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# Climate change mitigation policy and human health: Evidence from the forest farm carbon sink projects in China

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## ABSTRACT

Forest Farm Carbon Sink Projects (FFCSPs) represent a promising strategy for mitigating global climate change and improving public health. While the direct effects of such projects on carbon sequestration and participants' income are well researched, the potential co-benefits of FFCSPs on human health remain underexplored. The study bridges this research gap by examining the causal effect of FFCSPs on human health, measured through healthcare costs and the number of physician visits. Based on a panel dataset covering 140 counties in Sichuan, China, from 2002 to 2018, we employ Propensity Score Matching and Difference-in-Differences (PSM-DID) to mitigate potential endogeneity concerns. Our findings show that FFCSPs can significantly reduce healthcare costs by approximately 12.8% and decrease the number of physician visits by 0.31 times per resident per year. These health benefits primarily result from improvements in socioeconomic and ecological conditions, such as industrial upgrading, economic gains through income growth, and better air quality. Notably, these benefits are observed only in international projects and are absent in domestic initiatives. This study highlights the dual benefits of FFCSPs, showing that policies promoting these projects can simultaneously improve public health and achieve environmental goals. To fully realize these benefits, effective implementation methods, clear enforcement standards, effective regulation, and well-functioning carbon trading platforms are essential.

## 1. Introduction

Climate change negatively affects human health through both direct and indirect pathways (Kim et al., 2014; Patz and Olson, 2006; Wang et al., 2024; Murage et al., 2025). Extreme weather events such as heatwaves, cyclones, and droughts have been associated with increased mortality and the incidence of cardiovascular and respiratory diseases (Geiger et al., 2021; Sweileh, 2020). Rising temperatures can also worsen ambient air quality by elevating ozone levels and fine particulate matter concentrations (PM<sub>10</sub> and PM<sub>2.5</sub>), thereby increasing cardiopulmonary risks (Nowak et al., 2014). In addition, climate change can accelerate the spread of infectious diseases, including malaria in South America and Africa, and dengue fever in Southeast Asia (Tanser et al., 2003; Carlson et al., 2023). Beyond these adverse impacts, a growing body of research suggests that climate change mitigation policies may generate substantial ancillary health benefits by improving environmental quality and reducing pollution exposure. For instance, greenhouse gas mitigation has been estimated to prevent more than 10,000

premature deaths annually in the United States by 2050 through improved air quality, translating into significant economic gains (Fernando et al., 2015). This suggests that mitigation policies may simultaneously advance climate and public health objectives.

Forest-based climate mitigation actions have become an increasingly important component of national and global responses to climate change (Fan et al., 2024; Zhao et al., 2023). Over the past two decades, these initiatives have evolved from project-based afforestation and reforestation activities introduced under the Kyoto Protocol into a broader set of policy instruments aimed at enhancing carbon sequestration through forest conservation, restoration, and sustainable land-use management (Yin, 2024; Zhao et al., 2025). Following the Paris Agreement, such actions have been progressively integrated into national climate governance frameworks through mechanisms including jurisdictional REDD+ (Reducing Emissions from Deforestation and Forest Degradation) programs, ecosystem restoration initiatives, and carbon offset schemes supported by results-based payment (RBP) arrangements (Ke et al., 2023; Zhao et al., 2023; Zhu et al., 2025). As

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countries seek cost-effective mitigation options that can be implemented alongside development objectives, forest-based climate initiatives are being implemented at an accelerating pace across developing countries, including China, India, Brazil, and Ethiopia, as part of their nationally determined contributions (NDCs) (Yin, 2024; Zhao et al., 2025). In China, these mitigation efforts are operationalized through Forest Farm Carbon Sink Projects (FFCSPs), which are implemented under both international mechanisms such as the Clean Development Mechanism (CDM) and Verified Carbon Standard (VCS) as well as domestically funded offset programs including the China Certified Emission Reduction (CCER) scheme (Hu et al., 2023; Liu et al., 2023).

Despite their rapid expansion, empirical evidence on the broader welfare impacts of forest-based climate mitigation initiatives remains limited (Calderon et al., 2025). Existing impact evaluations have primarily focused on environmental outcomes such as carbon sequestration and emissions reductions (Ke et al., 2023; Zhu et al., 2025), as well as economic indicators including project income and livelihood changes among participating households (Hu et al., 2023; Smith and Scherr, 2003). However, these initiatives may also generate various indirect social benefits by improving environmental quality and reshaping local socioeconomic conditions, both of which are closely linked to local residents' health conditions (Liu et al., 2023). In particular, improvements in air quality, changes in land use, and shifts in income sources induced by forest carbon programs may influence healthcare utilization and health-related expenditures at the local level (Baumgardner et al., 2012). Yet, the potential public health effects of such mitigation actions have received comparatively little attention in the empirical literature, especially in the context of projects operating under diverse governance and financing arrangements, including results-based payment mechanisms (Lan and Yin, 2017; Zhao et al., 2025). A systematic evaluation of these broader impacts is therefore essential for assessing the overall effectiveness of forest sector climate mitigation policies.

This study aims to investigate the potential and dynamic effects of FFCSPs on local residents' health and to identify the underlying mechanisms, including both ecological and economic pathways. Using a balanced panel dataset covering 140 counties in Sichuan Province, China, from 2002 to 2018, we employ a quasi-experimental approach that combines propensity score matching with a difference-in-differences (PSM-DID) design to estimate the causal impacts of project implementation on local health outcomes. This empirical strategy accounts for the potential non-random selection of counties into FFCSP implementation, as project placement may be more likely in areas with greater forest resources or stronger administrative capacity. By combining matching with a difference-in-differences framework, we can mitigate selection bias and identify the causal effects of project implementation on local health outcomes (Zhao et al., 2025). By linking forest-based mitigation policies to population health indicators, this study provides new empirical evidence on how climate mitigation interventions may influence health through environmental improvement and local economic transformation.

This study contributes to the existing literature mainly in three ways. First, by assessing the human health impacts of FFCSPs, it moves beyond the environmental and economic outcomes that have dominated existing evaluations and extends the scope of impact assessments of forest-based climate mitigation policies to include broader social welfare dimensions. Second, by employing a quasi-experimental approach, this study provides new causal evidence on the public health co-benefits of climate mitigation interventions in a developing-country context, where empirical evaluations of forest carbon programs remain limited. Third, although the empirical analysis focuses on China, the findings may offer relevant insights for other developing countries such as India, Brazil, and Ethiopia, where similar carbon sink policies have been implemented under comparable levels of economic development and development conditions (Lan and Yin, 2017; Yin, 2024). These findings can inform researchers and policymakers on how forest-based mitigation programs may be designed and implemented to advance climate and public health

objectives by improving local environmental and socioeconomic conditions.

## 2. Theoretical framework

As noted above, the potential health impacts of forest-based climate mitigation initiatives have become increasingly relevant as such programs continue to expand across developing countries under diverse governance arrangements. These broader welfare effects are expected to arise through a set of ecological and socioeconomic pathways associated with project implementation (Liu et al., 2023; Zhao et al., 2023). In the context of this study, FFCSPs may not only contribute to climate change mitigation but also generate meaningful public health co-benefits through environmental improvement, behavioral changes, and structural economic adjustments.

From an ecological perspective, these programs can improve local health through several interconnected pathways. First, expanding forest cover can enhance air quality by trapping particulate matter on leaf surfaces and absorbing gaseous pollutants through stomata, thereby lowering residents' exposure to harmful ambient pollution (Murage et al., 2025). Second, increased forest cover can regulate local microclimates by providing shade and evapotranspiration cooling, thereby reducing heat exposure and related morbidity and mortality risks—an increasingly important benefit in regions facing more frequent and intense heat extremes under climate change (Wu et al., 2025). Third, forest restoration may strengthen biodiversity and ecosystem resilience, improving ecosystem stability and reducing vulnerability to environmental disturbances such as floods, soil erosion, and droughts, which, in turn, can affect health by damaging livelihoods, food security, and living conditions (Seddon et al., 2020). Finally, healthier and more diverse ecosystems may lower the risk of pathogen transmission by limiting habitat disruption and buffering human–wildlife interactions, thereby reducing exposure to infectious disease risks and other ecological health threats (Keesing and Ostfeld, 2021).

FFCSPs may also shape health outcomes by improving the living environment and enhancing everyday well-being. Greater access to green spaces can increase opportunities for contact with nature, which has been widely associated with reduced psychological stress, lower levels of anxiety and depression, and improved overall mental health (Gascon et al., 2015). In addition, greener surroundings may promote healthier lifestyles by encouraging outdoor recreation and physical activity, strengthening social interaction, and improving well-being and life satisfaction, particularly in counties where public health resources are often limited. Beyond these direct ecological and behavioral pathways, FFCSPs may also influence health indirectly by reshaping local economic structures. Compared with the primary and secondary industries, the service industry typically generates lower environmental pressures while offering higher, more stable income opportunities. This pattern is especially pronounced in developing countries (Wang et al., 2023). By prioritizing conservation goals and restricting resource-intensive forestry and extractive activities, forest protection and sustainable development initiatives may accelerate rural labor reallocation toward non-agricultural employment, thereby supporting industrial upgrading (Liu et al., 2023). Such structural shifts can improve health through multiple mechanisms, including cleaner production and reduced pollution exposure, rising household incomes that ease budget constraints for healthcare and nutrition, and more resilient livelihoods that help households better withstand economic and environmental shocks (Xu et al., 2020).

From an economic perspective, however, the health implications of FFCSPs may be more ambiguous, as potential gains can coexist with unintended costs. On the positive side, afforestation and forest management activities associated with these programs can create employment opportunities for local residents, including tree planting, seedling cultivation and maintenance, forest patrol and protection, and replanting when necessary (Liu et al., 2023). These jobs may increase

household income, reduce underemployment in rural areas, and improve material living conditions, thereby supporting health through better nutrition, improved housing, and greater affordability of health-care services (Fan et al., 2024). In addition, participants may benefit from new revenue streams linked to carbon sequestration, such as income from carbon credit sales in emerging carbon trading markets. Survey evidence indicates that during the project period, participants earned an average monthly income of approximately CNY 1500–2500 (about USD 236–393) (Hu et al., 2023; Lu et al., 2018), suggesting that FFCSPs can provide a meaningful income supplement in many low-income settings.

At the same time, potential downsides should not be overlooked. Limited incentives, unclear land-use rights, and weak monitoring may create perverse incentives for households or local governments to convert high-quality farmland into carbon forests, thereby reducing cultivated land area and potentially undermining grain production and local food security (Murage et al., 2025). Such land-use trade-offs are particularly concerning in regions where agricultural livelihoods remain dominant and where households have limited capacity to buffer production shocks. Moreover, because many FFCSPs prioritize carbon sequestration targets, they often impose restrictions on income-generating land uses and forest-based activities. In practice, this can constrain traditional livelihood strategies such as grazing, fuelwood collection, and the cultivation or harvesting of understory products (e.g., fruits, mushrooms, and medicinal herbs), reducing household flexibility and weakening local income sources (Smith and Scherr, 2003). Finally, although FFCSPs may accelerate the reallocation of agricultural labor toward secondary and tertiary industries, local labor markets may not always be able to absorb displaced workers (Fan et al., 2024; Liu et al., 2023). Where off-farm employment opportunities are scarce or unstable, households may face income losses or more precarious work conditions, which can translate into adverse health impacts through tighter budget constraints, poorer nutrition, delayed healthcare seeking, and heightened psychological stress. The theoretical framework is presented in Fig. 1.

### 3. Methods and data

#### 3.1. Difference-in-differences model

We employ a difference-in-differences (DID) model to estimate the average treatment effect of FFCSPs on residents' health. The DID approach, which has been widely applied in policy evaluation, public health, and environmental economics to assess the causal effects of place-based interventions (Lan and Yin, 2017; Liu et al., 2023), is

particularly suitable in this context because the implementation of FFCSPs is likely to follow a non-random pattern across counties, potentially introducing selection bias in cross-sectional comparisons (Fan et al., 2024; Hu et al., 2023). In such contexts, quasi-experimental approaches are commonly adopted to identify the causal impacts of forest carbon projects and related land-use policies (Lan and Yin, 2017). In particular, a growing body of impact evaluation studies integrates administrative socio-economic statistics with remotely sensed environmental indicators to construct spatial panel datasets and applies DID frameworks to account for time-invariant heterogeneity and policy selection bias in program implementation (Lan and Yin, 2017; Yin, 2024). Following this empirical strategy, we compare changes in health outcomes between treatment and control counties before and after policy implementation, thereby controlling for both common time trends and fixed group differences. A key identifying assumption of the DID approach is that, in the absence of the intervention, the treatment and control groups would have followed parallel trends over time. This assumption is assessed empirically using an event-study specification in the subsequent analysis. Therefore, the baseline model is set as follows:

$$Health_{it} = \beta_0 + \beta_1 P_{it} + \beta_2 C_{it} + \beta_3 T_{it} + \gamma I_{it} + \varepsilon_{it} \quad (1)$$

In Eq. (1),  $Health_{it}$  is the average health level of the residents in county  $i$ -th during year  $t$ .  $P_{it}$  is FFCSPs, which equals 1 if the county  $i$  conducted FFCSPs, and equals 0 if otherwise.  $\beta_1$  is the average treatment effect of the FFCSPs on the health of local residents.  $C_{it}$  denotes several control variables, including GDP, population, fixed assets, financial indicators, industrial output, and hospital bed capacity.  $T_{it}$  and  $I_{it}$  represent the time and individual fixed effects, respectively.  $\varepsilon_{it}$  denotes the random error term.

To assess the dynamic health effects of FFCSPs, we incorporate a number of dummy variables in the baseline regression model, as recommended by Liu et al. (2023) and Yin (2024). This method allows for examining the year-by-year impact of FFCSPs on residents' health. The extended model is set as Eq. (2):

$$Health_{it} = \beta_0 + \beta_1 P_{it}^{-10} + \dots + \beta_{20} P_{it}^{10} + \beta_{21} C_{it} + \beta_{22} T_{it} + \gamma I_{it} + \varepsilon_{it} \quad (2)$$

Where the FFCSPs variables are dummy variables, the “ $P$ s”, equal 0, except as follows:  $P_{it}^{-k}$  is 1 if county  $i$  is in the  $k$  years prior to implementation, while  $P_{it}^{+k}$  equals 1 if county  $i$  is in the  $k$  years after implementation. We excluded the implementation year to measure the dynamic impact of FFCSPs on local residents' health in comparison to the baseline year.  $C_{it}$ ,  $T_{it}$ , and  $I_{it}$  are the same as in Eq. (1).  $\varepsilon_{it}$  is the random error term.

This study also aims to identify the mechanisms by which FFCSPs affect residents' health. Here, we set the function as Eq. (3),  $D_{it}$

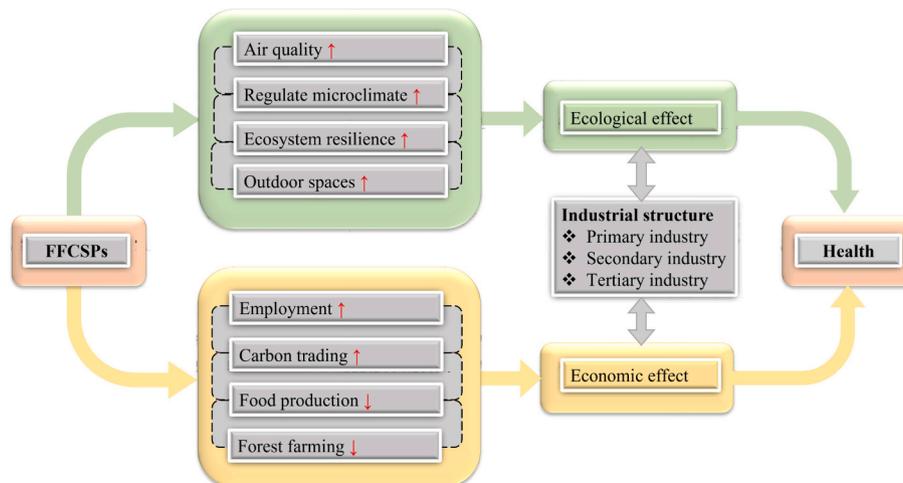


Fig. 1. The theoretical framework: how FFCSPs can benefit public health.

represents the channel variables, including natural environment changes, savings, and industrial structure.  $PM_{2.5}$  levels and  $CO_2$  emissions serve as indicators of environmental change, while the shares of the primary, secondary, and tertiary industries in GDP serve as proxies for the industrial structure. The coefficient  $\beta_1$  is the net effect of FFCSPs on channel variables.

$$D_{it} = \beta_0 + \beta_1 P_i + \beta_2 C_i + \beta_3 T_{it} + \gamma I_{it} + e_{it} \quad (3)$$

In this case, the FFCSPs may be more likely to be selected in counties rich in natural forest resources. Thus, the selection of FFCSPs may follow a non-random pattern, potentially introducing bias and inconsistencies in the estimated results. To address this sample selection issue, we use the PSM method to identify and match counties in the control group with those in the treatment group. By combining PSM and DID, we can effectively measure the net impact of FFCSPs on local residents' health.

### 3.2. Variables and data

This balanced county-level panel covers 140 counties in Sichuan Province, China, from 2002 to 2018, including 13 treated counties that implemented FFCSPs and 127 counties without FFCSPs implemented as the untreated group. County-level data offer broad population coverage and consistent long-term tracking, making them well-suited for evaluating place-based policies such as FFCSPs. However, compared with household data, these data are aggregated and may mask within-county heterogeneity, and they do not capture individual health status as directly as household survey data.

We use two variables to assess residents' health: the per capita healthcare costs and the average number of physician visits per person. These two variables are also widely used in health economics and preventive medicine studies (Chen et al., 2013; Feng et al., 2020). The policy variable is whether the county implements the FFCSPs. This dummy variable is 1 if the county implements FFCSPs; otherwise, it is 0. Additionally, we extracted the project's start year from the project documents. Fig. 2 shows that the health variables in the control and treatment groups display similar trends. Although both  $Health_1$  and  $Health_2$  increase over time, the changes are more pronounced in the control group than in the treatment group.

We consider three influence channels: natural environment change, savings, and industrial structure. Environmental improvement has a direct positive effect on health. Therefore, we use  $PM_{2.5}$  and  $CO_2$  levels as proxy variables for the natural environment. Savings serve as a proxy for income, as higher income facilitates better access to medical resources and services, thereby positively influencing health. Since the industrial structure affects both the environment and income, we also examine the impact of FFCSPs on the GDP shares of the primary, secondary, and tertiary industries. The control variables include two categories. First, we include the number of hospital beds to proxy for the availability of medical services at the county level. Second, we control for a set of county-level socioeconomic characteristics that may affect health outcomes and capture local development conditions, including GDP, fixed-asset investment, financial institutions' loans, population density, and industrial scale. These variables help account for alternative explanations and reduce omitted-variable bias in the estimated effects of the FFCSPs. Specifically, GDP captures overall economic development, which affects baseline health conditions and local capacity to promote and maintain carbon sink projects (Fan et al., 2024). Fixed-asset investment reflects the intensity of infrastructure and development, which may influence environmental conditions and public health (Lu et al., 2018). Loans of financial institutions proxy local financial development and credit access, which can shape households' livelihood choices and the feasibility of project participation (Liu et al., 2023). Population density measures population concentration and potential exposure to pollution and disease risks, while industrial scale captures the extent of industrial activity that may affect pollution emissions and health burdens in project areas (Hu et al., 2023; Liu et al.,

2023). The definitions of the main variables and their descriptive statistics are summarized in Appendix 1.

All the data are publicly available. Specifically, the dependent variables are taken from the Sichuan Health Statistical Yearbook and the Sichuan Statistical Yearbook. The policy variable FFCSPs is collected and organized based on the three official websites of forest carbon sink projects.<sup>1</sup> The annual  $PM_{2.5}$  grid data are sourced from the V6.GL.01 product of the Atmospheric Composition Analysis Group's Global dataset (ACAG, <https://sites.wustl.edu/acag/datasets/surface-pm2-5/>). This dataset integrates aerosol optical depth (AOD) data from NASA's MODIS, MISR, and SeaWiFS with the GEOS-Chem chemical transport model to estimate global annual surface levels of fine particulate matter ( $PM_{2.5}$ ). Here, we use China's administrative boundary map at the county level to match ACAG data and obtain the average  $PM_{2.5}$  levels for each county. Specifically, the ACAG  $PM_{2.5}$  product is provided as annual gridded data at a spatial resolution of  $0.01^\circ \times 0.01^\circ$ . We overlay the  $PM_{2.5}$  raster with county boundary shapefiles and compute the county-level annual average using zonal statistics. For each county and year, the  $PM_{2.5}$  measure is calculated as the mean of all grid cells whose centroids fall within the county boundary, yielding a county-year panel dataset consistent with our administrative units. The  $CO_2$  emission values are from the Database for Global Atmospheric Research (EDGAR, <https://edgar.jrc.ec.europa.eu/>), which provides gridded  $CO_2$  emissions at a spatial resolution of  $0.1^\circ \times 0.1^\circ$ . Using the same spatial matching procedure as for  $PM_{2.5}$ , we aggregate the gridded  $CO_2$  data to the county year level. The variables Saving, First, Second, and Third are all drawn from the China County Statistical Yearbook. Missing values were supplemented using data from the Sichuan Statistical Yearbook.

Two main reasons support the choice of Sichuan Province as the study site. First, Sichuan is rich in forest resources, serving as a critical natural carbon pool in China and globally. It has all the main types of FFCSPs, spanning 13 counties and covering a population of 2.72 million. Second, Sichuan is the only province in China with comprehensive county-level healthcare data available since 2000, whereas other provinces generally provide only provincial or municipal-level data. The spatial distribution of FFCSPs in Sichuan Province is presented in Fig. 3.

## 4. Results

### 4.1. The benchmark results

Fig. 4 reports the benchmark estimates of the effects of FFCSPs on local residents' health. We implement three specifications to examine the impacts of FFCSPs. We first estimate a baseline DID model with individual and time fixed effects. We then add a set of socio-economic controls to account for time-varying local characteristics. Finally, to further address potential selection bias in program participation, we apply a PSM-DID approach and re-estimate the average treatment effect. The reliability of our results is supported by the parallel trends test and by the PSM procedure achieving good covariate balance. Detailed evidence for these checks is provided in Appendix 2 and Appendix 3. In addition, since the policy dummy variable captures only limited information, we use the area of FFCSPs as an alternative treatment measure and re-estimate the model in Appendix 4. The results consistently confirm that our findings are reliable and robust.

Across all specifications, the estimated coefficient on the FFCSP indicator is negative and statistically significant, implying that the introduction of FFCSPs is associated with measurable improvements in health outcomes. In economic terms, the implementation of FFCSPs reduces physician visits by approximately 0.313–0.442 times and lowers

<sup>1</sup> All detailed information about the FFCSPs can be downloaded as follows: CCER: <http://cdm.cchina.org.cn/>, VCS: <https://registry.verra.org/app/search/VCS/All%20Projects>, CDM: <https://cdm.unfccc.int/Projects/projsearch.html>, access on 20, June, 2023.

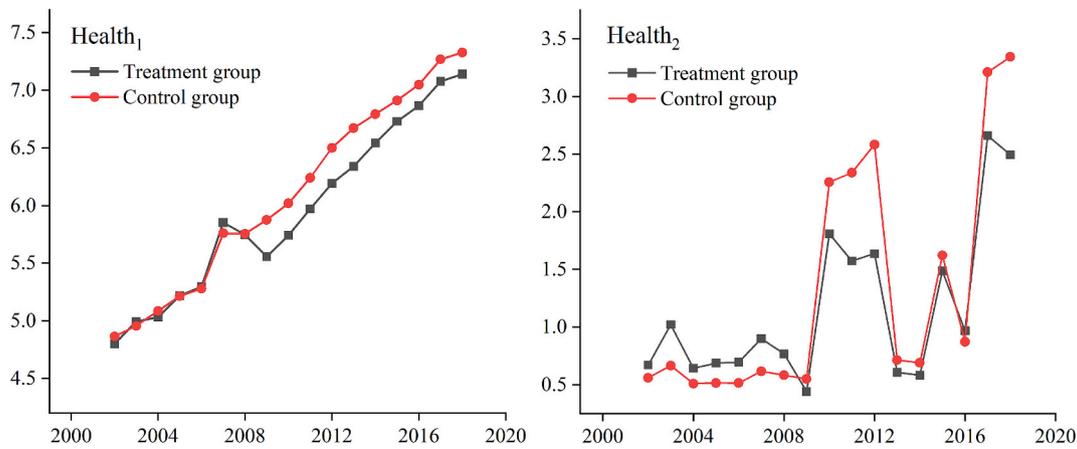


Fig. 2. Trends in health outcomes for treated and control counties. Notes: Health<sub>1</sub> is the logarithm of per capita healthcare costs (CNY); Health<sub>2</sub> is the average number of physician visits per person.

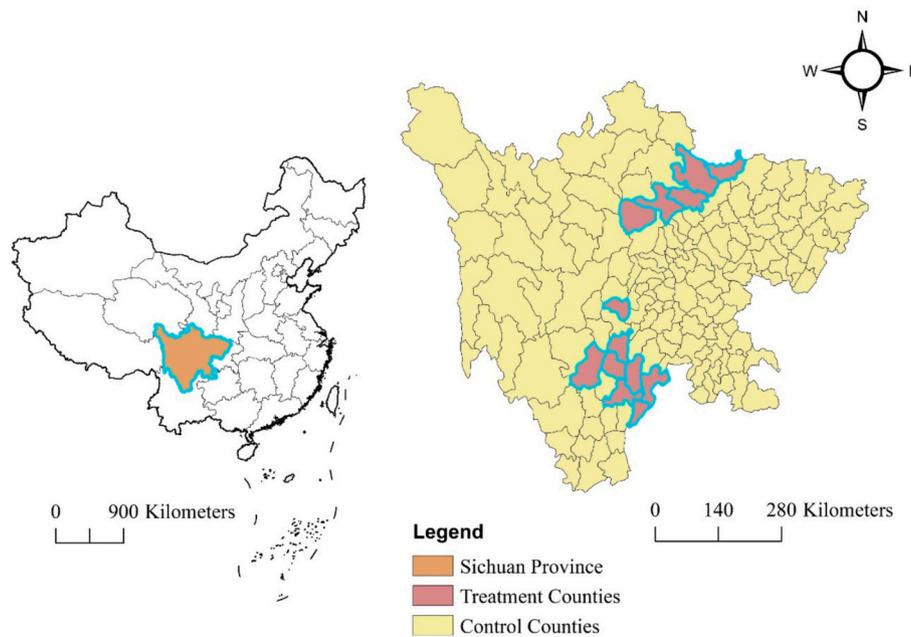


Fig. 3. The spatial distribution of FFCSPs. Source: Calculated by the authors using the gathered data.

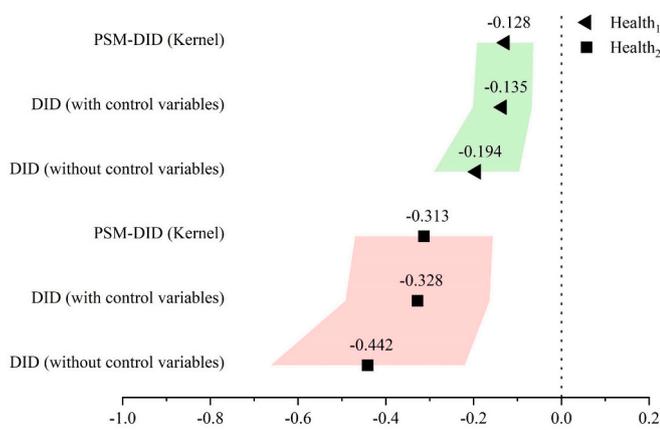
healthcare expenditures by about 12.8%–19.4%. These effects are not only statistically meaningful but also economically relevant, as they reflect a tangible reduction in medical service utilization and out-of-pocket health costs for residents in project areas. Notably, the PSM-DID estimates are smaller in absolute value than those from the conventional DID models, suggesting that failing to account for non-random program placement may overstate the health gains from FFCSPs. This evidence helps inform the broader evaluation of forest-based mitigation instruments in China, where achieving the “Dual Carbon” goals (i.e., carbon emission peak by 2030 and carbon neutrality by 2060 pledged by the Chinese government) requires policy packages that are both effective and socially beneficial.

#### 4.2. Robustness tests

There are two strategies to examine the robustness of the benchmark estimation results. Given potential heterogeneity across projects, domestic projects are excluded from our first robustness test, and only international projects are retained to re-estimate the health effects of FFCSPs. It can be known from columns (1) and (2) of Table 1 that the

coefficients of policy variable P are negative and significant at the 99% level, which are similar to the results in Fig. 4.

These results also suggest that the FFCSPs can improve the health of local residents. However, these coefficients are greater than those in Fig. 4, suggesting that the health effects of international FFCSPs may be more substantial than those of domestic projects. In the second robustness test strategy, we re-match the samples using a different matching method, and the PSM-DID methods are used again to calculate the net health effects of FFCSPs. As shown in Table 1, neighbour-matching results show that the FFCSPs can reduce the average number of physician visits by 0.305 and healthcare costs by 13.3%; Radius-matching results show that the FFCSPs reduce the average number of physician visits by 0.284 and healthcare costs by 11.7%. All of these results are consistent with our baseline findings, indicating that our estimates are robust. We also assessed the potential impact of omitted variables on our empirical results. The corresponding test results are reported in Appendix 5. The findings indicate that the omission of quantitative variables has a negligible effect on our estimates, suggesting that our results are robust.



**Fig. 4.** The impact of FFCSPs on human health. The figure plots the health effects of FFCSPs. We use fixed-effects models to control for year and individual fixed effects. The red and green areas indicate 95% confidence intervals. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

**4.3. Dynamic effects analysis**

The dynamic health effects of FFCSPs on residents are calculated using Eq. (2) and presented in Fig. 5. The vertical axis represents average health outcomes, including physician visits and healthcare expenditures. The horizontal axis indicates the years in which the FFCSPs are initiated. The initial years are derived from the project plans, where +k indicates the k-th year after the implementation of FFCSPs, and -k denotes the k-th year before their implementation.

The results show that all coefficients exhibit a statistically significant decreasing trend. It is worth noting that all our regression coefficients

are negative. These results suggest that the health effects of FFCSPs increase with the duration of project implementation. On the one hand, the trees and forests planted by FFCSPs will be better equipped to mitigate pollution and sequester carbon over time. In addition, the economic benefits from the carbon trading market are expected to increase with the year of implementation of FFCSPs. Therefore, the health effects of FFCSPs are long-lasting. Consider that international projects were implemented in 2010 and 2006, respectively, while the domestic projects were implemented in 2011. Thus, this is consistent with the previously mentioned result that international projects have greater health benefits than domestic projects.

**4.4. Influence channels analysis**

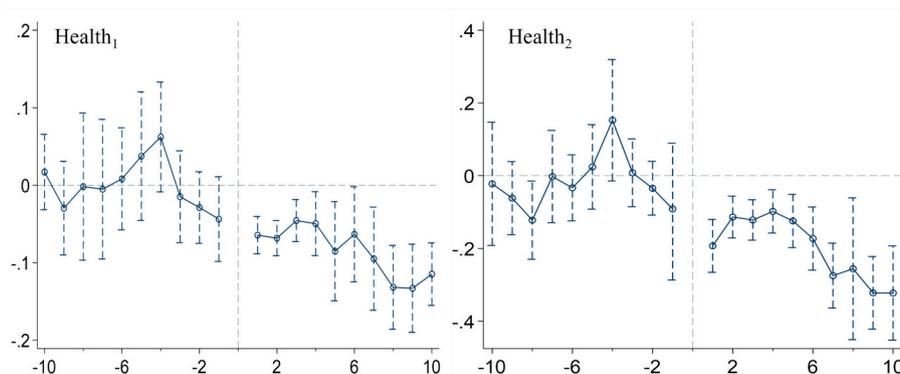
FFCSPs can improve the ecological environment and improve household livelihoods, thereby benefiting residents' health. Given data limitations, we focus on three representative channels: air quality, savings, and industrial structure. Air quality and savings capture the ecological and economic pathways, respectively, while industrial structure serves as a moderating factor shaping both environmental and economic effects. The results are as follows.

The results of the effect of FFCSPs on the air quality, savings, and industrial structure are presented in Table 2. PM<sub>2.5</sub> and CO<sub>2</sub> are used to measure changes in the air quality, and the impacts of FFCSPs on PM<sub>2.5</sub> and CO<sub>2</sub> are shown in columns (1) and (2), respectively. The coefficient of PM<sub>2.5</sub> is -0.105, which is significant at the 95% level, indicating that the FFCSPs can reduce PM<sub>2.5</sub> by 0.105 μg/m<sup>3</sup>. The coefficient of CO<sub>2</sub> is -0.096 and significant at the 99% level, suggesting that the FFCSPs have a positive impact on the natural environment. Besides, FFCSPs can promote industrial upgrading and restructuring. Here we can see from columns (4) to (6) of Table 2 that the share of the primary industry in GDP has decreased, and the share of the tertiary industry in GDP has increased. However, the estimated coefficient of the secondary industry

**Table 1**  
Robustness tests.

	Change sample		Neighbour matching		Radius matching	
	Health <sub>1</sub>	Health <sub>2</sub>	Health <sub>1</sub>	Health <sub>2</sub>	Health <sub>1</sub>	Health <sub>2</sub>
	(1)	(2)	(3)	(4)	(5)	(6)
P	-0.156*** (0.104)	-0.368*** (0.040)	-0.133*** (0.104)	-0.305*** (0.033)	-0.117*** (0.108)	-0.284*** (0.033)
Control variables	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Constant	-11.270*** (1.302)	-1.803** (0.793)	-12.561*** (1.424)	-3.034*** (0.712)	-12.883*** (1.623)	-2.886*** (0.815)
Observations	2346	2346	1955	1955	1649	1649
R-squared	0.815	0.970	0.796	0.969	0.782	0.967

Note: We use a fixed-effects model to control for year and individual effects. Robust standard error in parentheses.\*\*\* if  $p < 0.01$ ; \*\* if  $p < 0.05$ ; \* if  $p < 0.1$ .



**Fig. 5.** The dynamic effects of FFCSPs on human health. The figure plots the health effects of FFCSPs. We use fixed-effect models to control for year and individual effects. The dashed lines are 95% confidence intervals.

**Table 2**  
The influence channels analysis.

	PM <sub>2.5</sub>	CO <sub>2</sub>	Saving	First	Second	Third
	(1)	(2)	(3)	(4)	(5)	(6)
P	-0.105** (0.050)	-0.096*** (0.030)	0.152*** (0.024)	-0.034*** (0.006)	-0.007 (0.012)	0.041*** (0.011)
Control variables	Controlled	Controlled	Controlled	Controlled	Controlled	Controlled
Constant	4.512*** (0.518)	-3.275*** (0.030)	11.063*** (0.446)	2.412*** (0.103)	0.403 (0.396)	-1.815*** (0.404)
Observations	2380	2016	2380	2380	2380	2380
R-squared	0.973	0.968	0.991	0.926	0.819	0.687

Note: We use fixed-effects models to control for year and individual fixed effects. Robust standard error in parentheses \*\*\* if  $p < 0.01$ ; \*\* if  $p < 0.05$ ; \* if  $p < 0.1$ .

in GDP is not significant. Lastly, column 3 of Table 2 shows that FFCSPs can increase savings by 15.2%, suggesting that their economic effects are positive as well.

4.5. Heterogeneity analysis

The management institutions and implementation standards of international and domestic projects differ, which may lead to variations in their implementation outcomes. In counties with higher average PM<sub>2.5</sub> levels and more severe environmental pollution, the environmental improvement effects of FFCSPs may be more pronounced, leading to greater health benefits. Moreover, the level of economic development influences access to medical resources, nutritional intake, and overall living conditions, all of which affect health outcomes. Therefore, we examined the heterogeneity of the health effects of FFCSPs across counties with different project types, levels of economic development, and environmental conditions. The results, presented in Fig. 6, show that the health benefits of FFCSPs are more pronounced in counties with higher levels of economic development and higher average PM<sub>2.5</sub> concentrations. Interestingly, health effects are observed only in international projects, with no significant impact in domestic projects.

5. Discussion and conclusion

The results of this study indicate that FFCSPs play a significant role in enhancing human health by improving air quality, facilitating industrial transformation, and contributing to economic development via increased incomes. First, FFCSPs can improve health by reducing PM<sub>2.5</sub> and CO<sub>2</sub>. The relationship between environmental quality and public health has been extensively studied in the literature, with a significant portion of the research focusing on the health risks associated with air pollutants, such as PM<sub>2.5</sub> and CO<sub>2</sub>. High levels of PM<sub>2.5</sub> are linked to several health risks, including psychiatric disorders (Kim et al., 2019), anemia (Honda et al., 2017), acute respiratory infections (Adhikary et al., 2024), and low birth weight (Harris et al., 2014). Carbon emissions are associated with higher healthcare costs and increased infant

mortality (Adeleye et al., 2023; Nansai et al., 2020). Researches show that green spaces, such as forests (Nowak et al., 2014), grasslands (Gopalakrishnan et al., 2018), and parks (Kabaya, 2021), can reduce healthcare costs, chronic disease rates, and suicide rates among residents by improving air quality and providing opportunities for recreation and leisure. FFCSPs can improve air quality by expanding forested areas, which absorb carbon dioxide, release oxygen, and filter air pollutants such as PM<sub>2.5</sub>. As a result, they help reduce residents' healthcare costs and the number of physician visits. Additionally, FFCSPs may also indirectly promote public health by mitigating noise pollution and providing spaces for outdoor and cultural activities. These results are consistent with some existing literature. For instance, Lin et al. (2020) analyzed panel data from 255 cities between 2000 and 2015 and found that a 1% increase in forest area is associated with a 2.53% reduction in the average annual PM<sub>2.5</sub> concentration. Zhao et al. (2010) found that urban forests in Hangzhou sequester carbon each year, offsetting 18.57% of the carbon emissions from industrial activities. The amount of carbon stored is equivalent to 1.75 times the city's annual industrial energy-related emissions.

FFCSPs can improve health by increasing household income. A strong positive connection between income and health, known as the income-health gradient, has been widely documented in both developed and developing countries (Ecob and Davey Smith, 1999; Moradpour and Hollis, 2020). This relationship encompasses various dimensions, including mental and physical health, as well as health-related behaviours such as smoking and drinking (Kabaya, 2021; Kim et al., 2019; Murakami and Hashimoto, 2019). Households with higher incomes generally have better access to healthcare services and can more easily afford essential care (Wang et al., 2024). Our findings show that FFCSPs can increase savings by 15.2%, suggesting that their economic effects are also positive. Participation in FFCSPs restricts farmers from continuing agricultural activities or leasing land within project areas, thereby reducing income from grazing and land rental. However, reforestation activities under the FFCSPs can also create employment opportunities for local farmers, such as planting, overseeing growth, tending saplings, and replanting when needed (Liu et al., 2023). Which

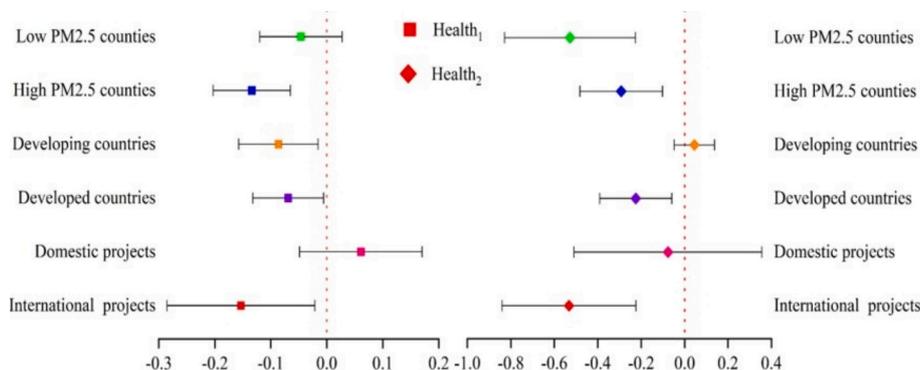


Fig. 6. Heterogeneity of health effects of FFCSPs heterogeneity groups. The figure plots the effects of FFCSPs. We use fixed-effects models to control for year and individual fixed effects. The lines are 95% confidence intervals.

in turn helps increase farmers' incomes. More importantly, the sale of carbon credits can provide a steady source of income growth for farmers. These additional revenues offset the economic losses from FFCSPs, making the overall economic impact of FFCSPs on county development positive.

FFCSPs can improve health by promoting industrial upgrading. The industrial structure can also influence residents' health levels through its ecological and economic channels. Existing literature suggests that the tertiary industry has a minor adverse environmental impact compared to the primary and secondary industries, particularly in developing nations (Li et al., 2020; Wang et al., 2023). In 2018, China's secondary industry consumed 3.1 billion tons of standard coal, accounting for 66% of the nation's total energy consumption (Chen et al., 2021). The secondary industry, mainly manufacturing, is the major contributor to environmental pollution and carbon emissions. The primary industry is a significant source of non-point source pollution, affecting water and land resources through excessive usage of chemical fertilizers and pesticides (Chen et al., 2023). Yu and Wang (2021) argued that China's environmental regulation policies have reduced the share of primary and secondary industries in GDP, while increasing the share of the tertiary industry, thereby improving environmental quality (Chen et al., 2020). Additionally, other studies suggest that upgrading the industrial structure enhances innovation capacity (Liu et al., 2023), which in turn positively impacts residents' health. FFCSPs allocate vast areas of forest land for conservation, restricting forestry-related activities. As a result, agricultural labor is encouraged to transition into the secondary and tertiary industries. Thus, FFCSPs may have played a role in China's rapid urbanization, which has seen the urbanization rate surge from 36.2% in 2000 to 63.9% in 2021. Our findings show that the share of the primary industry in GDP has decreased, while the tertiary industry's share has increased. However, the estimated coefficient for the secondary industry in GDP is not statistically significant. These results are similar to those of Zang et al. (2020) and Zheng et al. (2021). They explained how the policies of low-carbon cities and emission trading schemes affect the macro-industrial structure and economic development, respectively. Thus, we conclude that the ecological effects of the FFCSPs have a positive impact on human health.

It is worth noting that we find statistically significant health improvements associated with international FFCSPs, whereas the estimated effects of domestic projects are not statistically distinguishable from zero. This divergence likely reflects not only differences in project maturity within our observation window, but also systematic variation in institutional arrangements and governance structures across project types. Recent studies suggest that the effectiveness of forest-based climate interventions depends not only on technical issues such as monitoring and MRV systems, but also on broader institutional conditions related to climate governance and results-based payment mechanisms (Zhao et al., 2025). Compared with domestically financed initiatives, internationally supported projects are more likely to operate under standardised protocols, clearer additionality requirements, and externally verified performance benchmarks, which improve accountability and enhance the credibility of carbon revenue delivery. Governance-related factors, including land tenure arrangements, inter-sectoral policy coordination, and local investment incentives, have been shown to influence both the permanence of carbon gains and the distribution of project benefits at the community level (Yin, 2024). In this context, more reliable payment expectations and lower implementation uncertainty in international projects may facilitate sustained participation and income stability. These conditions can strengthen both the ecological pathway, such as improvements in air quality, and the economic pathway, such as the timely delivery of compensation, thereby contributing to more pronounced health co-benefits.

We also find no significant effect of FFCSPs on healthcare costs in low-income counties, likely because budget constraints limit residents' ability to increase medical spending even when health improves.

Finally, FFCSPs do not significantly affect the number of hospital visits in counties with relatively high baseline air quality. This is consistent with air quality being a key channel: where environmental conditions are already good, the marginal health gains from further improvements are limited, making the estimated effects statistically insignificant.

The policy implications of our findings extend beyond the environmental gains typically associated with forest carbon interventions. First, the observed reductions in PM<sub>2.5</sub> concentrations and improvements in health outcomes suggest that FFCSPs can function as integrated policy instruments that jointly advance climate mitigation and public health objectives. In this regard, routine project evaluation frameworks may benefit from incorporating health-related indicators alongside carbon metrics, particularly in regions where local exposure to air pollution remains a key public health concern.

Second, the economic improvements associated with FFCSP participation indicate that climate-oriented land-use policies can generate broader development effects through income stabilisation and structural transformation. However, prior studies have emphasised that the long-term effectiveness of forest-based climate actions depends not only on project-level implementation, but also on institutional conditions such as land tenure arrangements, policy coordination across sectors, and investment incentives at the local level (Yin, 2024). Strengthening complementary measures in these areas may therefore improve the ability of FFCSPs to translate carbon-related revenues into sustained livelihood improvements and service-sector development in mountainous regions.

Third, the stronger health effects observed in internationally supported projects point to the importance of governance arrangements and results-based payment mechanisms in shaping local outcomes. Recent research highlights that the success of forest climate interventions depends not only on technical monitoring systems but also on broader institutional frameworks that ensure credible implementation and timely compensation (Zhao et al., 2025). Enhancing the alignment between domestic FFCSPs and higher-level jurisdictional programs, as well as improving transparency in performance assessment and payment delivery, may help reduce implementation uncertainty and strengthen participation incentives. Such institutional adjustments could increase the likelihood that the environmental and health co-benefits of forest carbon programs are both scalable and durable across developing country contexts.

This study has several limitations. First, while we test the main mechanisms, data constraints prevent us from examining other potentially relevant channels, such as biodiversity and mental health. Second, our identification strategy relies on standard quasi-experimental assumptions. Despite extensive robustness checks, we cannot fully rule out confounding effects from concurrent shocks or policy changes. Finally, our estimates capture average effects across the sample counties in Sichuan Province, China, so caution is warranted when extrapolating to settings with different baseline conditions, institutional capacity, or levels of carbon market development.

In sum, this study examines the health effects of FFCSPs. The results suggest that FFCSPs not only mitigate climate change but also generate co-benefits for environmental quality and public health, mainly through improved air quality, higher household income, and industrial upgrading. However, these benefits are evident only in international projects, not in domestic initiatives. Therefore, FFCSPs have strong potential to curb global warming while improving population health, but realizing these gains also requires effective implementation and enforcement, robust regulation, and well-functioning carbon trading platforms.

#### Declaration of competing interest

We declare that all authors have no relevant or material financial interests that relate to the research described in this paper.

### Appendix A. Descriptive statistics

Appendix 1 provides the definitions and descriptive statistics of the main variables.

**Table A1**  
The summary of the main variables.

Variables	Definition	All (1)	FFCSPs (2)	Non-FFCSPs (3)	Difference <sup>a</sup> (4)
<b>Dependent variables</b>					
Health <sub>1</sub>	The healthcare costs per person (CNY) <sup>b</sup>	6.078 (0.921)	5.947 (0.811)	6.092 (0.930)	-0.145***
Health <sub>2</sub>	The number of physician visits per person	1.995 (2.319)	1.671 (3.059)	2.030 (2.228)	-0.359**
<b>Channel variables</b>					
PM <sub>2.5</sub>	PM <sub>2.5</sub> values (µg/m <sup>3</sup> ) <sup>b</sup>	3.123 (1.120)	2.773 (0.543)	3.158 (1.158)	-0.385***
CO <sub>2</sub>	CO <sub>2</sub> emissions (million tons) <sup>b</sup>	-0.638 (1.209)	-1.242 (0.841)	-0.569 (1.226)	-0.673***
Saving	Resident savings (million CNY) <sup>b</sup>	9.008 (1.000)	8.600 (1.048)	9.049 (0.986)	-0.449***
First	The share of the primary industry in GDP	0.273 (0.128)	0.297 (0.136)	0.268 (0.127)	0.029***
Second	The share of the secondary industry in GDP	0.434 (0.179)	0.444 (0.172)	0.433 (0.180)	0.013
Third	The share of the tertiary industry in GDP	0.293 (0.134)	0.262 (0.103)	0.299 (0.136)	-0.037***
<b>Control variables</b>					
GDP	Per capita gross domestic product (million CNY) <sup>b</sup>	12.775 (1.419)	12.076 (0.830)	12.847 (1.447)	-0.771***
Pop	Population per square kilometer (10,000 persons) <sup>b</sup>	4.328 (1.706)	5.041 (0.681)	4.255 (1.762)	0.786***
Fixed	Fixed asset investment (million CNY) <sup>b</sup>	12.440 (1.470)	11.894 (1.099)	12.496 (1.492)	-0.602***
Finance	Financial institution loans (million CNY) <sup>b</sup>	12.006 (1.593)	11.271 (1.145)	12.081 (1.613)	-0.810***
Indust	Industrial value above designated size (million CNY) <sup>b</sup>	11.937 (2.623)	11.190 (1.582)	12.013 (2.695)	-0.823***
Beds	Hospital bed capacity (thousand) <sup>b</sup>	6.695 (1.104)	6.208 (0.583)	6.745 (1.132)	-0.537***
Observations		2380	2159	221	

Notes: The dataset covers 140 county-level regions in Sichuan Province over 17 years, from 2002 to 2018. The values in parentheses are the standard deviations, and those without parentheses are the mean values; \*\*\* if  $p < 0.01$ ; \*\* if  $p < 0.05$ ; \* if  $p < 0.1$ . <sup>a</sup> Results of the *t*-test. <sup>b</sup> Natural logarithm value.

The definitions of the primary, secondary, and tertiary industries are as follows:

**Primary industry** refers to agriculture (including farming, forestry, animal husbandry, and fishery), excluding professional and auxiliary activities of agriculture, forestry, animal husbandry, and fishery.

**Secondary industry** refers to mining and quarrying (excluding support activities for mining), manufacturing (excluding repair services of metal products, machinery, and equipment), production and supply of electricity, heat, gas, and water, and construction.

**Tertiary industry** refers to all economic activities not included in the primary or secondary industries (i.e., the service industry).

**Notes:** The definitions of the primary, secondary, and tertiary industries used in this study follow those of the National Bureau of Statistics of China (NBS).

Source: <https://www.stats.gov.cn/>

### Appendix B. Results of the common trend test

Appendix 2 reports the results of the parallel trend test. In this study, we used two methods to examine parallel trends. The first test strategy involves comparing the changes in the health status of the treatment samples and control samples by visualizing the common trend. The results are shown in Fig. 2. The trends in the health status of the control and treatment groups are the same, indicating that the DID model is appropriate for this study. However, the traditional test method cannot control for confounding effects from other variables. Thus, the second strategy refers to the existing literature (Beck et al., 2010; Liu et al., 2023), which uses the event analysis method to compare trends in health status between the control and treatment groups, while controlling for other factors. Note that the second parallel trend test strategy and the estimation of the dynamic effects of FFCSPs on health effects are based on Eq. (3), and the results are shown together in Fig. 5. Results show no statistically significant differences in health variables between FFCSP counties and other counties prior to the policy's implementation. Thus, we can conclude that our treatment counties and control counties conform to the common trend hypothesis.

### Appendix C. The PSM validity test

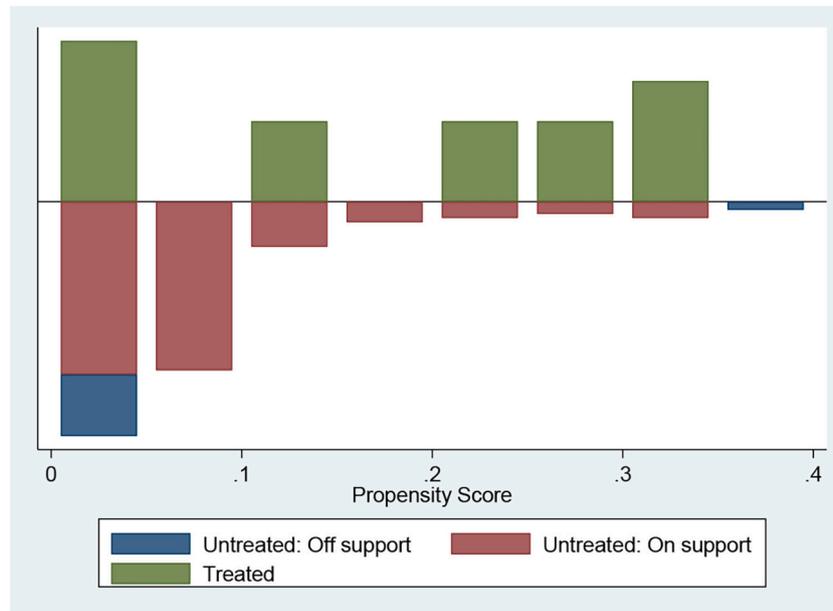
Appendix 3 reports the validity checks for the PSM procedure. Table A2 compares the post-matching means of key covariates between the treatment and control groups, including GDP, population size, fixed asset investment, fiscal capacity, industrial structure, and hospital beds. The differences in covariate means are small, suggesting that the treatment and control groups are well balanced after matching. Fig. A1 further illustrates the common support condition by plotting the propensity score distributions for treated units and matched controls. The two distributions largely

overlap, and only a small number of observations fall outside the common support region, indicating that the matching is conducted within a comparable range of propensity scores and that the PSM results are based on adequately similar treated and control units.

**Table A2**  
The PSM validity test.

	Control group mean	Treatment group mean	Difference
GDP	11.524	11.419	0.105
Pop	5.1001	5.3564	-0.2563
Fixed	11.227	11.259	-0.032
Finance	10.662	10.606	0.056
Industrial	10.266	10.281	-0.015
Beds	5.848	5.7142	0.1338

Notes: \*\*\* if  $p < 0.01$ ; \*\* if  $p < 0.05$ ; \* if  $p < 0.1$ .



**Fig. A1.** Common support area of PSM.

#### Appendix D. The marginal effects of FFCSPs on human health

Appendix 4 reports the marginal effects of FFCSPs on human health. Because the policy variable is a dummy, it captures only limited variation, potentially affecting the robustness of our results. To address this concern, we replace the dummy policy variable with a continuous measure, the total area of FFCSPs, and re-estimate the model, as shown in Fig. A2.

The estimated coefficients for Health1 and Health2 are negative, suggesting that expanding FFCSPs is associated with improved health outcomes. These findings are consistent with the baseline results in Fig. 3, providing robust support for our conclusions. Specifically, controlling for selection bias using PSM, we find that a 1% increase in the total area of FFCSPs is associated with a 0.017% reduction in average healthcare costs and a 0.038 decrease in the average number of physician visits.

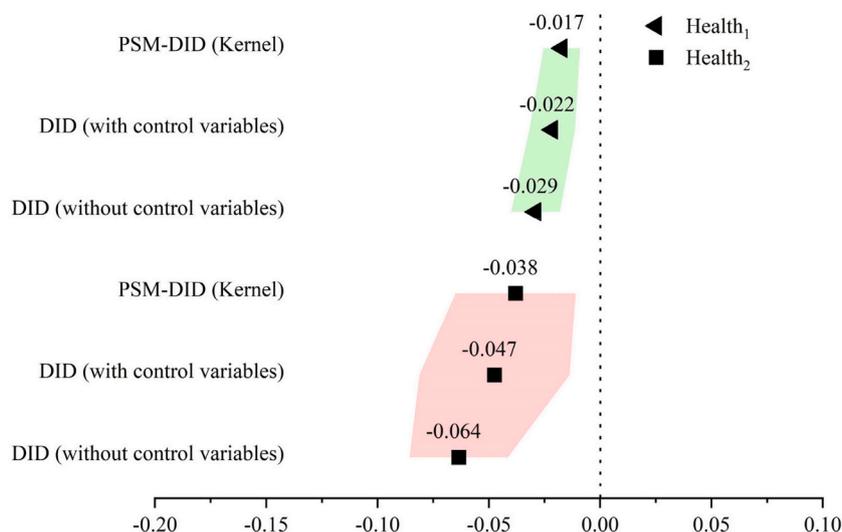


Fig. A2. The marginal effects of FFCSPs on human health. The figure plots the health effects of FFCSPs. We use fixed-effect models control for years and individual effects. The red and green areas indicate 95% confidence intervals. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

**Appendix E. Sensitivity to omitted variables**

Appendix 5 reports the results of the sensitivity analysis for omitted variables. Unobserved factors, such as local natural conditions, governance quality, and related elements, may also influence the FFCSPs. Here, we aim to investigate whether this bias, caused by unobservable variables, can undermine the causal relationship between FFCSPs and human health.

Specifically, we follow the approach from the literature (Altonji et al., 2005; Duan et al., 2024; Nunn and Wantchekon, 2011) to calculate a ratio based on observable variables, thereby evaluating the potential effect of unobservable variables on our empirical results. We run two regressions in which residents' health is the independent variable and the implementation of FFCSPs is the dependent variable. The first regression uses a restricted set of control variables. In the first and third columns of Table A3, we only control for year and individual effects. The second regression incorporates a complete set of control variables, and the results are presented in columns (2) and (4) of Table A3. Let  $\hat{\beta}^F$  represents the coefficient from the fully controlled model. The ratio is computed as follows:  $Ratio = \hat{\beta}^F / (\hat{\beta}^R - \hat{\beta}^F)$ .

A higher ratio indicates stronger explanatory power of the observed variables, reducing the likelihood of estimation bias caused by unobserved factors. If the ratio exceeds 1, it indicates that the effect of FFCSPs on residents' health is primarily driven by observable variables rather than unobservable ones. As shown in Table A3, the calculated ratios are 2.87 and 2.28, both of which exceed the critical threshold of 1. This suggests that the impact of FFCSPs on human health is primarily attributed to observable factors. In other words, unobservable variables are unlikely to overturn the benchmark findings, and our results are robust.

**Table A3**  
Results of the sensitivity analysis for omitted variables.

	DID				PSM-DID (Kernel)	
	Health <sub>1</sub>	Health <sub>2</sub>	Health <sub>1</sub>	Health <sub>2</sub>	Health <sub>1</sub>	Health <sub>2</sub>
	(1)	(2)	(3)	(4)	(5)	(6)
P	-0.442*** (0.145)	-0.194*** (0.059)	-0.328*** (0.103)	-0.135*** (0.031)	-0.313** (0.094)	-0.128*** (0.021)
GDP	-	-	0.039 (0.087)	-0.031 (0.041)	0.115 (0.140)	0.009 (0.050)
Pop	-	-	1.290*** (0.175)	0.604*** (0.120)	1.466*** (0.182)	0.893*** (0.105)
Fixed	-	-	0.036 (0.040)	-0.002 (0.018)	-0.002 (0.044)	0.018 (0.017)
Finance	-	-	-0.022 (0.044)	-0.075*** (0.026)	-0.042 (0.048)	-0.045 (0.028)
Industrial	-	-	-0.009 (0.025)	0.003 (0.013)	-0.042 (0.027)	-0.005 (0.014)
Beds	-	-	0.805*** (0.085)	0.710*** (0.042)	0.796*** (0.099)	0.654*** (0.047)
Constant	0.263*** (0.007)	6.089*** (0.003)	-11.287*** (1.297)	-1.812** (0.791)	-13.075*** (1.616)	-3.205*** (0.824)
Health <sub>1</sub> ratio	2.87					
Health <sub>2</sub> ratio	2.28					
Observations	2380	2380	2380	2380	1581	1581
R-squared	0.763	0.938	0.812	0.969	0.781	0.967

Note: We use fixed-effect models control for years and individual effects. Robust standard error in parentheses \*\*\* if  $p < 0.01$ ; \*\* if  $p < 0.05$ ; \* if  $p < 0.1$ .

- Altonji, J.G., Elder, T.E., Taber, C.R., 2005. Selection on Observed and Unobserved Variables: Assessing the Effectiveness of Catholic Schools. *Journal of Political Economy* 113, 151–184. doi:<https://doi.org/10.1086/426036>
- Beck, T., Levine, R., Levkov, A., 2010. Big Bad Banks? The Winners and Losers from Bank Deregulation in the United States. *The Journal of Finance* 65, 1637–1667. doi:<https://doi.org/10.1111/j.1540-6261.2010.01589.x>
- Duan, W., Jiang, M., Qi, J., 2024. Poverty or pollution: The environmental cost of E-commerce for poverty reduction in China. *Journal of Environmental Economics and Management* 127, 103029. doi:<https://doi.org/10.1016/j.jeem.2024.103029>
- Liu, J., Ren, Y., Hong, Y., Glauben, T., 2023. Does forest farm carbon sink projects affect agricultural development? Evidence from a Quasi-experiment in China. *Journal of Environmental Management* 335, 117500. doi:<https://doi.org/10.1016/j.jenvman.2023.117500>
- Nunn, N., Wantchekon, L., 2011. The Slave Trade and the Origins of Mistrust in Africa. *American Economic Review* 101, 3221–3252. doi:<https://doi.org/10.1257/aer.101.7.3221>

## Data availability

Data will be made available on request.

## References

- Adeleye, B.N., Azam, M., Bekun, F.V., 2023. Infant mortality rate and nonrenewable energy consumption in Asia and the Pacific: the mediating role of carbon emissions. *Air Qual. Atmos. Health* 16, 1333–1344. <https://doi.org/10.1007/s11869-023-01347-8>.
- Adhikary, M., Mal, P., Saikia, N., 2024. Exploring the link between particulate matter pollution and acute respiratory infection risk in children using generalized estimating equations analysis: a robust statistical approach. *Environ. Health* 23, 12. <https://doi.org/10.1186/s12940-024-01049-3>.
- Altonji, J.G., Elder, T.E., Taber, C.R., 2005. Selection on observed and unobserved variables: assessing the effectiveness of catholic schools. *J. Polit. Econ.* 113, 151–184. <https://doi.org/10.1086/426036>.
- Baumgardner, D., Varela, S., Escobedo, F.J., Chacalo, A., Ochoa, C., 2012. The role of a peri-urban forest on air quality improvement in the Mexico City megalopolis. *Environ. Pollut.* 163, 174–183. <https://doi.org/10.1016/j.envpol.2011.12.016>.
- Beck, T., Levine, R., Levkov, A., 2010. Big bad banks? The winners and losers from bank deregulation in the United States. *J. Financ.* 65, 1637–1667. <https://doi.org/10.1111/j.1540-6261.2010.01589.x>.
- Calderon, M., Campbell, M., Kopasker, D., Borbor-Cordova, M.J., Niedzwiedz, C., Rojeab Bravo, B., Firmino de SousaFilho, J., Broadbent, P., Olsen, J.R., Vittal Katikireddi, S., 2025. Payments for ecosystem services and their impacts on health and wellbeing: a systematic review. *Eur. J. Pub. Health* 35, ckaf161.1330. <https://doi.org/10.1093/eurpub/ckaf161.1330>.
- Carlson, C.J., Albery, G.F., Merow, C., Trisos, C.H., Zipfel, C.M., Eskew, E.A., Olival, K.J., Ross, N., Bansal, S., 2023. Climate change increases cross-species viral transmission risk. *Nat. Clim. Chang.* 13, 106–112. <https://doi.org/10.1038/s41558-022-01502-1>.
- Chen, R., Zhao, Z., Kan, H., 2013. Heavy smog and hospital visits in Beijing, China. *Am. J. Respir. Crit. Care Med.* 188, 1170–1171. <https://doi.org/10.1164/rccm.201304-0678LE>.
- Chen, S., Shi, A., Wang, X., 2020. Carbon emission curbing effects and influencing mechanisms of China's emission trading scheme: the mediating roles of technique effect, composition effect and allocation effect. *J. Clean. Prod.* 264, 121700. <https://doi.org/10.1016/j.jclepro.2020.121700>.
- Chen, L., Li, K., Chen, S., Wang, X., Tang, L., 2021. Industrial activity, energy structure, and environmental pollution in China. *Energy Econ.* 104, 105633. <https://doi.org/10.1016/j.eneco.2021.105633>.
- Chen, T., Lu, J., Lu, T., Yang, X., Zhong, Z., Feng, H., Wang, M., Yin, J., 2023. Agricultural non-point source pollution and rural transformation in a plain river network: insights from Jiaying city, China. *Environ. Pollut.* 333, 121953. <https://doi.org/10.1016/j.envpol.2023.121953>.
- Duan, W., Jiang, M., Qi, J., 2024. Poverty or pollution: the environmental cost of E-commerce for poverty reduction in China. *J. Environ. Econ. Manag.* 127, 103029. <https://doi.org/10.1016/j.jeem.2024.103029>.
- Ecob, R., Davey Smith, G., 1999. Income and health: what is the nature of the relationship? *Soc. Sci. Med.* 48, 693–705. [https://doi.org/10.1016/S0277-9536\(98\)00385-2](https://doi.org/10.1016/S0277-9536(98)00385-2).
- Fan, D., Wei, C., Zhao, M., Wang, K., 2024. Forest-based climate change mitigation measures can generate economy-environment-bioenergy synergistic benefits in China. *Appl. Energy* 373, 123929. <https://doi.org/10.1016/j.apenergy.2024.123929>.
- Feng, J., Wang, Z., Yu, Y., 2020. Does long-term care insurance reduce hospital utilization and medical expenditures? Evidence from China. *Soc. Sci. Med.* 258, 113081. <https://doi.org/10.1016/j.socscimed.2020.113081>.
- Fernando, G.-M., Saari, R.K., Monier, E., Selin, N.E., 2015. U.S. air quality and health benefits from avoided climate change under greenhouse gas mitigation. *Environ. Sci. Technol.* 49, 7580–7588. <https://doi.org/10.1021/acs.est.5b01324>.
- Gascon, M., Triguero-Mas, M., Martínez, D., Davdand, P., Forn, J., Plasència, A., Nieuwenhuijsen, M., 2015. Residential green spaces and mortality: a systematic review. *Environ. Int.* 86, 60–67. <https://doi.org/10.1016/j.envint.2015.10.013>.
- Geiger, T., Gütschow, J., Bresch, D.N., Emanuel, K., Frieler, K., 2021. Double benefit of limiting global warming for tropical cyclone exposure. *Nat. Clim. Chang.* 11, 861–866. <https://doi.org/10.1038/s41558-021-01157-9>.
- Gopalakrishnan, V., Hirabayashi, S., Ziv, G., Bakshi, B.R., 2018. Air quality and human health impacts of grasslands and shrublands in the United States. *Atmos. Environ.* 182, 193–199. <https://doi.org/10.1016/j.atmosenv.2018.03.039>.
- Harris, G., Thompson, W.D., Fitzgerald, E., Wartenberg, D., 2014. The association of PM2.5 with full term low birth weight at different spatial scales. *Environ. Res.* 134, 427–434. <https://doi.org/10.1016/j.envres.2014.05.034>.
- Honda, T., Pun, V.C., Manjourides, J., Suh, H., 2017. Anemia prevalence and hemoglobin levels are associated with long-term exposure to air pollution in an older population. *Environ. Int.* 101, 125–132. <https://doi.org/10.1016/j.envint.2017.01.017>.
- Hu, Y., Kuhn, L., Zeng, W., Glauben, T., 2023. Who benefits from payments for ecosystem services? Policy lessons from a forest carbon sink program in China. *Ecol. Econ.* 214, 107976. <https://doi.org/10.1016/j.ecolecon.2023.107976>.
- Kabaya, K., 2021. Empirical analysis of associations between health expenditure and forest environments: a case of Japan. *Ecol. Econ.* 181, 106927. <https://doi.org/10.1016/j.ecolecon.2020.106927>.
- Ke, S., Zhang, Z., Wang, Y., 2023. China's forest carbon sinks and mitigation potential from carbon sequestration trading perspective. *Ecol. Indic.* 148, 110054. <https://doi.org/10.1016/j.ecolind.2023.110054>.
- Keesing, F., Ostfeld, R.S., 2021. Impacts of biodiversity and biodiversity loss on zoonotic diseases. *Proc. Natl. Acad. Sci.* 118, e2023540118. <https://doi.org/10.1073/pnas.2023540118>.
- Kim, K.-H., Kabir, E., Ara Jahan, S., 2014. A review of the consequences of global climate change on human health. *J. Environ. Sci. Health C* 32, 299–318. <https://doi.org/10.1080/10590501.2014.941279>.
- Kim, S.H., Shin, S.D., Song, K.J., Ro, Y.S., Kong, S.Y., Kim, J., Ko, S.Y., Lee, S.Y., 2019. Association between ambient PM2.5 and emergency department visits for psychiatric emergency diseases. *Am. J. Emerg. Med.* 37, 1649–1656. <https://doi.org/10.1016/j.ajem.2018.11.034>.
- Lan, J., Yin, R., 2017. Research trends: policy impact evaluation: future contributions from economics. In: *Forest Policy and Economics, Special Feature: Trends in European Forest Policy Research - Selection of the 1st International Forest Policy Meeting*, 83, pp. 142–145. <https://doi.org/10.1016/j.forpol.2017.07.009>.
- Li, H., Lu, J., Li, B., 2020. Does pollution-intensive industrial agglomeration increase residents' health expenditure? *Sustain. Cities Soc.* 56, 102092. <https://doi.org/10.1016/j.scs.2020.102092>.
- Lin, Y., Yang, X., Li, Y., Yao, S., 2020. The effect of forest on PM2.5 concentrations: a spatial panel approach. *Forest Policy Econ.* 118, 102261. <https://doi.org/10.1016/j.forpol.2020.102261>.
- Liu, J., Ren, Y., Hong, Y., Glauben, T., 2023. Does forest farm carbon sink projects affect agricultural development? Evidence from a quasi-experiment in China. *J. Environ. Manag.* 335, 117500. <https://doi.org/10.1016/j.jenvman.2023.117500>.
- Lu, F., Hu, H., Sun, W., Zhu, J., Liu, Guobin, Zhou, W., Zhang, Q., Shi, P., Liu, X., Wu, X., Zhang, L., Wei, X., Dai, L., Zhang, K., Sun, Y., Xue, S., Zhang, W., Xiong, D., Deng, L., Liu, B., Zhou, L., Zhang, C., Zheng, X., Cao, J., Huang, Y., He, N., Zhou, G., Bai, Y., Xie, Z., Tang, Z., Wu, B., Fang, J., Liu, Guohua, Yu, G., 2018. Effects of national ecological restoration projects on carbon sequestration in China from 2001 to 2010. *Proc. Natl. Acad. Sci.* 115, 4039–4044. <https://doi.org/10.1073/pnas.1700294115>.
- Moradpour, J., Hollis, A., 2020. Patient income and health innovation. *Health Econ.* 29, 1795–1803. <https://doi.org/10.1002/hec.4160>.
- Murage, P., Anton, B., Chiwanga, F., Picetti, R., Njunge, T., Hassan, S., Whitmee, S., Falconer, J., Sharma Waddington, H., Green, R., 2025. Impact of tree-based interventions in addressing health and wellbeing outcomes in rural low-income and middle-income settings: a systematic review and meta-analysis. *Lancet Planet. Health* 9, e157–e168. [https://doi.org/10.1016/S2542-5196\(25\)00003-8](https://doi.org/10.1016/S2542-5196(25)00003-8).
- Murakami, K., Hashimoto, H., 2019. Associations of education and income with heavy drinking and problem drinking among men: evidence from a population-based study in Japan. *BMC Public Health* 19, 420. <https://doi.org/10.1186/s12889-019-6790-5>.
- Nansai, K., Fry, J., Malik, A., Takayanagi, W., Kondo, N., 2020. Carbon footprint of Japanese health care services from 2011 to 2015. *Resour. Conserv. Recycl.* 152, 104525. <https://doi.org/10.1016/j.resconrec.2019.104525>.
- Nowak, D.J., Hirabayashi, S., Bodine, A., Greenfield, E., 2014. Tree and forest effects on air quality and human health in the United States. *Environ. Pollut.* 193, 119–129. <https://doi.org/10.1016/j.envpol.2014.05.028>.
- Nunn, N., Wantchekon, L., 2011. The slave trade and the origins of mistrust in Africa. *Am. Econ. Rev.* 101, 3221–3252. <https://doi.org/10.1257/aer.101.7.3221>.
- Patz, J.A., Olson, S.H., 2006. Climate change and health: global to local influences on disease risk. *Ann. Trop. Med. Parasitol.* 100, 535–549. <https://doi.org/10.1179/136485906X97426>.
- Seddon, N., Chausson, A., Berry, P., Girardin, C.A.J., Smith, A., Turner, B., 2020. Understanding the value and limits of nature-based solutions to climate change and

- other global challenges. *Philos. Trans. R. Soc. Lond. Ser. B Biol. Sci.* 375, 20190120. <https://doi.org/10.1098/rstb.2019.0120>.
- Smith, J., Scherr, S.J., 2003. Capturing the value of forest carbon for local livelihoods. *World Dev.* 31, 2143–2160. <https://doi.org/10.1016/j.worlddev.2003.06.011>.
- Sweileh, W.M., 2020. Bibliometric analysis of peer-reviewed literature on climate change and human health with an emphasis on infectious diseases. *Glob. Health* 16, 44. <https://doi.org/10.1186/s12992-020-00576-1>.
- Tanser, F.C., Sharp, B., le Sueur, D., 2003. Potential effect of climate change on malaria transmission in Africa. *Lancet* 362, 1792–1798. [https://doi.org/10.1016/S0140-6736\(03\)14898-2](https://doi.org/10.1016/S0140-6736(03)14898-2).
- Wang, C., Feng, C., Bai, C., 2023. Industrial policy and resident health: historical evidence from China's third front construction. *J. Asian Econ.* 89, 101668. <https://doi.org/10.1016/j.asieco.2023.101668>.
- Wang, X., Lei, X., Ren, Y., Yu, J., 2024. Richer and healthier? Social pensions and unhealthy consumption behavior in China. *Econ. Dev. Cult. Chang.* <https://doi.org/10.1086/727535>.
- Wu, Y., Wen, B., Ye, T., Huang, W., Liu, Y., Gasparrini, A., Sera, F., Tong, S., Lavigne, E., Roye, D., Achilleos, S., Rytí, N., Pascal, M., Zeka, A., de' Donato, F., das Neves Pereira da Silva, S., Madureira, J., Mistry, M., Armstrong, B., Bell, M.L., Schwartz, J., Guo, Y., Li, S., 2025. Estimating the urban heat-related mortality burden due to greenness: a global modelling study. *Lancet Planet. Health* 9, 101235. [https://doi.org/10.1016/S2542-5196\(25\)00062-2](https://doi.org/10.1016/S2542-5196(25)00062-2).
- Xu, X., Sun, M., Zhang, L., Fu, C., Bai, Y., Li, C., 2020. Factory employment exposure and human health: evidence from rural China. *Environ. Pollut.* 259, 113619. <https://doi.org/10.1016/j.envpol.2019.113619>.
- Yin, R., 2024. *Global Forest Carbon: Policy, Economics and Finance*. Routledge, London. <https://doi.org/10.4324/9781003436652>.
- Yu, X., Wang, P., 2021. Economic effects analysis of environmental regulation policy in the process of industrial structure upgrading: evidence from Chinese provincial panel data. *Sci. Total Environ.* 753, 142004. <https://doi.org/10.1016/j.scitotenv.2020.142004>.
- Zang, J., Wan, L., Li, Z., Wang, C., Wang, S., 2020. Does emission trading scheme have spillover effect on industrial structure upgrading? Evidence from the EU based on a PSM-DID approach. *Environ. Sci. Pollut. Res.* 27, 12345–12357. <https://doi.org/10.1007/s11356-020-07818-0>.
- Zhao, M., Kong, Z., Escobedo, F.J., Gao, J., 2010. Impacts of urban forests on offsetting carbon emissions from industrial energy use in Hangzhou, China. *J. Environ. Manag.* 91, 807–813. <https://doi.org/10.1016/j.jenvman.2009.10.010>.
- Zhao, N., Wang, K., Yuan, Y., 2023. Toward the carbon neutrality: forest carbon sinks and its spatial spillover effect in China. *Ecol. Econ.* 209, 107837. <https://doi.org/10.1016/j.ecolecon.2023.107837>.
- Zhao, F., Shen, Y., Yin, R., 2025. Reframing forest-based climate actions. *Environ. Sci. Adv.* <https://doi.org/10.1039/D4VA00361F>.
- Zheng, J., Shao, X., Liu, W., Kong, J., Zuo, G., 2021. The impact of the pilot program on industrial structure upgrading in low-carbon cities. *J. Clean. Prod.* 290, 125868. <https://doi.org/10.1016/j.jclepro.2021.125868>.
- Zhu, X., Long, Y., Zhang, H., 2025. Impact of carbon policies on forest carbon sequestration supply at intensive and extensive margins. *Forest Policy Econ.* 181, 103665. <https://doi.org/10.1016/j.forpol.2025.103665>.