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How does air pollution perception affect farmers' decisions on agricultural mechanisation? Evidence from rural China

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Abstract: Air pollution is beyond an environmental or health issue. The impact of air pollution on farmers' decisions on agricultural mechanisation has always been overlooked and debate persists over subjective and objective pollution. Adopting data set from the China Labour Force Dynamics Survey, we investigate the influence of air pollution perceptions on farmers' mechanised farming. The endogeneity problem is addressed through the instrumental variable method. The consequences reveal that air pollution perceptions strengthen farm mechanisation, and reduced farming time is the key intrinsic mechanism through which perceived air pollution affects farmers' decisions on agricultural machinery. Additionally, this impact is more pronounced in male household heads and farmers in the plains. These findings render valuable policy implications for farmers chronically exposed to air pollution and for agricultural modernisation in China, including the necessity of improving air conditions and encouraging agricultural machinery services.

Keywords: agricultural economics; environmental perception; farm modernisation; identity; machinery investment; rural areas of China, subjective perception

Today, several issues have challenged the sustainability of smallholder agriculture, encompassing labour shortages due to rural-urban migration, rising prices of agricultural materials, climate change, and environmental degradation (Jayne et al. 2010; Hull 2014; Himanshu and Kundu 2016; Yamauchi 2016; Qiu et al. 2022). Agricultural mechanisation could serve as an effective solution and play a significant role in fuelling transformative change towards agricultural modernisation, higher utilisation rates of farm resources, and sustainable agriculture, thanks to its efficiency in reducing production costs and replacing labour. Therefore, agricultural mechanisation has been vigorously promoted worldwide, especially in developing countries. In accordance with the National Bureau of Statistics of China, the total power of agricultural machinery in China exceeded 1.1 billion kW in 2023, witnessing a substantial increase from 117.50 million kW in 1978. The number of small agricultural tractors has lifted from 1.373 million to 16.75 million, and the number of large agricultural tractors has risen from 557 000 to 4.981 million. Sustainable mechanisation with adequate agricultural machinery services could propel the evolution

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of food systems as it not only boosts land productivity by enhancing timeliness and quality of farming but renders opportunities that lighten the burden of labour shortages and empowers farmers to withstand shocks better.

However, despite the importance of agricultural mechanisation research, the gradual expansion of in-depth research has predominantly centred around farmland fragmentation, labour shortages, large-scale farmland management, and financial support (Mottaleb et al. 2017; Liu et al. 2019; Daum and Birner 2020; Belton et al. 2021; Qiu et al. 2022), with less attention paid to how air pollution affects agricultural mechanisation. Since the Industrial Revolution, air pollution caused by industrial production, coal heating, and vehicle exhaust has become one of the world's most severe challenges and has profoundly impacted human health and economic development (Ostro 1983; Deschenes et al. 2020; Hanlon 2020). Worldwide, about 800 000 people die from air pollution every year. Of these 800 000 deaths, about 300 000 occur in China (Ma et al. 2016; Li and Li 2022). In 2020, only 202 out of 337 cities in China met the ambient air quality standards, with the mean concentration of PM2.5 far from the World Health Organisation's (WHO) standard (Jiao et al. 2022). China is facing severe air pollution, and its impact extends beyond farmers' health to agricultural production decisions.

Air pollution also has the potential to affect agricultural mechanisation due to its adverse impact on labour supply (Hanna and Oliva 2015; Chen et al. 2022; Li and Li 2022). Air pollution affects production decisions, especially those involving outdoor work, owing to concerns about elevated health costs and reduced agricultural economic benefits caused by polluted air (Wei and Wang 2021). For every unit increase in the average PM2.5 concentration, the total working time of the middle-aged and elderly population in China's rural areas would decrease by 3.75% (Huang et al. 2021). Additionally, the labour force participation rate as well as the length of working hours of rural women are significantly lowered by polluted air conditions, regardless of their area of residence or type of domicile (Zivin and Neidell 2012; Gu et al. 2020). Air contamination affects not only the participation of labour supply but also labour productivity (Zivin and Neidell 2012; He et al. 2019) and output (Heck et al. 1988). In the context of a reduced supply of agricultural labour, farmers turn to agricultural machinery as an efficient and low-loss replacement for agricultural labour. As a result, when faced with air pollution, farmers may reduce their labour supply and choose to use agricultural machinery as an alternative to agricultural labour, thus affecting the development of agricultural mechanisation. To date, there remains a research gap that necessitates exploring the link between air pollution and agricultural mechanisation.

Meanwhile, debate persists over pathways through which pollution influences subjective decisions. The primary measures of air pollution include objective and perceived air pollution (Liao et al. 2015). Objective air pollution often refers to the air pollution index, an objective assessment of air quality conditions, and the current measures have mainly relied on physical indicators. A higher air pollution index is linked to a higher severity of air pollution and harm to human health. Perceived air pollution stands for people's subjective judgment and assessment of objective environmental pollution, a synthesis of objective environmental contamination and resident psychological experiences (Chiarini et al. 2020). Nevertheless, residents possess varying sensitivity to the level of air pollution, even in similarly contaminated environments, resulting in different perceptions. Besides, human-perceived air pollution plays a direct role in mediating and influencing individual mental state and behaviour (Bala et al. 2023). Thus, given the aim of agricultural machinery adoption to replace agricultural labour (Martin and Olmstead 1985), does air pollution perception affect labour supply and thereby agricultural machinery choice? It has been well established that objective air pollution conditions affect the behavioural decisions of farm households, for instance, labour migration in the agricultural population (Li et al. 2017; Carrasco-Escobar et al. 2020). However, these studies concentrate on objective measures and neglect individual perceptions and the distinction between the impacts of measured and perceived air pollution. Considering that the decision-making process of individuals is often based on their feelings of air pollution rather than on the air pollution index (Li and Li 2022), our study focuses on the role of perceived air pollution on farmers' decisions on agricultural mechanisation, and objective measure is also examined in the robustness test section.

The current study provides robust empirical evidence of the causal relationship between perceived air pollution on agricultural mechanisation. Employing a dataset from the 2016 China Labour Force

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Dynamics Survey (2017), we assess the effects of perceived air pollution on agricultural mechanisation using an ordered probit model. On the one hand, the analysis offers far-reaching insights for policymakers in China as well as other developing countries, providing strong momentum for high-quality agricultural development and solid support for agricultural modernisation. On the other hand, through a comparison between subjective and objective measures of exposure to air pollution, the study contributes to a comprehensive and holistic view of environmental quality by employing subjective perceptions jointly with objective indicators.

Our investigation can contribute to the existing body of knowledge in three aspects:

We offer new insights and a deeper comprehension of how air pollution influences agricultural mechanisation in China and its extent from an economic perspective.

We test and uncover the mechanistic role of agricultural labour time through an econometric model (mediating effects model).

Since fossil raw materials, such as oil, consumed by the development of agricultural mechanisation contribute to air pollution, more careful consideration of endogeneity is required when investigating the causal link between air contamination and agricultural mechanisation. It would be advantageous to adopt thermal inversion as an instrumental variable (IV) to address the problem of reverse causality.

MATERIAL AND METHODS

Data

The dataset employed in the empirical analysis originates from the 2016 wave of the China Labour Force Dynamics Survey (CLDS) data, launched by the Centre for Social Survey of Sun Yat-Sen University, Guangzhou, China. As the first national longitudinal social survey on the Chinese labour force, CLDS has established a comprehensive database through the biennial follow-up survey and has been updated to 2018. However, given the absence of key variables and insufficient sample size in CLDS2018, our dataset is gleaned from CLDS2016 data. The survey targeted households aged 15–64 of working age and covered a range of topics, namely demographics, family, labour, income, land, household consumption, household production, household property, health, well-being, satisfaction and economic and social development. Its sample involved 29 Chinese provinces (excluding Tibet, Hainan, Taiwan, Hong Kong, and Macao), yielding a sample size of 401 villages, 14 226 households and 21 086 individuals. Therefore, the sample adopted in our research is nationally and regionally representative. Ultimately, after data cleaning, we obtain data from 5 881 valid rural samples.

Measure

In this study, we select ‚What is the current mechanised farming method on your household farmland' in CLDS2016 as the outcome variable to portray the mechanisation choice. The mechanised tillage selection included three options: non-mechanised farming, semi-mechanised farming and fully-mechanised farming. Specifically, 34.96% of households adopted non-mechanised farming (i.e. did not employ farm machinery at any stage of production), 41.30% adopted semi-mechanised farming (i.e. employed agricultural machinery at some stages of production) and 23.74% adopted fully mechanised farming (i.e. employed agricultural machinery at each stage of production).

Our key explanatory variable is farmers' perceptions of air contamination, which originates from the response to the question, 'How serious do you think air pollution is in your area?' within the CLDS household questionnaire. Respondents chose from a four-point scale for their perceived severity, with 1 denoting 'not at all serious', 2 denoting 'not too serious', 3 denoting 'somewhat serious' and 4 denoting 'very serious'. Consequently, approximately 48.13% of the sample households believed that air pollution was not serious, whilst 51.87% believed that air pollution existed. Among those who thought air pollution existed, 37.00% thought it was 'not too serious', 11.47% thought it was 'somewhat serious' and 3.40% thought it was 'very serious'.

Based on a synthesis of existing research on mechanisation and aimed to alleviate the problem of variable omission, we further introduce control variables in the regression analysis as follows:

i) characteristics of the household head, encompassing age, education background, health status, and communist party membership,

ii) household characteristics, involving household size, average age, and household cultivated land area,

iii) village characteristics, including the presence of a non-agricultural economy, the size of village farmland, distance to the county town, availability of agricultural machinery services, availability of production materials, and availability of planting services. Their definitions and descriptive statistics are displayed in Table 1.

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Table 1. Definitions and results of descriptive statistics

Variable	Definitions	Mean (SD)
Mechanisation choice	1 = non-mechanised farming; 2 = semi-mechanised farming; 3 = fully-mechanised farming	1.99 (0.97)
Perceived air pollution	1 = not serious at all; 2 = not too serious; 3 = quite serious; 4 = very serious	1.68 (0.79)
Age	age of household head (HH) in years	51.50 (11.30)
Education level[1]	education attainment of household head	2.62 (1.15)
Health status	self-reported health status (from 1 = unhealthy to 5 = healthy)	3.54 (1.04)
Communist	1 = HH is a Communist Party member, 0 otherwise	0.08 (0.28)
Household size	number of persons living in a household	1.86 (0.90)
Mean age	mean age of the household workforce in years	47.22 (12.06)
Household cropland area	total farm size cultivated by a household (ln)	1.53 (0.97)
Non-agricultural economy	1 = non-agricultural economy exists in the village, otherwise 0	0.27 (0.44)
Village cropland area	total farm size cultivated by village (ln)	7.27 (1.63)
Location	distance of the village from the township government (km)	2.86 (0.98)
Mechanical services	1 = mechanical agricultural services are available in the village, 0 otherwise	0.26 (0.44)
Production materials	1 = the village provided production materials, 0 otherwise	0.10 (0.31)
Planting planning service	1 = the village unify procurement of production materials, 0 otherwise	0.25 (0.43)

[1]1 = illiterate, 2 = primary school, 3 = middle school, 4 = high school, 5 = vocational high school, 6 = technical school, 7 = technical secondary school, 8 = college, 9 = bachelor's degree, and 10 = postgraduate
Source: Authors' construction

Empirical strategy

An ordered probit model in Equation (1) is employed to examine the effects of air pollution perception on agricultural mechanisation.

$$AMS_i = \beta_0 + \beta_1 Pollution_i + \beta_2 X_i + \varepsilon \tag{1}$$

where: AMS_i – the agricultural mechanisation choice of household i, it is assigned a value of 1 for households adopting mechanised farming, 2 for those adopting semi-mechanised farming and 3 for those adopting fully mechanised farming; *Pollution* – the independent variable, air pollution perception, ranging from 'not serious at all' to 'very serious'; X_i – a vector of control variables containing the characteristics of individual farmers, households and villages (Yamauchi 2016; Qiu et al. 2022); β_0 – the intercept; β_1 and β_2 – the model parameters; ε – the error term.

Equation (1) introduces endogeneity concerns when directly estimating the relation between perceived air pollution and agricultural mechanisation is estimated directly. First, a potential bidirectional causality is inherent since agricultural mechanisation is accompanied by the widespread utilisation of fossil fuels and chemicals, which may contribute to deterioration of air quality (Peng et al. 2018; Khan et al. 2022). Second, there may be unobservable factors affecting perceived air pollution levels and agricultural mechanisation. To address these types of endogeneity, we construct an instrumental variable for the indicator of air pollution perception and further regress the IV-ordered probit model, whose corresponding estimation methods can be expressed by Equations (2 and 3):

$$\widehat{Pollution_i} = \gamma_0 + \gamma_1 TI_i + \gamma_2 X_i + \mu \tag{2}$$

$$AMS_i = \varphi_0 + \varphi_1 \widehat{Pollution_i} + \varphi_2 X_i + \sigma \tag{3}$$

where: $\widehat{Pollution_i}$ – the estimation result after considering the endogenous variables in Equation (2); γ_0 – intercept; γ_1 and γ_2 – model parameters; TI_i – the instrumental variable (IV); X_i – control variables; μ – error term; φ_0 – intercept; φ_1 and φ_2 – model parameters; σ – error term.

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Based on the existing body of knowledge, meteorological conditions are often employed as an IV for air pollution (Hanna and Oliva 2015; Chen et al. 2022). This approach is based on the fact that inversions exacerbate air pollution, which is well documented in natural science research. Generally, cold air sinks at high altitudes and hot air increases at the surface, a mechanism that reduces air pollution levels at the surface. However, under the circumstance of inversions, the higher the altitude, the higher the temperature, where the hot air condenses overhead and the cold air stagnates at the surface, adding to air pollution. Drawing on Arceo et al. (2016), who first proposed the IV of thermal inversion for air pollution, this study employs the thermal inversion strength as our IV. It is expected to affect perceived air pollution but not agricultural mechanisation.

RESULTS AND DISCUSSION

Table 2 depicts the impact of air pollution perception on agricultural mechanisation. The results indicate that perceived air pollution positively affects agricultural mechanisation at the 1% significance level without considering endogenous problems. The effect is significant after controlling for province fixed effects, suggesting that some province-level unobservable factors might have contributed to the underestimation of outcomes. Additionally, other factors that positively affect agricultural mechanisation include age, education level, household head health status, household farmland size, village farmland size and mechanical agricultural services. For instance, according to Table 2, education plays a positive and significant role in agricultural mechanisation. This finding aligns with the preceding analysis of Mottaleb et al. (2017), implying that education could encourage farmers to take risks associated with investment in agricultural machinery.

Robustness check

Air pollution perception is a subjective assessment of air quality by farmers, thereby objective air quality influences people's perception of air pollution (Geng et al. 2019). Therefore, in the robustness check, we examine the influence of air quality on agricultural mechanisation. Since the 2016 China Labour Force Dynamics Survey questionnaire was conducted from late July to early August 2016, the average local air quality index (AQI) of the three months (May–July) prior to the survey visit is adopted as an objective air pollution indicator. AQI is the level of air pollution in the sky. The higher the index of an area, the more serious the air pollution. The AQI, PM2.5, PM10, NO_2 and SO_2 data employed in this study stem from the Ministry of Ecology and Environment of the People's Republic of China. Then, an ordered probit model is adopted to estimate the links between AQI and agricultural mechanisation and Table 3 presents its results.

Table 2. Baseline estimations: impact of perceived air pollution on agricultural mechanisation

Variable	Ordered probit agricultural mechanisation	
Perceived air pollution	0.146*** (0.025)	0.067** (0.027)
Age	0.005** (0.003)	0.003 (0.003)
Education	0.126*** (0.020)	0.066*** (0.021)
Health status	0.162*** (0.020)	0.074*** (0.022)
Communist	0.082 (0.072)	0.076 (0.077)
Household size	0.040* (0.024)	0.023 (0.026)
Mean age	0.001 (0.002)	0.002 (0.002)
Household cropland area	0.384*** (0.027)	0.299*** (0.032)
Non-agricultural economy	–0.094* (0.053)	0.063 (0.067)
Village cropland area	0.074*** (0.022)	0.117*** (0.025)
Location	–0.162*** (0.022)	0.022 (0.027)
Mechanical services	0.166*** (0.042)	0.111** (0.050)
Planting planning service	0.035 (0.078)	–0.099 (0.095)
Production materials	–0.132*** (0.048)	–0.111* (0.059)
_cons	1.897*** (0.247)	5.319*** (0.286)
Regional effect	no	yes
Sample size	3 379	3 379

***, **, and *significance level at 0.01, 0.05 and 0.1, respectively; robust SEs are in parentheses
Source: Authors' calculation

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Table 3. Robustness check estimates

Variable	Ordered probit – agricultural mechanisation				
AQI	0.0100*** (0.0030)	–	–	–	–
PM2.5	–	0.0070** (0.0030)	–	–	–
PM10	–	–	0.0050** (0.0020)	–	–
NO_2	–	–	–	0.0090*** (0.0020)	–
SO_2	–	–	–	–	0.0040*** (0.0010)
Control	yes	yes	yes	yes	yes
Regional effect	yes	yes	yes	yes	yes
Pseudo R^2	0.1810	0.1866	0.1868	0.1910	0.1861
Sample size	3 271	3 271	3 271	3 271	3 271

*** and **significance level at 0.01 and 0.05, respectively; robust SEs are in parentheses; AQI – air quality index; PM – particulate matter
Source: Authors' calculation

According to Table 3, the AQI coefficient is significantly positive, demonstrating that AQI significantly affects agricultural mechanisation choices. Moreover, we measure air pollution further through PM2.5, PM10, NO_2 and SO_2, and the regression results remain significant. This is consistent with our argument that subjective air pollution impacts agricultural mechanisation.

Solving the problem of endogeneity

Aimed at accurately assessing the impact of perceived air pollution on agricultural mechanisation, we employ an IV approach to address endogeneity problems. Based on previous analyses, the current research utilises thermal inversion as an IV for air pollution and the empirical outcomes derived from the IV regressions are displayed in Table 4. The first-stage regression results express a significant positive correlation between the inversion IV and subjective air pollution at the 1% significance level, indicating that the instrumental variable meets the relevance condition. The second-stage Atanhrho_12 value differs significantly from zero at the 1% level, indicating a more accurate estimation of the IV-ordered probit model. In conclusion, the positive effect of perceived air pollution on agricultural mechanisation adoption remains statistically significant after eliminating endogeneity through IV.

Significant heterogeneous characterises air pollution perception, as perception results from the interaction of individual and environmental factors with objective air pollution levels. Thus, delving into the mechanism and heterogeneity is gaining significance in boosting labour supply, facilitating agricultural mechanisation and advancing sustainable agricultural development.

Mechanism analysis

Although the above analysis shows that perceived air pollution can affect agricultural mechanisation, its mechanisms require further analysis. There is an enduring and rising concern among the public regarding air pollution and people alter their tendencies and behaviour in response to it (Tu et al. 2020). Many scholars have argued that air pollution reduces the time that family farmers spend on agricultural production (Gu et al. 2020; Huang et al. 2021). Furthermore, farmers replace labour with machinery (Qian et al. 2022). To further explore how perceptions of air pollution influence agricultural mechanisation, this paper adopts the total farming time of farm households in the year as a mediating variable. We then apply stepwise regression and the Sobel test to analyse the mediation effect. Table 5 indicates that the mediating effect is significant. Additionally, for every one-level increase

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Table 4. Instrumental variable regressions

Variable	IV-ordered probit	
	First stage	Second stage
Perceived air pollution	0.006*** (0.001)	0.912*** (0.180)
Age	–0.001 (0.001)	–0.005** (0.002)
Education	0.029*** (0.009)	–0.074*** (0.028)
Health status	–0.032***(0.010)	–0.154*** (0.023)
Communist	0.027 (0.037)	–0.049 (0.068)
Household size	0.017 (0.012)	–0.022 (0.023)
Mean age	–0.003*** (0.001)	–0.003 (0.002)
Household cropland area	–0.077*** (0.012)	–0.348*** (0.044)
Non-agricultural economy	0.289*** (0.024)	0.310*** (0.062)
Village cropland area	0.024*** (0.007)	–0.044* (0.026)
Location	–0.065*** (0.011)	0.061 (0.040)
Mechanical services	0.122*** (0.023)	–0.070 (0.064)
Production materials	–0.096*** (0.035)	–0.119 (0.076)
Planting planning service	–0.162*** (0.024)	–0.030 (0.067)
Atanhrho_12	–0.696*** (0.232)	–
Wald chi^2	1 990.38***	–
Sample size	5 881	–

***, **, and *significance level at 0.01, 0.05 and 0.1, respectively; robust SEs are in parentheses; IV – instrumental variable
Source: Authors' calculation

Table 5. Results of the mediating effect

Variable	Ordered probit agricultural mechanisation	OLS farming time	Ordered probit agricultural mechanisation
Perceived air pollution	0.150*** (0.028)	–6.828* (4.102)	0.134*** (0.031)
Farming time	–	–	–0.001*** (0.000)
Control	yes	yes	yes
Constant	–	92.116*** (33.035)	–
Pseudo R^2	0.181 0	0.339 6	0.193 0
Sample size	2 828	3 760	2 265
Sobel test	0.007***	–	–

*** and *significance level at 0.01 and 0.1, respectively; robust SEs are in parentheses; OLS – ordinary least squares
Source: Authors' calculation

in perceived air pollution, farmers' farming time decreases by 6.83 days. This finding demonstrates that perceived air pollution affects farmers' decisions regarding agricultural mechanisation by reducing the agricultural labour supply.

Robustness tests

In rural areas of China, men migrate in pursuit of higher incomes, while women stay at home to engage in agricultural and domestic labour (Ma et al. 2018). When affected by air pollution, male heads of households may reduce agricultural labour supply and be more inclined to leave for off-farm employment. Consequently, the role that air pollution plays in agricultural mechanisation is expected to be more significant for male-headed households than for female-headed households. Therefore, we disaggregate the influence of air pollution perception on agricultural mechanisation by gender, and the results in Table 6 align with our expectations.

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Table 6. Disaggregated analysis by gender and terrain

Variable	Gender		Terrain	
	male	female	non-plain	plain
Perceived air pollution	0.1410*** (0.0280)	0.1020 (0.0760)	0.0720 (0.0530)	0.1440*** (0.0290)
Control	yes	yes	yes	yes
Pseudo R^2	0.1784	0.1859	0.2033	0.1541
Sample size	2 940	439	883	2 409

***significance level at 0.01; robust SEs are in parentheses
Source: Authors' calculation

Furthermore, the agricultural mechanisation strategy could be influenced by the topography of agricultural land, with plain land being more conducive to agricultural mechanisation, as has been recognised by many scholars (Deng et al. 2019; Aryal et al. 2021; Brown et al. 2021). Farmers in plains have more potential to use machinery as an alternative to agricultural labour when affected by air pollution. The consequences reveal the effect of air pollution perception on agricultural mechanisation is heterogeneous across land types.

CONCLUSION

Although prior literature has examined the factors influencing agricultural mechanisation, there remains a significant gap concerning the influence of air pollution perception on agricultural mechanisation. Our findings demonstrate that farmers' perceptions of air pollution affect their agricultural production decisions, particularly the adoption of agricultural machinery. Specifically, perceived air pollution significantly reduces household farming time whilst positively impacts agricultural mechanisation. This phenomenon may be attributed to air pollution potentially causing adverse health effects among farmers, directly diminishing labour efficiency and compelling farmers to curtail effective farming time to preserve their health. Consequently, this reduction in farming time may generate demand for mechanisation as a substitute for human labour. For instance, the utilisation of seeders and harvesters can compensate for labour input deficiencies by expeditiously completing tasks that would otherwise require prolonged human effort. Regarding key control variables, household and village cultivated area exhibits a positive impact on agricultural mechanisation adoption. This correlation may exist because the expansion of household and village cultivated land directly contributes to the dissemination and enhancement of agricultural mechanisation through mechanisms of large-scale production, infrastructure optimisation, and labour substitution. Furthermore, heterogeneity analysis reveals that the agricultural mechanisation decisions of male household heads and farmers in plains regions are more significantly affected by air pollution perceptions.

Furthermore, these findings yield valuable policy implications for farmers chronically exposed to air pollution and for agricultural mechanisation advancement in China. Notably, air pollution, due to its direct adverse effects on health, may result in diminished availability of labour force or working hours. This underscores the necessity of improving air quality in China to enhance agricultural labour supply. Our research offers new directions for future research in this domain. The ramifications of air pollution warrant increased attention, and mitigation measures require further reinforcement. Moreover, within the context of continuing large-scale migration of rural labour in China, agricultural machinery services function as a primary mechanism for addressing agricultural labour migration. Concomitantly, the environmental implications, including energy consumption and resultant air pollution generated by agricultural machinery, must be integrated into comprehensive strategies for agricultural mechanisation development.

Considering air pollution's impact on agricultural mechanisation, we propose a two-pronged policy approach. First, governmental bodies should prioritise the promotion of agricultural machinery services, particularly in plains regions. Robust machinery service provision would not only accommodate labour migration but also accelerate agricultural mechanisation processes. When integrated with conservation agriculture practices, this approach could substantially reduce agriculture's environmental footprint, ultimately facilitating sustainable agricultural development. Second, authorities must address the environmental

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consequences stemming from agricultural machinery proliferation. Governmental initiatives should actively facilitate the phased withdrawal of obsolete, energy-intensive and polluting equipment, whilst implementing comprehensive training programmes encompassing various agricultural operation competencies, including instruction in contemporary intelligent machinery. Such measures would simultaneously minimise energy expenditure and environmental degradation, whilst enhancing operational efficiency.

REFERENCES

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.

Aryal J.P., Rahut D.B., Thapa G., Simtowe F. (2021): Mechanisation of small-scale farms in South Asia: Empirical evidence derived from farm households survey. Technology in Society, 65: 101591.

Bala R., Singh S., Sharma K.K. (2023): Relationship between environmental knowledge, environmental sensitivity, environmental attitude and environmental behavioural intention – A segmented mediation approach. Management of Environmental Quality: An International Journal, 34: 119–136.

Belton B., Win M.T., Zhang X., Filipski M. (2021): The rapid rise of agricultural mechanization in Myanmar. Food Policy, 101: 102095.

Brown B., Paudel G.P., Krupnik T.J. (2021): Visualising adoption processes through a stepwise framework: A case study of mechanisation on the Nepal Terai. Agricultural Systems, 192: 103200.

Carrasco-Escobar G., Schwarz L., Miranda J.J., Benmarhnia T. (2020): Revealing the air pollution burden associated with internal migration in Peru. Scientific Reports, 10: 7147.

Center for Social Science Survey, Sun Yat-sen University (2017): China Labour Force Dynamics Survey 2016. [Dataset]. Guangzhou, Center for Social Science Survey, Sun Yat-sen University. Available at https://www.researchgate.net/publication/320633732_China_Labor-force_Dynamics_Survey_Design_and_practice (accessed Oct 2, 2023).

Chen S., Oliva P., Zhang P. (2022): The effect of air pollution on migration: Evidence from China. Journal of Development Economics, 156: 102833.

Chiarini B., D'Agostino A., Marzano E., Regoli A. (2020): The perception of air pollution and noise in urban environments: A subjective indicator across European countries. Journal of Environmental Management, 263: 110272.

Daum T., Birner R. (2020): Agricultural mechanization in Africa: Myths, realities and an emerging research agenda. Global Food Security, 26: 100393.

Deng X., Xu D., Zeng M., Qi Y. (2019): Does Internet use help reduce rural cropland abandonment? Evidence from China. Land Use Policy, 89: 104243.

Deschenes O., Wang H., Wang S., Zhang P. (2020): The effect of air pollution on body weight and obesity: Evidence from China. Journal of Development Economics, 145: 102461.

Geng L., Wu Z., Zhang S., Zhou K. (2019): The end effect in air pollution: The role of perceived difference. Journal of Environmental Management, 232: 413–420.

Gu H., Bian F., Elahi E. (2020): Effect of air pollution on female labor supply: An empirical analysis based on data of labor force dynamic survey of China. Social Work in Public Health, 35: 187–196.

Hanlon W.W. (2020): Coal smoke, city growth, and the costs of the industrial revolution. The Economic Journal, 130: 462–488.

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 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.

Heck W.W., Taylor O.C., Tingey D.T. (1988): Assessment of crop loss from air pollutants. Dordrecht, Springer: 65–138.

Huang Q., Zhang Y.Y., Chen Q., Ning M. (2021): Does air pollution decrease labor supply of the rural middle-aged and elderly? Sustainability, 13: 2906.

Hull E. (2014): The social dynamics of labor shortage in South African small-scale agriculture. World Development, 59: 451–460.

Jayne T.S., Mather D., Mghenyi E. (2010): Principal challenges confronting smallholder agriculture in Sub-Saharan Africa. World Development, 38: 1384–1398.

Jiao L., Luo F., Wu F., Zhang Y., Huo X., Wu Y. (2022): Can the opening of urban rail transit improve urban air quality? Evidence from 94 lines in China. Environmental Impact Assessment Review, 97: 106857.

Khan Z.A., Koondhar M.A., Tiantong M., Khan A., Nurgazina Z., Tianjun L., Fengwang M. (2022): Do chemical fertilizers, area under greenhouses, and renewable energies drive agricultural economic growth owing the targets of carbon neutrality in China? Energy Economics, 115: 106397.

Himanshu, Kundu S. (2016): Rural wages in India: Recent trends and determinants. The Indian Journal of Labour Economics, 59: 217–244.

https://doi.org/10.17221/328/2024-AGRICECON

Li D., Zhang Y., Ma S. (2017): Would smog lead to outflow of labor force? Empirical evidence from China. Emerging Markets Finance and Trade, 53: 1122–1134.

Li X., Li Y. (2022): The impact of perceived air pollution on labour supply: Evidence from China. Journal of Environmental Management, 306: 114455.

Liao P., Shaw D., Lin Y. (2015): Environmental quality and life satisfaction: Subjective versus objective measures of air quality. Social Indicators Research, 124: 599–616

Liu J., Jin X., Xu W., Sun R., Han B., Yang X., Gu Z., Xu C., Sui X., Zhou Y. (2019): Influential factors and classification of cultivated land fragmentation, and implications for future land consolidation: A case study of Jiangsu Province in eastern China. Land Use Policy, 88: 104185.

Ma G., Wang J., Yu F., Guo X., Zhang Y., Li C. (2016): Assessing the premature death due to ambient particulate matter in China's urban areas from 2004 to 2013. Frontiers of Environmental Science & Engineering, 10: 7.

Ma W., Renwick A., Grafton Q. (2018): Farm machinery use, off-farm employment and farm performance in China. The Australian Journal of Agricultural Resource Economics, 62: 279–298.

Martin P.L., Olmstead A.L. (1985): The agricultural mechanization controversy. Science, 227: 601–606.

Mottaleb K.A., Rahut D.B., Ali A., Gérard B., Erenstein O. (2017): Enhancing smallholder access to agricultural machinery services: Lessons from Bangladesh. Journal of Development Studies, 53: 1502–1517.

Ostro B.D. (1983): The effects of air pollution on work loss and morbidity. Journal of Environmental Economics and Management, 10: 371–382.

Peng J., Zhang Y., Xie R., Liu Y. (2018): Analysis of driving factors on China's air pollution emissions from the view of critical supply chains. Journal of Cleaner Production, 203: 197–209.

Qian L., Lu H., Gao Q., Lu H. (2022): Household-owned farm machinery vs. outsourced machinery services: The impact of agricultural mechanization on the land leasing behavior of relatively large-scale farmers in China. Land Use Policy, 115: 106008.

Tu M., Zhang B., Xu J., Lu F. (2020): Mass media, information and demand for environmental quality: Evidence from the 'Under the Dome'. Journal of Development Economics, 143: 102402.

Yamauchi F. (2016): Rising real wages, mechanization and growing advantage of large farms: Evidence from Indonesia. Food Policy, 58: 62–69.

Wei W., Wang Z. (2021): Impact of industrial air pollution on agricultural production. Atmosphere, 12: 639.

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

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