table 3 reveals that farmer working days spent on agriculture significantly decrease by 4.58 days for a 1 μg/m3 increase in average $PM_{2.5}$ concentration throughout the year. Based on the results in Tables 2 and 3, it can be concluded that air pollution induces a reduction in both agricultural labor participation and intensity, ultimately reducing the supply of agricultural labor.

We did not find directly comparable literature results on the reasonableness of the Extensive margin coefficient size due to the technical difficulty in studying labor participation and intensity simultaneously. Most of the literature selects industries with low labor supply elasticity to avoid the influence of air pollution on labor participation and focuses on the impact of air pollution on labor intensity. For instance, previous studies on workers responsible for packaging in a pear factory (Chang et al., 2016), hotline operators (Chang et al., 2019), and farmers during busy seasons (Zivin & Neidell, 2012) have highlighted that these workers have to work every

Table 2
Regression results for intensive margin.

	2SLS			OLS
	(1)	(2)	(3)	(4)
Panel A: *1st-stage estimation*	*Dependent variable*: $PM_{2.5}$-BFS			
Inversions-BFS	0.0530***	0.0728***	0.0724**	–
	(0.0065)	(0.008)	(0.0292)	–
KP F-statistics	453.0	387.4	61.7	–
Panel B: *2nd-stage estimation*	*Dependent variable*: Working hours-BFS			
$PM_{2.5}$-BFS	−0.0206**	−0.0310**	−0.0437**	−0.0102
	(0.0087)	(0.0138)	(0.0203)	(0.0063)
Weather controls	Yes	Yes	Yes	Yes
Province-by-year *FE*	No	Yes	Yes	Yes
Individual *FE*	No	No	Yes	Yes

Notes: $N = 9926$. We merge air pollution, weather conditions, and thermal inversions for each farmer during their BFS. Weather controls include temperature, relative humidity, sunshine duration, wind speed, precipitation, and air pressure. To capture the potential nonlinear impacts of meteorological variables more accurately, we have created flexible bins for each 3 °C temperature, each 1 m/s wind speed, and every 10% relative humidity, respectively. Other climatic variables were modeled using both their linear and quadratic terms. Standard errors are clustered at county level, and are reported in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3
Regression results for extensive margin.

	2SLS			OLS
	(1)	(2)	(3)	(4)
Panel A: *1st-stage estimation*	*Dependent variable*: $PM_{2.5}$			
Inversions	0.7633***	0.9236***	1.7796***	–
	(0.0284)	(0.0235)	(0.6199)	–
KP F-statistics	226.9	80.4	53.5	–
Panel B: *2nd-stage estimation*	*Dependent variable*: Working days			
$PM_{2.5}$	−1.3240***	−2.2926***	−2.7508**	−0.7579
	(0.4283)	(0.8227)	(1.0888)	(0.8081)
Weather controls	Yes	Yes	Yes	Yes
Province-by-year *FE*	No	Yes	Yes	Yes
Individual *FE*	No	No	Yes	Yes

Notes: $N = 10,516$. We merge air pollution, weather conditions, and thermal inversions for each county by years. Weather controls include temperature, relative humidity, sunshine duration, wind speed, precipitation, and air pressure. To better capture arbitrary nonlinear effects of weather variables, we construct flexible bins for each 3 °C temperature, each 1 m/s wind speed, and every 10% relative humidity, respectively. Other climatic variables were modeled using both their linear and quadratic terms. Standard errors are clustered at county level, and are reported in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

day and their discretion over labor participation is generally limited, but they can adjust labor intensity, which researchers can use to measure labor intensity.

Despite the lack of directly comparable literature results, we assessed the reasonableness of the coefficient size from both statistical significance and intuition. Firstly, we noted that the standard deviation (SD) of $PM_{2.5}$ in the statistical description table is 24.2, but this mainly reflects spatial differences rather than changes within the county. We determined that the SD of air pollution variation within the county between different years was only 3.4, indicating that the variation in air pollution within the county between different years is minimal. Therefore, the estimation coefficient of the Extensive margin regression primarily represents the marginal impact of air pollution increase within the county on farmers' agricultural labor participation. Secondly, we considered the intuition behind the coefficient size. To increase the annual average $PM_{2.5}$ in a county by 1 unit, it would require a continuous increase of 1 unit every day for 365 days or the occurrence of continuous heavy air pollution for some days. Based on these two points, we conclude that the relatively large marginal impact observed in the Extensive margin regression is reasonable.

4.2. Robustness checks

In Table 4, we present a series of robustness checks to ensure that the baseline findings are not driven by variable definitions, model specifications, or significance biases. For ease of comparison, we present the baseline results in Column (1) and report the robustness checks in Columns (2) to (5).

At the baseline, we counted the number of thermal inversions in 24 h intervals. To verify the validity of the IV further, we recalculated the total number of temperature inversions in 6 h intervals and performed 2SLS regression again. The estimation results reported in Column (2) confirm that our baseline findings, including the direction, significance, and magnitude of the estimated coefficient, as well as the first-stage KP *F*-statistics, are all stable for the alternative definition of the IV.

To verify that the results are not driven by a few counties with intensive inversions (Hicks et al., 2016). In Column (3), we re-estimated our model after excluding regions that never experienced temperature inversion, as well as regions where temperature inversion was frequent (representing >95% of the sample). Encouragingly, the findings from this analysis were consistent with our baseline results.

For the baseline, we used the most representative air pollutant of $PM_{2.5}$ to measure air pollution. As a robustness check, a composite measurement of air pollution, namely the air pollution index (AQI), was considered. The results present in Column (4) reveal the same findings as the baseline results.

As discussed in Section 2.2, it is very important to control for flexible weather conditions when inversion is considered as an IV. Therefore, we adopted the setting of weather variables in our baseline regression, where every 3 °C temperature interval was defined as a criterion for constructing temperature bin variables. Column (5) indicates that our results are robust to a cruder criterion, namely 10 °C temperature intervals. In other words, the weather variables in our baseline regression were sufficiently flexible.

In addition to the robustness check, Table A5 further presents the results of placebo tests using mismatched time windows for air pollution. For the intensive margin regression, Columns (1) and (2) show that farmer working hours during their BFS are insensitive to either $PM_{2.5}$ during their SFS (Column (1)) or $PM_{2.5}$ during their BFS, but in the preceding year (Column (2)). Similarly, for the extensive margin regression in Column (3), farmer working days spent on agriculture during the entire year are also unresponsive to future air pollution.

To rule out the concern that air pollution may affect farmers' BFS, causing an endogeneity problem, we constructed regression analysis to test if air pollution affects the changes in the BFS from two angles. Firstly, we summed up the number of months covered by farmers' BFS in a year to examine whether air pollution would extend or shorten the busy season. As shown in Column (1) of the Table A6, air pollution levels did not significantly affect the length of the BFS in a year. Secondly, we examined whether air pollution would cause farmers to advance or postpone their BFS. Specifically, we used two dummy variables based on a sample of 2506 farmers successfully tracked in both 2014 and 2016 to determine whether they advanced or postponed their first BFS month in 2016 compared to 2014. In Columns (2) and (3) of the Table A6, we tested whether changes in air pollution would lead to adjustments in the BFS by using the difference between the local air pollution level in 2016 and that in 2014. The results show that changes in air pollution did not significantly cause farmers to advance or postpone their busy seasons.

4.3. Labor relocation effect

The main idea behind Proposition 1 from Section 2.1 is that air pollution induces changes in farmers' labor supply, which result in labor force relocation. Table 5 presents the empirical results that test this proposition by examining the labor relocation effect under air pollution, both between sectors (agriculture versus off-farm employment) and between different job categories within the off-farm sector (indoor versus outdoor work).

For easy comparison, in Column (1), we present the baseline estimation results for the extensive margin regression in Panel B of

Table 4
Robustness checks.

	Baseline	Alternative IVs	Removed outliers (Keep 5% - 95%)	Alternative pollutant	Alternative weather
	(1)	(2)	(3)	(4)	(5)
Panel A: *Dependent variable*: Working hours-BFS (Intensive margin)					
Air pollution-BFS	−0.0437**	−0.0449**	−0.0448**	−0.0358**	−0.0462**
	(0.0331)	(0.0223)	(0.0224)	(0.0178)	(0.0235)
KP F-statistics	61.7	51.7	39.6	34.6	43.9
Panel B: *Dependent variable*: Working days (Extensive margin)					
Air pollution	−2.7508**	−3.0141**	−3.2557***	−2.9628***	−3.1077**
	(1.4608)	(1.2753)	(1.1194)	(1.0451)	(1.5793)
KP F-statistics	53.5	42.8	60.0	54.6	19.1
Scenarios					
Type of Air pollution	$PM_{2.5}$	$PM_{2.5}$	$PM_{2.5}$	AQI	$PM_{2.5}$
Weather	3 °C Temp bins	3 °C Temp bins	3 °C Temp bins	3 °C Temp bins	10 °C Temp bins
Clustering	County - BFS	County - BFS	County - BFS	County - BFS	County - BFS
Inversion	24-h measure	6-h measure	24-h measure	24-h measure	24-h measure

Notes: $N = 9926$ for extensive margin and $N = 10{,}516$ for extensive margin. Consistent with the baseline model, all regression models incorporate weather controls, province-by-year FE, and individual FE, unless otherwise indicated. Panel A displays the estimates of the intensive margin regressions, while Panel B presents the estimates of the extensive margin regressions. The first-stage estimation outcomes are available from the authors upon request. Standard errors are clustered at county level, and are reported in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3. Columns (2) and (3) report the estimates of the effects of air pollution on farmers' off-farm employment participation (Column (2)) and off-farm working days (Column (3)) during the year. The results show that for a 1 μg/m3 increase in annual average $PM_{2.5}$, the probability of farmers participating in off-farm employment increases by 0.88%, and their off-farm working duration increases by 2.6 days per year.

In Columns (4) to (7), we divide off-farm employment into indoor and outdoor work. We observe an increase in the probability of farmers participating in off-farm employment, and the number of days they participate in off-farm employment is dominated by indoor work. Indoor work is less exposed to air pollution, which is direct evidence that farmers avoid air pollution damage through labor allocation. In contrast, farmers' participation in outdoor work and working hours show a negative (though not significant) response to air pollution.

To further enhance the empirical evidence in Table 6, we differentiate the industries of off-farm employment. The results indicate that air pollution significantly promotes the employment and labor intensity of farmers in the manufacturing and service industries (Columns (1) to (4)), but significantly reduces their employment and labor intensity in the construction industry (Columns (5) to (6)). These results can be attributed to the different levels of air pollution exposure in workplaces in different industries. The manufacturing and service industries mainly use indoor workplaces, unlike the construction industry.

In terms of public awareness, indoor air pollution in workplaces has garnered increasing attention and has been addressed to varying degrees (Ji, Li, Zhao, & Deng, 2018).[14] The evidence from Table 5 and Table 6 indicates that Chinese farmers avoid air pollution damage through labor relocation by reducing their participation and labor intensity in agriculture and correspondingly increasing their participation and labor intensity in indoor non-agricultural employment.

4.4. Income effect

To empirically test Proposition 2 from Section 2.1, we examined whether farmers' income structures changed due to labor relocation. We established an empirical connection between air pollution and four categories of farmer income: total income, agricultural income, off-farm income, and self-employment income. Since off-farm employment depends on industry rather than spatial boundaries, and air pollution varies regionally, our regression analyses focused solely on farmers' off-farm employment within the county.

The results presented in Column (1) of Table 7 demonstrate that air pollution led to a significant 14.5% reduction in total farmer income. This reduction is evident in the simultaneous decline in both agricultural and non-agricultural income, as indicated in Columns (2) and (3). This suggests that farmer labor reallocation primarily aims to avoid exposure to poor air quality rather than increasing income. It also implies that when farmers adjust their labor allocation away from the equilibrium due to air pollution, restoring equilibrium would result in utility losses for farmers due to the income loss associated with avoidance behaviors.

4.5. Mechanisms

In this section, we explore two important channels that support our research - health and productivity - through which air pollution affects farmers' labor supply and allocation.

Firstly, we conducted tests on the health channel using both direct and indirect evidence. For the direct channel, we utilized health variables from the CLDS questionnaire and found that air pollution directly impacts farmers' self-rated health and increases their susceptibility to illness (Columns (1) and (2) in Table 8). For the indirect channel, we investigated the impact of air pollution during the slack farming season (SFS) on labor supply during the subsequent busy farming season (BFS). We found that even if air pollution during the SFS affects farmers' health status, they still need to reduce their labor supply during the following BFS. This indicates that the continuous impact of air pollution on labor supply is actually achieved through its effect on farmers' health (Table A7).

Secondly, we tested the agricultural productivity channel using both subjective and objective indicators. Regarding the subjective indicators, we further used two questions on the CLDS questionnaire about how health affects labor productivity, namely,

- "In the past month, has your work or other daily activities been affected by health problems?"
- "In the past month, have your work or other daily activities been affected by emotional problems (such as feeling depressed or anxious)?"

Our results showed that air pollution significantly affects farmers' self-rated productivity and work status negatively (Columns (4) and (5) in Table 8). Regarding the objective indicators, we constructed the unit labor wage, as suggested by Chang et al. (2016) and Zivin & Neidell, 2012, to reflect farmers' agricultural labor productivity. By dividing farmers' annual agricultural income by their agricultural labor days, we obtained their daily agricultural income, which represents their agricultural labor productivity. Our findings showed that air pollution significantly reduces the unit labor income of agricultural labor; for every 10-unit increase in air

[14] For example, researches by Sun, Kahn, and Zheng (2017) and Zhang and Mu (2018) suggest that air purifiers and ventilation systems are increasingly used in indoor workplaces.

Table 5
The effect of air pollution on farmers' labor allocation.

Dependent variable:	Working days	Participate	Working days	Participate	Working days	Participate	Working days
	Agriculture	Off-farm		Indoor off-farm		Outdoor off-farm	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$PM_{2.5}$	−2.7508**	0.0088*	2.6234*	0.0099**	2.8006**	−0.0011	−0.1913
	(1.0888)	(0.0047)	(1.5318)	(0.0044)	(1.3074)	(0.0016)	(0.5256)
KP F-statistics	53.5	56.7	56.7	56.7	56.7	56.7	56.7
Mean [SD] of D·V.	198.30 [103.80]	0.04 [0.20]	248.55 [99.39]	0.02 [0.15]	256.35 [101.41]	0.02 [0.14]	238.27 [99.27]

Notes: $N = 10{,}516$. Research samples in this table are based only on our defined "farmer" sample. For a comprehensive definition and statistical depiction of the dependent variables mentioned in the table, please refer to Table A3. Consistent with the baseline model, all regression models incorporate weather controls, province-by-year FE, and individual FE. Standard errors are clustered at county level, and are reported in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6
The effect of air pollution on farmers' off-farm work by industry.

Dependent variable:	Participate	Working days	Participate	Working days	Participate	Working days	Participate	Working days
	Manufacturing		Services		Construction		Transportation	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$PM_{2.5}$	0.0022**	0.9866**	0.0064**	1.6035**	−0.0058***	−1.0031**	−0.0007	0.1375
	(0.0011)	(0.4380)	(0.0031)	(0.6759)	(0.0022)	(0.4633)	(0.0011)	(0.2847)
KP F-statistics	56.7	56.7	56.7	56.7	56.7	56.7	56.7	56.7
Mean [SD] of D.V.	0.01 [0.08]	265.55 [91.61]	0.01 [0.11]	277.93 [74.11]	0.01 [0.01]	218.79 [101.09]	0.01 [0.05]	263.72 [80.39]

Notes: $N = 10{,}516$. Research samples in this table are based only on our defined "farmer" sample. For a comprehensive definition and statistical depiction of the dependent variables mentioned in the table, please refer to Table A3. Consistent with the baseline model, all regression models incorporate weather controls, province-by-year FE, and individual FE. Standard errors are clustered at county level, and are reported in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7
The effect of air pollution on farmers' income.

Dependent variable:	Log (Total income)	Log (Agricultural income)	Log (Off-farm income)
	(1)	(2)	(3)
$PM_{2.5}$	−0.1343**	−0.1570**	−0.1184*
	(0.0600)	(0.0749)	(0.0718)
KP F-statistics	77.0	77.0	83.8
Mean [SD] of D.V.	9.31 [2.77]	4.44 [4.66]	10.02 [1.05]
Observation	10,416	10,416	10,416

Notes: This table includes only those farmers who are working within their respective counties of residence. Total income comprises agricultural income, off-farm income (such as wages, bonuses, subsidies, personal income tax deductions, social insurance, and housing provident fund). Consistent with the baseline model, all regression models incorporate weather controls, province-by-year FE, and individual FE. Standard errors are clustered at county level, and are reported in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

pollution, farmers' daily agricultural income decreases by 4.7% (Columns (3) in Table 8).

4.6. *Additional evidence*

To provide additional evidence, we distinguished between non-agricultural employment within counties and across counties and explored the differential impacts of air pollution on these two types of employment. This analysis was motivated by the intuition that farmers may be able to reduce their exposure to air pollution during agricultural work by transitioning to non-agricultural employment. To this end, we identified two options for farmers: they can shift to non-agricultural sectors within their own county, where the air pollution level may be similar, but indoor work eliminates the need for outdoor work, reducing their exposure to air pollution. Alternatively, they can transition to non-agricultural sectors in other counties, which enables them to avoid local air pollution altogether and further reduce their exposure.

If our hypothesis is valid, then air pollution should increase farmers' participation in non-agricultural employment, with a greater marginal impact on their involvement in non-agricultural employment outside their own counties. Our results support this hypothesis, as we found that the marginal effect of air pollution on farmers who shifted to non-local non-agricultural employment was greater than that on those who shifted to local non-agricultural employment. This finding suggests that, when faced with air pollution, farmers prefer to avoid both local pollution and outdoor exposure by moving away from agriculture and engaging in non-agricultural employment elsewhere (Table A8).

Table 8
Mechanisms.

Dependent variable:	Health channel		Productivity channel		
	Self-rated health (Level 1–5)	Illness (0: No; 1: Yes)	Daily earning (1000 yuan/day)	Work affected by health (1: very often - 5: not at all)	Work affected by emotion (1: very often - 5: not at all)
	(1)	(2)	(3)	(4)	(5)
$PM_{2.5}$	−0.0272**	0.0154**	−0.0047**	−0.0350**	−0.0279**
	(0.0136)	(0.0065)	(0.0023)	(0.0118)	(0.0129)
KP F-statistics	23.6	85.4	32.6	23.6	23.6
Mean [SD] of D.V	3.42 [1.03]	0.09 [0.28]	0.07 [0.10]	4.06 [1.11]	4.26 [0.95]
Observation	10,516	11,651	10,774	10,516	10,516

Notes: $N = 10{,}516$. The health-related variables in this table, such as "Self-rated health", "Work affected by health", and "Work affected by emotion", ask about the respondents' conditions in the past month. The variable "Illness" asks about the respondents' conditions in the past two weeks, while the productivity-related variable "Daily earning" asks about the respondents' conditions in the last year. Accordingly, we constructed the regression using $PM_{2.5}$ and thermal inversion in the same period. The other settings of the regression model in this table, including weather controls, province-by-year FE, and individual FE, are identical to those of the baseline regression model. Standard errors are clustered at the county level and are reported in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Finally, we conducted a series of heterogeneous analyses based on farmers' health status, income level, and interpersonal relationships to examine whether the effect of air pollution on farmers' labor supply varies across different subgroups. The detailed discussion and results of these analyses can be found in Online Appendix 3. Additionally, we tested the regional heterogeneity of the impact of air pollution on farmers' agricultural labor supply by constructing interaction terms between regional dummies and air pollution (or thermal inversions. Based on the regional differences in this impact, combined with the variations in average pollution and inversion levels in each region, we provided empirical support for the nonlinear effect of air pollution on farmers' labor supply. For a detailed discussion of this matter, please refer to Online Appendix 3.

5. Discussions and conclusions

There is a wealth of evidence demonstrating that individuals adopt avoidance behaviors to mitigate the harm of air pollution (Bayer et al., 2009; Chang et al., 2018; Chen et al., 2021; Ito & Zhang, 2020; Zhang & Mu, 2018). Our research, which examined a two-period individual-level panel dataset from China, confirms that farmers also engage in avoidance behaviors in response to air pollution. We found that farmers reduce their labor supply in agriculture, both in terms of working hours during their BFS at the intensive margin and working days in agriculture throughout the year at the extensive margin. Furthermore, farmers shift their labor from agriculture to off-farm employment, particularly indoor work, to mitigate the damage caused by pollution, despite the resulting changes in their income structure.

Our findings extend the existing literature on air quality valuations associated with low-income and vulnerable groups, which facilitates a more comprehensive cost-benefit analysis of environmental policies. In recent years, more studies have emerged that provide air quality valuations based on the negative externality of air pollution induced by aversion behaviors (Chang et al., 2018; Ito & Zhang, 2020; Khanna et al., 2021; Zhang & Mu, 2018). For instance, Khanna et al. (2021) found that pollution alters the spatial pattern of skilled and unskilled workers, leading to higher returns to skilled positions in cities, where educated individuals tend to migrate. Likewise, Zhang and Mu (2018) discovered that Chinese urban residents buy particulate-filtering facemasks to safeguard themselves against ambient air pollution. This study sheds light on avoidance behaviors in a low-income group in the developing world, making a contribution to a more accurate policy evaluation when considering aversion behaviors, particularly those of the farmer group.

From the perspective of labor economics, an increasing number of scholars have pointed out the considerable influence of environmental factors on agricultural labor allocation between farm work, off-farm employment, and leisure time (Colmer, 2021; Hoang et al., 2020; Huang et al., 2020; Karadja & Prawitz, 2019). Huang et al. (2020) identified a long-term effect of climate change on the labor market, where an increase in temperature decreases the time allocated to farm work while increasing the time allocated to off-farm work. Hoang et al. (2020) discovered that a large-scale marine environmental crisis had negative and uneven impacts on fishery income and employment. Because farmers are more vulnerable to environmental factors than the rest of the population, research has revealed the crucial topic of environmental justice. This study advances this issue and highlights air pollution has an impact on farmer labor allocation, as well as economic consequences.

This paper has three limitations. Firstly, it concerns measurement errors, which are common when farmers are required to recall their previous year's BFS while responding to the questionnaire. Our study discovered that respondents in our sample had to recall information from an average of eight months ago (Fig. A8), inevitably introducing recall bias.[15] Secondly, our sample consists of

[15] Addressing this challenge is difficult, as any bias in the BFS would result in biased air pollution calculations for that period, leading to measurement errors associated with the key explanatory variable. Another issue is that farmers may have inconsistent understandings of the number of days worked per year and the number of hours worked per day during the busy farming period. In the context of this study, such inconsistencies represent measurement errors based on the dependent variable, although the problem is relatively minor.

farmers continuously or previously involved in agricultural production during the study period. This excludes most migrant workers who have transitioned to non-agricultural jobs while no longer actively farming. These farmers do not fully represent the broader population of rural migrant workers; instead, they primarily engage in agriculture while occasionally participating in non-agricultural work. Thirdly, the paper's narrative may appear disconnected from the institutional details of the agricultural process, a critique often leveled at economists by non-economists. Although we have incorporated explanatory cases into the paper, they remain insufficient.

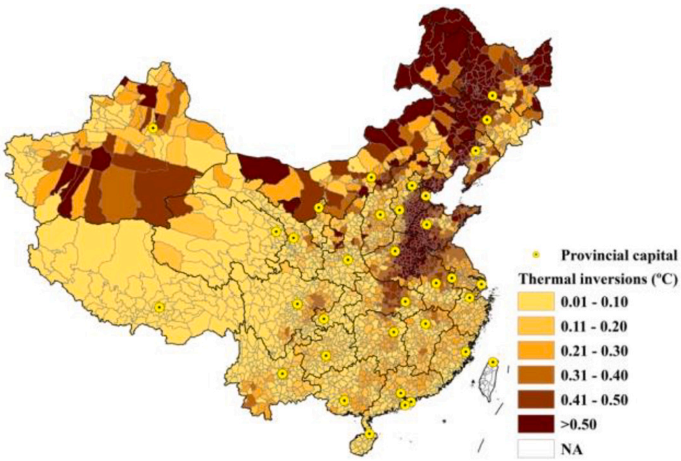
Data availability

Data will be made available on request.

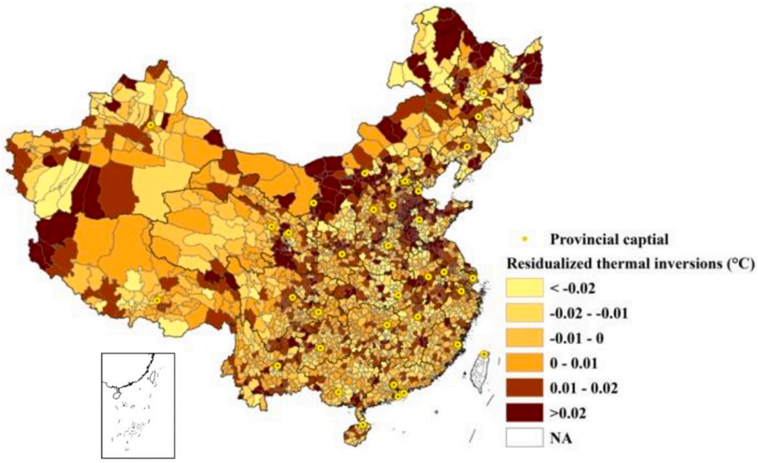
Acknowledgements

All three authors have made equal contributions to the article. The corresponding author is Shuai Chen, and can be reached via email at shuaichen@zju.edu.cn. We are grateful to two anonymous referees and handling editor for providing helpful comments. Generous financial support was given by the Major Program of National Fund of Philosophy and Social Science of China (23ZDA035); Natural Science Foundation of Zhejiang Province (LR22G030003); National Natural Science Foundation of China (72273131; 72134006); Humanities and Social Sciences Program of the Ministry of Education (22JJD790075); National Key Research and Development Program of the Ministry of Science and Technology of China (2020YFA0608600); NSFC-BMGF Joint Agricultural Research Project (72261147758); CGIAR Mitigate+: Research for Low Emissions Food Systems.

Appendix A. Appendix



Panel A: Average of inversions



Panel B: Residualized inversions

Fig. A1. Spatial distribution of thermal inversion.
Notes: This map displays the spatial distribution of thermal inversions in China, based on the average levels from 1980 to 2016. Panel A shows the annual average intensity of thermal inversions at the county level, where the intensity of inversion refers to the temperature difference in Celsius (°C) between the second layer (320 m) and the first layer during the occurrence of this phenomenon. Panel B presents the residual variation in the average intensity of the inversion after removing the county-level FE and year FE.

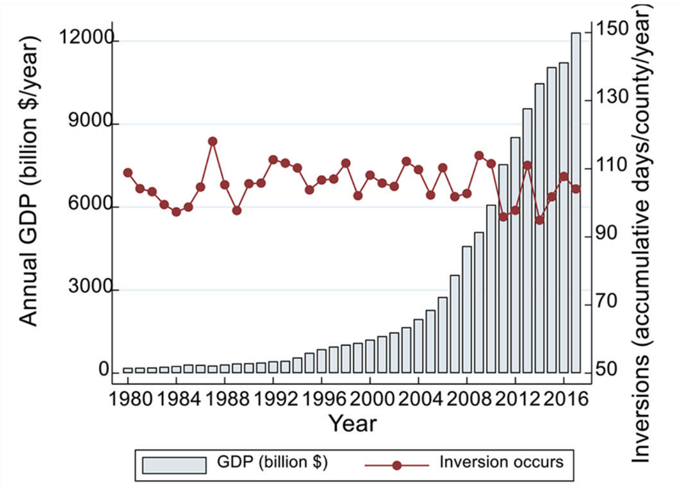


Fig. A2. Time trend of thermal inversions and GDP in China.
Notes: This figure illustrates the time trend of China's average annual frequency of thermal inversions (accumulated days/county/year) and annual GDP (billions of dollars/year) from 1980 to 2017. The connected curve represents the trend of thermal inversions, while the bars represent the level of GDP.

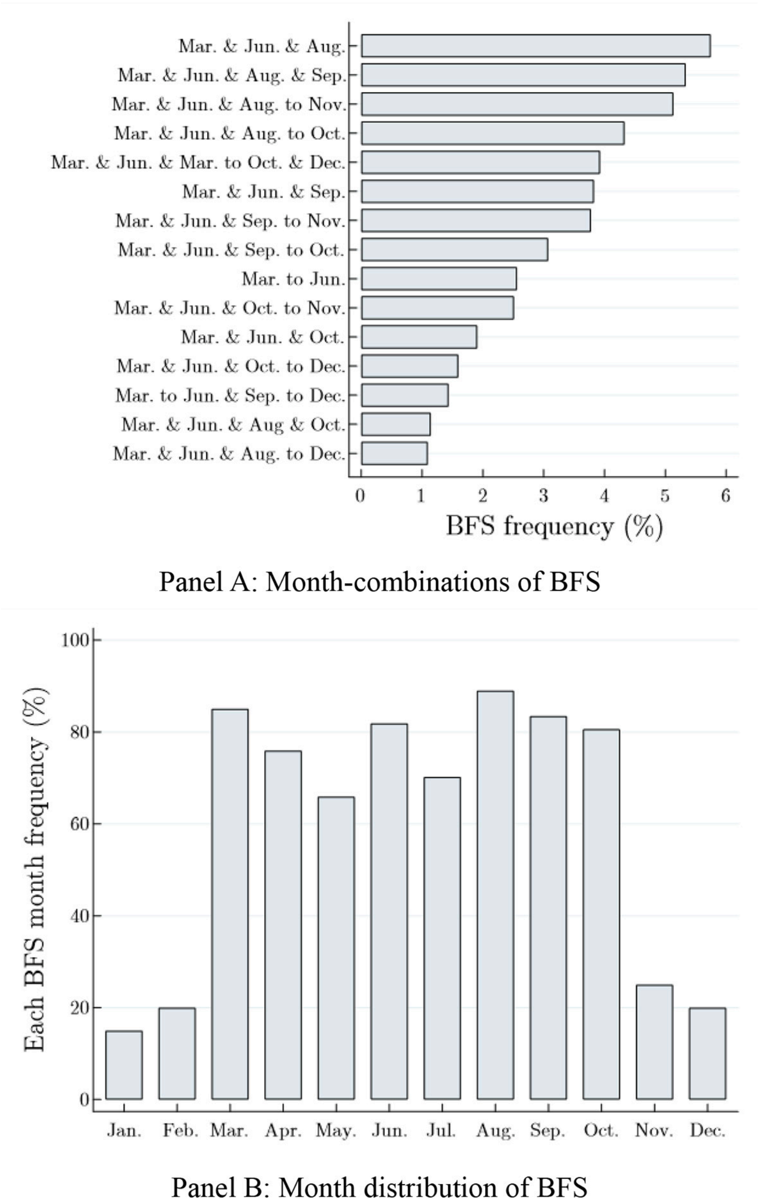


Fig. A3. Distribution of BFS
Notes: Panel A of the figure illustrates the top 15 month-combinations of the BFS reported by farmers in our sample. Panel B displays the frequency of each month in which the BFS occurs throughout the year.

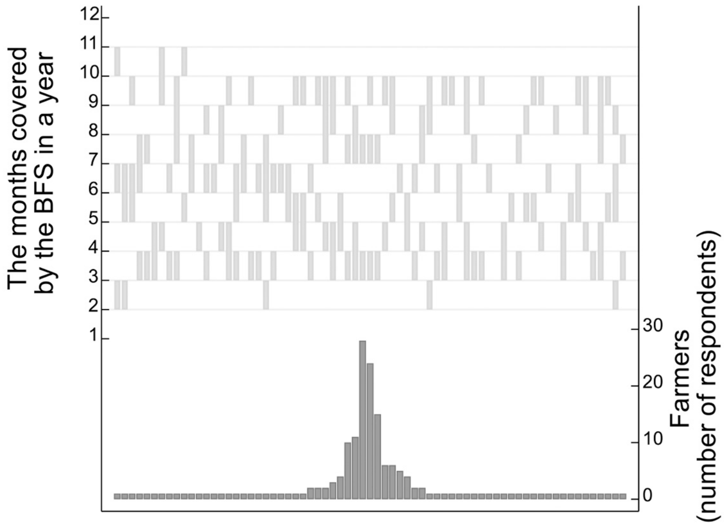


Fig. A4. Distribution of farmers' BFS within the county.

Notes: To demonstrate the variation of BFS within a county, we have selected Shuyang District in Suqian City, Jiangsu Province as an example. The shaded area in the chart represents the months covered by the BFS in a year, while the bars indicate the corresponding number of interviewed farmers during each month.

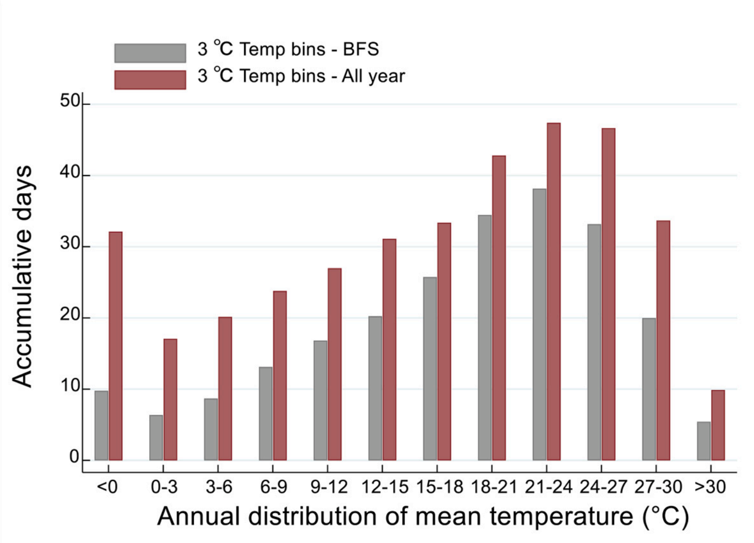


Fig. A5. Distribution of temperature bins.

Notes: This figure displays the distribution of temperature bins, with gray bars representing temperature bins during the BFS and red bars representing temperature bins during the entire year period. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

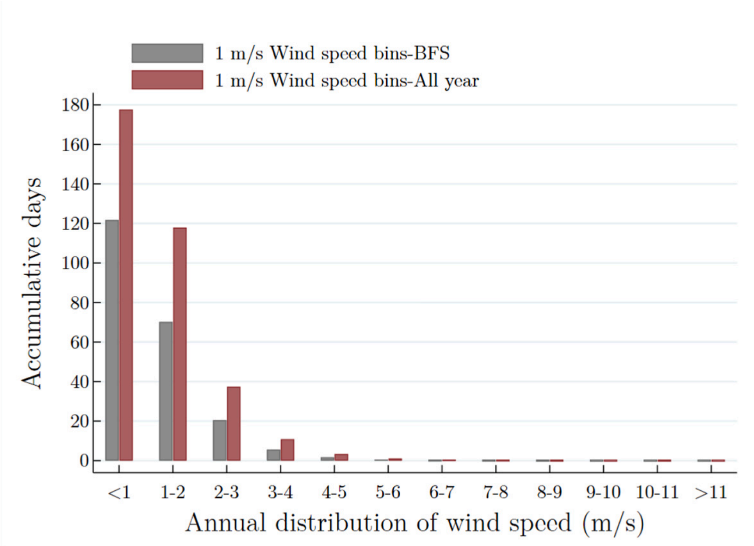


Fig. A6. Distribution of wind speed bins.
Notes: This figure displays the distribution of wind speed bins, with gray bars representing wind speed bins during the BFS and red bars representing wind speed bins during the entire year period. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

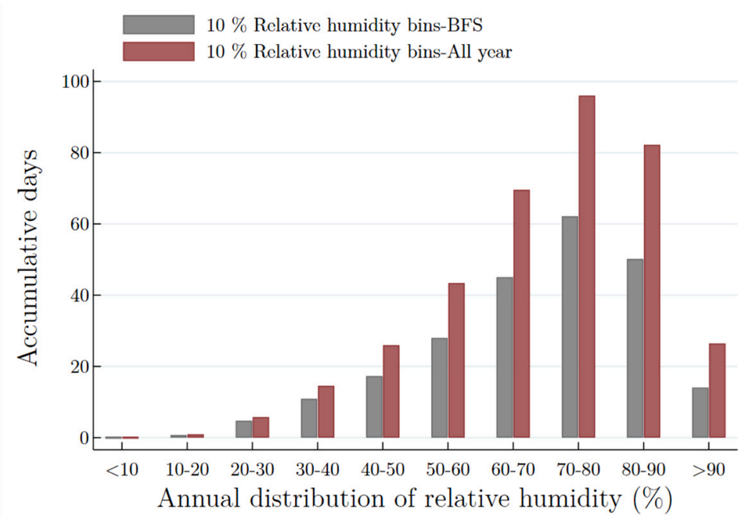


Fig. A7. Distribution of relative humidity bins.
Notes: This figure displays the distribution of relative humidity bins, with gray bars representing humidity bins during the BFS and red bars representing humidity bins during the entire year period. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

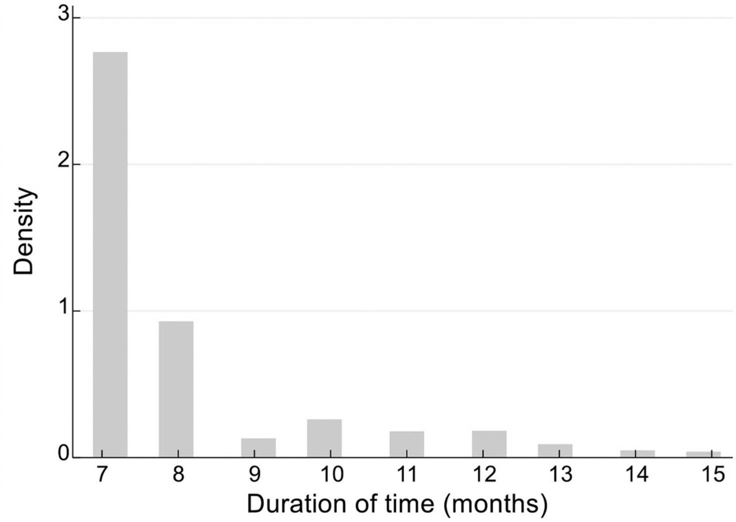


Fig. A8. Time interval between the survey time point and the end of the BFS in the previous year.
Notes: The bar chart depicts the distribution of the duration of time (the time interval between the survey time point and the end of the BFS in the previous year).

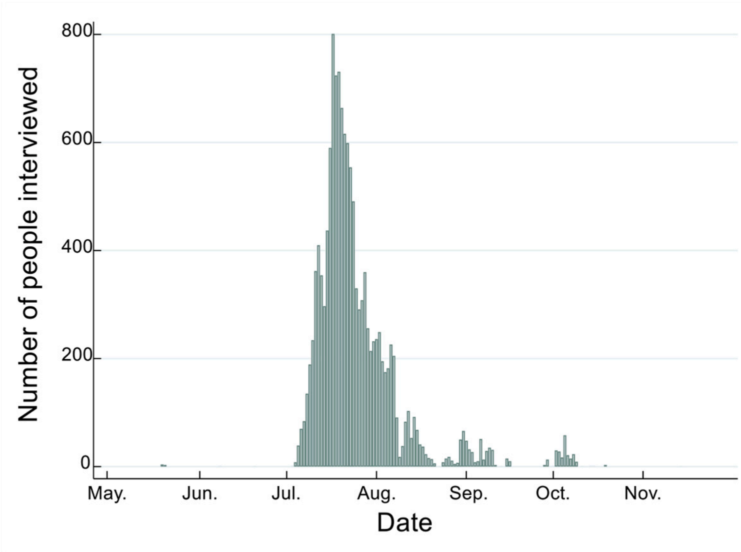


Fig. A9. Number of People Interviewed by date.
Notes: This figure plots the number of people interviewed in each day from May 20th 2014 to November 15th 2016 the course of our study period.

Table A1
Tracking loss of multiple surveys in the CLDS.

Year	2012	2014	2016	2018
Data disclosure	Y	Y	Y	NY
Individual sample	16,253	23,594	21,086	UN
Sample tracking loss	–	Tracking 9953; +New 13,641; -Attrition 6300	Tracking 9228; +New 11,858; -Attrition 14,366	UN
Farmer sample	4150	6705	6360	UN
Farmer tracking loss	–	Tracking 3599; +New 3106; -Attrition 551	Tracking 3270; +New 3090; -Attrition 3435	UN
Question about BFS	N	Y	Y	UN

Notes: The abbreviations “Y”, “N”, “NY”, and “UN” in this table respectively stand for “Yes”, “No”, “Not available”, and “Unknown”.

Table A2
Summary statistics for weather variables.

Variable	Definition (Unit)	Mean	SD	Min	Max	Obs.
Weather variable for busy farming season						
Precipitation-BFS	Average precipitation during busy farming seasons (0.1 mm)	1.36	0.98	0.02	8.67	9926
Sunshine duration-BFS	Average sunshine duration during busy farming seasons (h)	5.48	1.95	1.89	9.59	9926
Wind speed-BFS	Average wind speed during busy farming seasons (m/s)	1.94	0.71	1.00	4.22	9926
Atmospheric pressure-BFS	Average atmospheric pressure during busy farming seasons (hPa)	897.7	241.6	793.42	1028	9926
Temperature-BFS	Average temperature during busy farming seasons (°C)	16.60	6.41	−18.48	30.04	9926
Relative humidity-BFS	Average relative humidity during busy farming seasons (%)	64.50	19.02	32.93	90.15	9926
Weather variable for slack farming season						
Precipitation-SFS	Average precipitation during slack farming seasons (0.1 mm)	0.84	1.07	0	12.70	9926
Sunshine duration-SFS	Average sunshine duration during slack farming seasons (h)	4.57	1.90	0.59	10.74	9926
Wind speed-SFS	Average wind speed during slack farming seasons (m/s)	1.81	0.70	0.78	4.68	9926
Atmospheric pressure-SFS	Average atmospheric pressure during slack farming seasons (hPa)	903.4	243.4	794.8	1029	9926
Temperature-SFS	Average temperature during slack farming seasons (°C)	8.60	8.63	−14.37	31.33	9926
Relative humidity-SFS	Average relative humidity during slack farming seasons (%)	64.72	18.96	30.48	89.14	9926
Weather variable for all year						
Precipitation	Annual average precipitation (0.1 mm)	1.26	0.82	0.09	4.11	10,516
Sunshine duration	Annual average sunshine duration (h)	5.52	1.28	2.54	8.58	10,516
Wind speed	Annual average wind speed (m/s)	2.03	0.51	0.99	4.18	10,516
Atmospheric pressure	Annual average atmospheric pressure (hPa)	959.5	60.91	795.2	1019	10,516
Temperature	Annual average temperature (°C)	14.76	4.59	1.43	23.76	10,516
Relative humidity	Annual average relative humidity (%)	68.81	8.76	41.45	82.25	10,516

Notes: Summary statistics is based on farmer respondents in CLDS 2014 and 2016.

Table A3
Summary statistics for socioeconomic variables.

Variable	Definition (Unit)	Mean	SD	Min	Max
Individual employment (by location)					
Off-farm participate	Whether to participate in non-farm work (0: no; 1: yes)	0.04	0.20	0	1
Off-farm working days	The number of working days in off-farm employment (days/year)	248.5	99.4	3	360
Indoor off-farm participate	Whether to participate in indoor off-farm work (0: no; 1: yes)	0.02	0.15	0	1
Indoor off-farm working days	The number of working days in indoor off-farm employment (days/year)	256.35	101.4	3	360
Outdoor off-farm participate	Whether to participate in outdoor off-farm work (0: no; 1: yes)	0.02	0.14	0	1
Outdoor off-farm working days	The number of working days in outdoor off-farm employment (days/year)	263.72	80.4	6	360
Individual employment (by industry)					
Manufacturing participate	Whether to participate in manufacturing work (0: no; 1: yes)	0.01	0.80	0	1
Manufacturing working days	The number of working days in manufacturing employment (days/year)	265.6	91.6	60	360
Services participate	Whether to participate in services work (0: no; 1: yes)	0.01	0.64	0	1
Services working days	The number of working days in services employment (days/year)	282.9	98.1	10	360
Construction participate	Whether to participate in construction work (0: no; 1: yes)	0.01	0.98	0	1
Construction working days	The number of working days in construction employment (days/year)	256.3	101.4	6	360
Transportation participate	Whether to participate in transportation work (0: no; 1: yes)	0.01	0.48	0	1
Transportation working days	The number of working days in transportation employment (days/year)	263.7	80.4	90	360
Mechanisms (by health and productivity)					
Self-rated health	How is your current state of health? (In the past month, 1–5; 1: very bad - 5:very good)	3.42	1.03	1	5
Work affected by health	Have you experienced any impact on your work due to health issues? (In the past month, 1: very often - 5: not at all)	4.06	1.11	1	5
Work affected by emotion	Have you experienced any impact on your work due to emotional issues? (In the past month, 1: very often - 5: not at all)	4.26	0.95	1	5
Illness	Have you experienced any illnesses or injuries? (In the past two weeks, 0: No; 1: Yes)	0.10	0.30	0	1
Daily earning	Annual agriculture income divided by agriculture working days (Last year, 1000 yuan/day)	0.09	0.14	0	1.17
Individual characters					
Health status	Farmers' overall health status (0–8, from very bad to very good)	5.26	1.91	0	8
Income levels	Monthly agricultural income-BFS (agricultural income/number of BFS months)	2.14	4.47	0	70
Interpersonal relationship	Number of local friends and acquaintances.	8.87	11.77	0	99

Notes: $N = 10{,}516$. Summary statistics in this table is based only on farmer respondents in CLDS 2014 and 2016 (respondents who answered "4 farmers" while answering "employed", please refer to Section 3.1.1 in details). The retained "farmers" sample is almost entirely composed of full-time farmers engaged in agricultural production activities throughout the year; otherwise, they would not have answered "4 farmers." That is to say, when we selected the "farmers," we had already excluded the vast majority of rural people who primarily engaged in off-farm employment. Therefore, the mean value of the non-farm employment participation variable is only 0.04, meaning that only 4% of our defined "farmers" participate in non-farm employment. For the "Working days" variables, which measures non-farm labor days, only refers to the total number of labor days per year for those 4% of "farmers" who participate in non-farm employment. Thus, only 440 actual farmers who participated in non-farm employment were summarized in this table. We classified the industries and workplace locations of workers based on specific information provided by the CLDS questionnaire regarding their job content and location. For those respondents who answered "employed" to the employment status question (our "response 1"), the CLDS asked about the "type of employment" and "where is your workplace located." For the former, the original questionnaire asked, "What industry does your job belong to: ___? 1. Agriculture, forestry, animal husbandry, and fishery; 2. Mining; 3. Manufacturing; 4. Production and supply of electricity, gas, and water; 5. Construction; 6. Geological surveying and mapping, water conservancy management; 7. Transportation, warehousing, and postal and telecommunications services; 8. Wholesale and retail trade, accommodation and catering services; 9. Financial insurance; 10. Real estate industry; 11. Social services; 12. Health, sports, and social welfare; 13. Education, culture, art, and radio, film, and television industries; 14. Scientific research and comprehensive technical services; 15. National agencies, party and government agencies, and social organizations; 16. Other industries; 99,998. Not applicable." We classified respondents as belonging to the manufacturing, construction, transportation, or service industry if they answered with the codes "3", "5", "7" for manufacturing, construction, and transportation industry, respectively. Or they answered with the codes "8", "9", "10", "11", "12", "13", "14", "15" for service industry. For the latter, the original questionnaire asked, "Where is your workplace located: ___? 1. Outdoors; 2. Workshop; 3. Indoor business place; 4. Office; 5. Home; 6. Transportation vehicle; 9. Other [please specify]." We classified workers who worked outdoors as "outdoor" and those who worked in "2–5" as "indoor."

Table A4
Results comparison.

Literature	Objective	Air pollution	Region	Period	Findings	Our results
					A 10-unit increase in air pollution is associated to a reduction of	
Aragón et al. (2017)	Working hours	$PM_{2.5}$	Peru.	2007–2011	labor working hour by 4.6%	
Kim et al. (2017)	Working hours	API	Indonesia	1993\1997\2000\2007\2015	labor working hour by 3.7%	
Fan & Grainger (2023)	Working hours	$PM_{2.5}$	China	2010\2012\2014	labor working hour by 5.4%	Labor working hours by 4.5%
Chang et al. (2019)	Worker productivity	API	China	2010–2012	Worker productivity by 0.35%	
Chang et al. (2016)	Hours earning	$PM_{2.5}$	America	2001–2003	Hours earning by 6%	
Hanna & Oliva (2015)	Working hours	SO_2	Mexico	1989–1993	Working hours by 25%	
He et al. (2019)	Daily output	$PM_{2.5}$	China	2014\2015	Daily output by 0.5% to 3.3%	

Notes: To facilitate a more direct comparison between the literature and our results, we converted the findings of Hanna & Oliva (2015) and Chang et al. (2019) into an elasticity interpretation, while we transformed the results of Chang et al. (2016), and He et al. (2019) into a semi-elastic interpretation. It should be noted that in the semi-elastic economic interpretation, the economic significance of the coefficient of the explanatory variable in different studies can be sensitively influenced by its mean and unit size. This results in the incomparability of SO_2 with PM and AQI in Table A4, given the mean values of SO_2 at 4.46 pphm (Hanna & Oliva, 2015), $PM_{2.5}$ at 45.5 μg/m^3 (Aragón et al., 2017), 44.27 μg/m^3 (Fan & Grainger, 2023), and 64.10 μg/m^3 (this study).

Table A5
Placebo test for farmers' labor supply.

Dependent variable:	Working hours-BFS	Working hours-BFS	Working days
	(1)	(2)	(3)
$PM_{2.5}$	0.0126 (0.0136)	−0.0975 (0.0852)	−9.3871 (14.7805)
Scenarios			
Type of $PM_{2.5}$	$PM_{2.5}$-SFS	$PM_{2.5}$-BFS	$PM_{2.5}$
Year of $PM_{2.5}$	2013 & 2015	2014 & 2016	2014 & 2016
KP F-statistics	25.3	17.4	16.4
Weather controls	Yes	Yes	Yes
County-by-year *FE*	Yes	Yes	No
Province-by-year *FE*	No	No	Yes
Individual *FE*	Yes	Yes	Yes
Observation	9926	9926	10,516

Notes: Consistent with the baseline model, all regression models incorporate weather controls, province-by-year FE, and individual FE, unless otherwise indicated. Standard errors are clustered at county level, and are reported in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A6
Effects of air pollution on farmers' BFS.

Dependent variable:	Number of months covered by BFS in a year	The first BFS month in 2016 compared to 2014	
		Advance (0/1)	Delay (0/1)
	(1)	(2)	(3)
$PM_{2.5}$	0.0153 (0.0222)		
$\triangle PM_{2.5}$(2016–2014)		0.0187	−0.0054

(*continued on next page*)

Table A6 (*continued*)

Dependent variable:	Number of months covered by BFS in a year	The first BFS month in 2016 compared to 2014	
		Advance (0/1)	Delay (0/1)
	(1)	(2)	(3)
		(0.0173)	(0.0089)
KP F-statistics	20.1	16.7	16.7
Weather controls	Yes	Yes	Yes
Individual *FE*	Yes	No	No
Province-by-year *FE*	Yes	No	No
Observation	10,516	2506	2506

Notes: $\triangle PM_{2.5}$(2016–2014) represents the difference between the local air pollution levels in 2016 and 2014. We constructed the thermal inversion variables in the same manner as the air pollution variables and used it as an instrumental variable (IV) for endogenous air pollution. The second-stage regression results for the two-stage least squares (2SLS) are presented in the table. The variable labels and FE labels are identical to those in the baseline regression model of this paper. Standard errors are clustered at the county level and are reported in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A7
Additional evidence of health mechanism.

Dependent variable:	Working hours-BFS (subsequent)		
	(1)	(2)	(3)
$PM_{2.5}$-SFS	−0.0344**	−0.0304***	−0.0325**
	(0.0154)	(0.0146)	(0.0163)
SFS period	Jun.	Jun. & Feb.	2012 & 2014 SFS
KP F-statistics	20.8	21.4	60.3
Mean [SD] of D.V.	10.33 [2.89]	10.29 [2.92]	8.84 [3.47]
Observation	6879	4662	10,516

In line with the baseline model, all regression models control for weather conditions, province-by year fixed effect, and individual fixed effect. Unless otherwise specified, standard errors are clustered at county level, and are reported in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A8
The effect of air pollution on farmers' off-farm work by location.

Dependent variable:	Participate	Working days	Participate	Working days	Participate	Working days
	Off-farm		Local off-farm		Non-local off-farm	
	(1)	(2)	(3)	(4)	(5)	(6)
$PM_{2.5}$	0.0088*	2.6234*	0.0068**	2.4680**	0.0111**	3.2860**
	(0.0047)	(1.5318)	(0.0036)	(1.2555)	(0.0052)	(1.6150)
KP F-statistics	56.7	56.7	56.7	56.7	56.7	56.7
Mean [SD] of D.V.	0.04 [0.20]	248.55 [99.39]	0.04 [0.19]	225.58 [91.59]	0.04 [0.21]	253.78 [81.22]

Notes: $N = 10{,}516$. Consistent with the baseline model, all regression models incorporate weather controls, province-by-year FE, and individual FE, unless otherwise indicated. Standard errors are clustered at county level, and are reported in parentheses; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Appendix B. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.chieco.2023.102075.

References

Angrist, J. D., Imbens, G. W., & Rubin, D. B. (1996). Identification of causal effects using instrumental variables. *Journal of the American Statistical Association, 91*, 444–455.

Aragón, F. M., Miranda, J. J., & Oliva, P. (2017). Particulate matter and labor supply: The role of caregiving and non-linearities. *Journal of Environmental Economics and Management, 86*, 295–309.

Aragón, F. M., & Rud, J. P. (2016). Polluting industries and agricultural productivity: Evidence from mining in Ghana. *The Economic Journal, 126*, 1980–2011.

Arceo, E., Hanna, R., & Oliva, P. (2016). Does the effect of pollution on infant mortality differ between developing and developed countries? Evidence from Mexico City. *The Economic Journal, 126*, 257–280.

Bayer, P., Keohane, N., & Timmins, C. (2009). Migration and hedonic valuation: The case of air quality. *Journal of Environmental Economics and Management, 58*, 1–14.

Carter, M. R., & Yao, Y. (2002). Local versus global separability in agricultural household models: The factor price equalization effect of land transfer rights. *American Journal of Agricultural Economics, 84*, 702–715.

Chang, T., Graff Zivin, J., Gross, T., & Neidell, M. (2016). Particulate pollution and the productivity of pear packers. *American Economic Journal: Economic Policy, 8*, 141–169.

Chang, T. Y., Graff Zivin, J., Gross, T., & Neidell, M. (2019). The effect of pollution on worker productivity: Evidence from call center workers in China. *American Economic Journal: Applied Economics, 11*, 151–172.

Chang, T. Y., Huang, W., & Wang, Y. (2018). Something in the air: Pollution and the demand for health insurance. *The Review of Economic Studies, 85*, 1609–1634.

Chay, K. Y., & Greenstone, M. (2003). The impact of air pollution on infant mortality: Evidence from geographic variation in pollution shocks induced by a recession. *Quarterly Journal of Economics, 118*, 1121–1167.

Chen, S., Chen, Y., Lei, Z., & Tan-Soo, J.-S. (2020). Chasing clean air: Pollution-induced travels in China. *Journal of the Association of Environmental and Resource Economists, 8*(1), 59–89.

Chen, S., Chen, Y., Lei, Z., & Tan-Soo, J.-S. (2021). Chasing clean air: Pollution-induced travels in China. *Journal of the Association of Environmental and Resource Economists, 8*, 59–89.

Chen, S., Oliva, P., & Zhang, P. (2017). *The effect of air pollution on migration: Evidence from China*. National Bureau of Economic Research.

Chen, S., Oliva, P., & Zhang, P. (2018). Air pollution and mental health: Evidence from China. *National Bureau of Economic Research*.

Chen, Y., Ebenstein, A., Greenstone, M., & Li, H. (2013). Evidence on the impact of sustained exposure to air pollution on life expectancy from ChinaΓÇÔs Huai River policy. *Proceedings of the National Academy of Sciences, 110*, 12936–12941.

Colmer, J. (2021). Temperature, labor reallocation, and industrial production: Evidence from India. *American Economic Journal: Applied Economics, 13*, 101–124.

Conley, T. G., Hansen, C. B., & Rossi, P. E. (2012). PLAUSIBLY EXOGENOUS. *Review of Economics and Statistics, 94*, 260–272.

Deryugina, T., Heutel, G., Miller, N. H., Molitor, D., & Reif, J. (2019). The mortality and medical costs of air pollution: Evidence from changes in wind direction. *American Economic Review, 109*, 4178–4219.

Deschênes, O., & Greenstone, M. (2007). The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather. *American economic review, 97*(1), 354–385.

Fan, M., & Grainger, C. (2023). The impact of air pollution on labor supply in China. *Sustainability, 15*(17), 13082.

Freeman, R., Liang, W., Song, R., & Timmins, C. (2017). Willingness to pay for clean air in China. In *National Bureau of Economic Research Working Paper Series No. 24157*.

Hanna, R., & Oliva, P. (2015). The effect of pollution on labor supply: Evidence from a natural experiment in Mexico City. *Journal of Public Economics, 122*, 68–79.

He, G., Liu, T., & Zhou, M. (2020). Straw burning, $PM_{2.5}$, and death: Evidence from China. *Journal of Development Economics, 145*.

He, J., Liu, H., & Salvo, A. (2019). Severe air pollution and labor productivity: Evidence from industrial towns in China. *American Economic Journal: Applied Economics, 11*, 173–201.

Hicks, D., Marsh, P., & Oliva, P. (2016). Air pollution and procyclical mortality: Causal evidence from thermal inversions. In *Working Paper*. Jacobson, M.(2002). Atmospheric Pollution. History, Science.

Hoang, T. X., Le, D. T., Nguyen, H. M., & Vuong, N. D. T. (2020). Labor market impacts and responses: The economic consequences of a marine environmental disaster. *Journal of Development Economics, 147*.

Huang, K., Zhao, H., Huang, J., Wang, J., & Findlay, C. (2020). The impact of climate change on the labor allocation: Empirical evidence from China. *Journal of Environmental Economics and Management, 104*.

Imbens, G. W., & Angrist, J. D. (1994). Identification and Estimation of Local Average Treatment Effects. *Econometrica, 62*(2), 467–475.

Ito, K., & Zhang, S. (2020). Willingness to pay for clean air: Evidence from air purifier markets in China. *Journal of Political Economy, 128*, 1627–1672.

Ji, W., Li, H., Zhao, B., & Deng, F. (2018). Tracer element for indoor PM2. 5 in China migrated from outdoor. *Atmospheric Environment, 176*, 171–178.

Karadja, M., & Prawitz, E. (2019). Exit, voice, and political change: Evidence from Swedish mass migration to the United States. *Journal of Political Economy, 127*, 1864–1925.

Khanna, G., Liang, W., Mobarak, A. M., & Song, R. (2021). The productivity consequences of pollution-induced migration in China. In *National Bureau of Economic Research Working Paper Series No. 28401*.

Kim, Y., Manley, J., & Radoias, V. (2017). Medium-and long-term consequences of pollution on labor supply: Evidence from Indonesia. *IZA Journal of Labor Economics, 6*, 1–15.

Lazear, E. P. (2000). Performance pay and productivity. *American Economic Review, 90*, 1346–1361.

Minale, L. (2018). Agricultural productivity shocks, labour reallocation and rural–urban migration in China. *Journal of Economic Geography, 18*, 795–821.

Munshi, K. (2003). Networks in the modern economy: Mexican migrants in the US labor market. *The Quarterly Journal of Economics, 118*, 549–599.

Schlenker, W., & Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to US crop yields under climate change. *Proceedings of the National Academy of sciences, 106*(37), 15594–15598.

Schlenker, W., & Walker, W. R. (2016). Airports, air pollution, and contemporaneous health. *Review of Economic Studies, 83*, 768–809.

Schwartz, J. (1994). Air pollution and daily mortality: A review and meta analysis. *Environmental Research, 64*, 36–52.

Sun, C., Kahn, M. E., & Zheng, S. (2017). Self-protection investment exacerbates air pollution exposure inequality in urban China. *Ecological Economics, 131*, 468–474.

Tiebout, C. M. (1956). A pure theory of local expenditures. *Journal of Political Economy, 64*, 416–424.

Viard, V. B., & Fu, S. (2015). The effect of Beijing's driving restrictions on pollution and economic activity. *Journal of Public Economics, 125*, 98–115.

Ward, P. S., & Shively, G. E. (2011). *Migration and land rental as risk response in rural China*.

Yi, F., Ye, H., Wu, X., Zhang, Y. Y., & Jiang, F. (2020). Self-aggravation effect of air pollution: Evidence from residential electricity consumption in China. *Energy Economics, 86*, Article 104684.

Zhang, J., & Mu, Q. (2018). Air pollution and defensive expenditures: Evidence from particulate-filtering facemasks. *Journal of Environmental Economics and Management, 92*, 517–536.

Zivin, J. G., & Neidell, M. (2012). The impact of pollution on worker productivity. *American Economic Review, 102*(7), 3652–3673.