Crops, Bugs, and Disease: The Unintended Consequences of Environmental Policies on Ecosystem and Human Health*

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Abstract

Environmental policies can disrupt ecosystems, leading to unexpected health consequences. This paper examines how China's straw-burning ban, implemented to reduce air pollution, unintentionally increases vector-borne diseases by altering agricultural landscapes. Leveraging the policy's staggered implementation and a large hospitalization database spanning a broad geographic area (2011-2022), we employ a difference-in-differences (DID) approach for causal identification. Our results show that the ban has increased hospitalizations and medical expenditures for vector-borne diseases by 60 to 180%, raising annual hospital medical costs by $280 million. To trace the impact pathway, we show that the policy led to a decline in cropland fires, an increase in insect abundance, and a surge in online searches for insect bites and pest control measures. The results highlight the complex interactions between human interventions and natural ecosystems, emphasizing the need for policy designs that account for unintended ecological and health effects.

Keywords: Ecosystem disruptions, Vector-borne diseases, Straw burning, Agricultural fires

JEL Classification: Q57, Q51, Q15, Q50

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1. Introduction

Human activities are deeply intertwined with natural ecosystems. Interventions in the environment can disrupt other species, triggering feedback loops that ultimately affect human well-being. This dynamic is evident in global challenges such as climate change and biodiversity loss, where ecological disruptions contribute to broader health and economic risks (Frank and Sudarshan, 2024; Frank et al., 2024). Despite growing recognition of these interconnections, the causal pathways through which policy-driven ecological changes impact public health remain insufficiently studied. This paper contributes to this discussion by examining how a policy aimed at improving air quality inadvertently alters ecosystems, leading to unforeseen human health consequences.

Understanding the ecological and health-related economic costs of human interventions is essential for policymakers seeking to refine and optimize policies. However, estimating these costs presents significant empirical challenges for three key reasons. First, changes in species composition following ecological disruptions are often difficult to observe. Second, policies targeting ecosystems or public health are typically implemented in response to pre-existing ecological or health conditions, introducing endogeneity that can bias causal estimates. Third, neighborhoods without direct policy intervention may still experience indirect effects from ecological changes in nearby areas, particularly through the movement of large animal species, complicating causal identification. This study leverages China's top-down air pollution policies — specifically the straw-burning ban — as a natural experiment. The policy induced unintended biological changes and influenced diseases closely linked to local insect population dynamics, providing a setting for the causal identification of its ecological impact on human health.

China's straw-burning ban, implemented in stages over the past two decades, is considered one of the most stringent measures to combat air pollution.[1] Research has suggested its effectiveness in reducing air pollution from on-site straw burning,[2] but its unintended ecological consequences have been largely overlooked by both academics and policymakers. Figure 1 illustrates how the straw-burning ban policy unintentionally impacts human health by altering land use and insect ecosystems. The accumulation of unburned crop residues has inadvertently created a more favorable habitat for insects,[3] particularly by improving overwintering conditions, which has contributed to a rise in vector-borne disease prevalence.[4] These diseases, closely tied to insect

[1] Beginning in 2007, ahead of the 2008 Beijing Olympics, concerns over air pollution from straw burning prompted the central government to intensify efforts to phase out this practice nationwide. The rollout sequence of the ban was primarily determined by the economic and social importance of cities, rather than by health, climate, or other regional characteristics.

[2] Existing literature finds that straw burning significantly increases air pollution (Rangel and Vogl, 2019; He et al., 2020; Zivin et al., 2020; Guo, 2021; Pullabhotla and Souza, 2022; Garg et al., 2024). He et al. (2020) also finds that China's straw recycling policy, which incentivized farmers and enterprises to recycle straw by providing subsidies, significantly reduced air pollution caused by straw burning.

[3] Studies in natural sciences suggest that changes in land management practices influence vector populations, such as ticks and other arthropods (Allan, 2009; Samish and Alekseev, 2001; Gleim et al., 2014; Gallagher et al., 2022).

[4] Vector-borne diseases represent a critical link in human-nature interactions. They are caused by pathogens — including parasites, viruses, and bacteria — that are transmitted to humans and animals through bites, stings, or contact

population dynamics, account for 17% of all infectious diseases globally and cause over 700,000 deaths annually (WHO, 2025), posing a significant threat to human well-being.[5]

Figure 1 about here.

This study relies a comprehensive database of hospitalization records from 2,788 public hospitals across China. We identify vector-borne diseases (listed in Table C1-C2) by cross-referencing extensive literature on arthropod-borne diseases with the ICD-10 code list (Fang et al., 2005; Jiang et al., 2011; WHO, 2014). To ensure robustness, we specifically examine the hospitalization effects of tick-borne diseases. These diseases, including Lyme disease, tick-borne encephalitis, and severe fever with thrombocytopenia syndrome, are among the most prevalent vector-borne illnesses affecting agricultural workers and pose significant public health challenges in China and beyond.

We use the staggered implementation of the straw-burning ban across prefectural-level cities and employ a Difference-in-Differences (DID) approach.[6] The unit of analysis is the county-by-quarter-year level. To address potential confounding from time-varying factors correlated with both policy rollout and hospitalization outcomes, we include flexible fixed effects at the county-by-year and province-by-quarter-year levels. Additionally, we control for hospital characteristics, contemporaneous weather conditions, and forest fire frequency, which may affect both insect survival and hospitalization rates.

We conduct several tests to validate the key identification assumption of our methodology: First, we find evidence supporting parallel trends between treated and untreated groups before the ban. Second, we show that the rollout sequence of the straw-burning ban is strongly correlated with that of the Air Pollution Monitoring and Disclosure Program, a top-down policy determined by administrative hierarchies (Barwick et al., 2024). Moreover, we confirm that air pollution is unrelated to vector-borne disease prevalence. Third, we perform placebo tests using the same empirical specification on diseases unlikely to be influenced by insect populations.

Main Findings Our findings indicate that the straw-burning ban unintentionally increased hospitalizations and medical expenditures for vector-borne diseases by 60–180%. These effects persist for up to four years after policy implementation with consistent magnitude, suggesting a

with infected bodily fluids from blood-feeding arthropods. In this paper, we use the terms *insect* and *arthropod* interchangably for ease of understanding. More relevant details are provided in Section 2.2.

[5]Beyond their public health implications, vector-borne diseases impose substantial economic burdens on healthcare systems, labor productivity, and public health expenditures. For example, the annual economic cost of Lyme disease in the U.S. is estimated to range from $345 million to $968 million (2016 U.S. dollars), with an average healthcare and treatment cost of approximately $3,000 per patient (Hook et al., 2022).

[6]Our benchmark estimation follows the two-stage DID (2SDD) method proposed by Gardner et al. (2024), which first identifies regional and temporal effects using untreated observations before comparing treated and untreated outcomes. This method preserves a sufficient number of observations after accounting for time-varying controls and fixed effects while outperforming alternative heterogeneity-robust estimators in efficiency and computational speed. It also produces standard errors comparable to two-way fixed effects regressions with homogeneous treatment effects. For robustness, we also apply the method of Callaway and Sant'Anna (2021) and Poisson regression, obtaining similar results.

long-term ecological shift affecting human health. The results remain robust across various policy definitions and model specifications. A back-of-the-envelope calculation estimates that the additional hospitalization costs attributable to the policy exceed $280 million annually. The total economic burden is likely higher, as our estimates account only for hospitalizations, exclude outpatient cases, and focus solely on public hospitals in urban areas.

We further examine the heterogeneous effects of the straw-burning ban across factors influencing agricultural burning practices and insect habitat conditions. First, we assess spatial variation by major grain type and find that the policy's impact is greater in wheat-producing counties than in those dominated by corn. This aligns with historical practices — wheat straw was typically burned due to its low economic value and collection challenges, whereas corn straw was rarely burned onsite. These findings confirm that changes in straw-burning practices drive the observed effects. Second, we analyze precipitation levels and find that the policy's impact is stronger in more humid regions, where favorable conditions for insect survival amplify the role of vector habitat changes in shaping our results. Third, we examine temporal variation and find that the effect is most pronounced during the harvest season, when increased field activity heightens human exposure to vector-borne diseases. These results support the robustness of our findings and reinforce the mechanism by which the policy affects human health through its impact on insect populations in agricultural fields.

To further investigate the policy's impact pathway, we integrate multiple datasets to assess changes in straw burning, insect abundance, public awareness of insects, and defensive investments. Using high-resolution remote sensing data on land cover and fire records, we construct measures of straw-burning incidence and burned area. Applying the same DID model, we find that the ban reduces cropland fires by an average of three per year and decreases the total burned area by 141.7 hectares across all counties. We also assess the policy's effect on insect abundance across various taxonomic categories and find that it increases observations of species within Arthropoda, Coleoptera, and Staphylinidae. These findings provide supporting evidence for the mechanism through which the policy influences vector-borne disease incidence.

To complement our hospitalization data with measures of public awareness and defensive investments, we leverage Baidu web search indices to analyze search activity related to insect bites and sightings. The results indicate that the ban significantly increases searches for these topics, suggesting more frequent human encounters with and bites from insects. Search indices for protective measures against insect bites show that the ban led to a sharp rise in searches for insect repellents, pest control, and bite-related medical inquiries. These findings suggest that milder insect bites — those not requiring hospitalization — also became more prevalent, further reinforcing the mechanism linking policy implementation to increased insect exposure.

Related Literature This paper contributes to the literature on the unintended ecological consequences of public policies. Research has shown that species decline can adversely affect human health. Frank and Sudarshan (2024) finds that the functional extinction of vultures in In-

dia increased mortality due to deteriorating sanitation, while Frank et al. (2024) documents how the eradication of sparrows during China's Four Pests Campaign in the late 1950s reduced crop yields and increased mortality. Extending this literature, we provide the first evidence that straw-burning bans, an environmental policy aimed at improving air quality, can disrupt insect populations and, in turn, have unintended health consequences.

Second, this paper contributes to the literature on the ecological effects of socioeconomic activities. Existing research has examined the ecological impacts of economic production, transportation and energy infrastructure, agricultural trade, and place-based economic programs (Asher et al., 2020; Garg and Shenoy, 2021; Hess et al., 2021; Liang et al., 2021; Abman and Lundberg, 2024; Carreira et al., 2024; Costa et al., 2025; Meng et al., 2025). This study extends the literature by investigating the health effects of an air pollution control policy through its disruption of vector ecosystems. While prior research — aside from a few notable exceptions (Du et al., 2024) — has primarily focused on direct ecological consequences, it has largely overlooked the subsequent health impacts mediated by disturbance to the habitat of other species. Furthermore, whereas much of the literature emphasizes forest loss and bird biodiversity, this study broadens the scope by examining how straw-burning bans alter insect populations and, in turn, affect human health.

Third, this paper is closely related to the literature on the relationship between other species and human health (Garg, 2019). While most research has focused on invasive species that disrupt ecosystems (Jones, 2019, 2023),[7] our findings offer a distinct perspective. Unlike invasive species, the pathogen vectors in our study — arthropods — are native and have long coexisted with humans and nature in a stable manner, without causing noticeable harm or attracting significant concern historically.

Finally, this paper complements research on the health and labor costs of agricultural fires. Existing studies show that agricultural fires significantly increase mortality rates (He et al., 2020; Garg et al., 2024), elevate hypertension risks (Pullabhotla and Souza, 2022), reduce birth weight and gestation length, and lower in-utero survival rates (Rangel and Vogl, 2019). They also impair high-stakes exam performance (Zivin et al., 2020) and diminish cognitive abilities (Lai et al., 2022), primarily due to elevated particulate matter levels. However, this literature has largely overlooked the effects of agricultural fires on arthropod populations. This study examines how banning agricultural fires, which are widespread across many countries (Vagg, 2015; Pandey et al., 2017; Singh et al., 2018; Huang et al., 2021),[8] may have unintended health effects beyond air pollution.

[7] Jones (2023) finds that deforestation caused by the emerald ash borer increases obesity rates and reduces physical activity. Jones (2019) finds that improved water quality resulting from the die-off of zebra mussels increases birth weight and length of gestation.

[8] For example, in the United States, straw burning has been increasingly restricted since the 1990s to improve air quality, with exceptions for fields affected by disease (USDA). In India, the National Green Tribunal has imposed bans and penalties on straw burning across several states. Brazil's Law 11.241, enacted in 2002, aimed to phase out sugarcane straw burning, initially covering 20% of mechanized areas and reaching 100% by 2021 (SciELO Brazil).

Policy Implications Our findings do not suggest that straw burning should continue; rather, they highlight the importance of considering the ecological and biodiversity impacts of fire management when altering long-standing human–nature interactions. The results indicate that air pollution reduction and vector-borne disease prevention can be achieved simultaneously if straw is effectively recycled and reused instead of being left in fields.[9] In addition, simple interventions — such as educating farmers on preventive practices like wearing protective clothing, using bed nets, and seeking timely medical care for bites — can help mitigate vector-borne disease risks and are fully compatible with the ban. By applying causal inference methods, this paper aims to raise awareness of these unintended consequences and promote more cautious and ecologically informed policy design in the future.

Moreover, those most affected by vector-borne diseases following the ban are farmers — a socially disadvantaged group. In our data, over half of the reported cases are covered by rural health insurance, while a substantial share lack any insurance, underscoring their heightened vulnerability. Although urban residents are also exposed — given the potential for insect- and animal-borne transmission — the primary burden of the policy falls on rural populations. Furthermore, cases span all age groups, reflecting the broad and widespread nature of the health impact.

A comprehensive cost-benefit analysis of the straw-burning ban is beyond the scope of this paper for two main reasons. First, our primary contribution is to establish the *existence* of this unintended effect, rather than to precisely quantify its magnitude, given data limitations that may lead to underestimation. Second, the costs associated with the ban extend beyond vector-borne diseases. These negative effects stem not solely from the ban itself, but from inadequate straw management, as crop residues are left in fields rather than being centrally processed or burned using cleaner methods. Accordingly, policymakers should consider complementing the ban with improved straw disposal strategies. Without such measures, farmers may respond in unintended ways — such as reducing cultivated land area — resulting in broader economic and agricultural consequences.[10]

The rest of the paper is organized as follows. Section 2 describes the background of straw-burning ban policies in China and vector-borne diseases. Section 3 introduces the datasets. Section 4 illustrates the empirical strategy. Section 5 describes the impact of the straw-burning ban policy on hospitalizations of vector-borne and tick-borne diseases, heterogeneity analyses, and robustness checks. Section 6 displays evidence on the impact pathway of the policy. Section 7 discusses the policy implications. Finally, Section 8 concludes.

[9] Consistent with existing literature, our difference-in-differences estimation confirms that the ban has contributed to a reduction in PM2.5 concentrations.

[10] Our results show a substantial decline in total cropland area and a reduction in wheat cultivation, as documented in the Appendix. We also observe an increase in biomass power plants (BPPs) as an alternative for straw disposal; however, their capacity remains far too limited to process all crop residues.

2. Straw Burning, Agricultural Ecosystem, and Health

2.1. Straw Burning Ban Policy

On-site straw burning, a traditional agricultural practice used to clear crop residues after harvest, was considered an important contributor to air pollution in China, particularly during the harvest season in rural regions. The practice can rapidly generate large amounts of air pollutants, including particulate matter ($PM_{2.5}$ and PM_{10}), carbon monoxide, nitrogen oxides, and volatile organic compounds, all of which significantly deteriorate air quality (He et al., 2020). During the harvest season, straw burning often led to severe smog episodes, impacting visibility, public health, and even regional transportation systems.[11]

To address these concerns, China's straw burning ban emerged as part of the country's broader efforts to combat air pollution and promote environmental sustainability. The policy gained momentum in two key phases: (1) starting from 2007, in preparation for the 2008 Beijing Olympics, when the government aimed to improve air quality for this major international sporting event,[12] and (2) after 2013, following the implementation of the *Action Plan for Air Pollution Prevention and Control* (hereafter the *APPC plan*), which strengthened nationwide air pollution regulations amid rising public awareness of air quality concerns (Barwick et al., 2024).

The straw-burning ban policy was staggeredly implemented at the sub-provincial level. Figure 2 illustrates the cumulative number of counties implementing the ban each year. Between 2007 and 2022, more than 1,000 counties came under regulations prohibiting open-air straw burning within their jurisdictions, either through policies implemented at the county level or by their respective city governments. As shown in the figure, many of these policies incorporated strict assessment mechanisms and reward-punishment frameworks to enhance enforcement.[13] In addition, China mandated the use of satellites to monitor and identify fire spots of straw burning in 2011.[14] In other words, the implementation of the straw-burning ban policy is largely guaranteed since 2011.

Figure 2 about here.

The policy rollout allows us to examine the impact of the straw burning ban on health due to

[11] For example, straw burning caused as many as 90 flight delays in Shandong Province in 2001 alone. (Ministry of Agriculture, 2008)

[12] On the eve of the 2008 Beijing Olympics, the Ministry of Environmental Protection issued the "Notice on Further Strengthening Straw Burning Prohibition Work," which explicitly banned open-air straw burning across all direct-controlled municipalities, provincial capitals, and fifteen sub-provincial cities to improve air quality ahead of the event.

[13] Since the late 1990s, the Chinese government has introduced a series of national-level regulations to ban straw burning. However, effective enforcement requires substantial human and financial resources, making implementation feasible only when local governments enacted their own policies. For instance, records from the Ministry of Agriculture document the high enforcement costs of the ban in Henan Province (see this link, in Chinese). Earlier national-level policies primarily provided broad guidelines with weak enforcement mechanisms, resulting in limited effectiveness.

[14] According to the *Notice on Implementing the 2011 National Environmental Protection Standards Formulation and Revision Projects*, the Satellite Environmental Application Center of the Ministry of Environmental Protection would revise the *Technical Specifications for the Application of Satellite Remote Sensing Monitoring of Straw Burning* since 2011, implying that satellites had been used to monitor straw burning by 2011.

ecosystem changes using a staggered difference-in-differences (DID) approach. Two key aspects of the policy's implementation merit attention. First, the sequence of policy adoption was not random but followed top-down decision based on administrative hierarchies. For example, regions surrounding Beijing and provincial capital cities implemented enforcement requirements in early rounds. Figure 3 plots the rollout of the policy. During 2005 and 2010, the straw-burning ban was primarily implemented in Beijing's surrounding areas and the North China Plain. Over time, the policy was gradually extended to northeastern China and most of the northern regions.

Figure 3 about here.

Second, the degree of implementation can vary across regions. Policies issued without clear enforcement mechanisms or evaluation criteria often resulted in lax implementation. To avoid the measurement errors in the policy variable due to lax enforcement of straw-burning bans, we define a straw-burning ban policy only when it includes assessment measures and use it as our primary treatment variable. However, we also incorporate ban policies without assessment measures for robustness checks.[15]

Following the implementation of the straw-burning ban, cropland fires in China declined significantly. Figure E1 in the appendix compares the distribution of fires in 2011 and 2021, illustrating a notable reduction in fire incidents, particularly in regions that adopted the ban earlier. However, with the implementation of straw-burning bans, farmers have increasingly left crop residues in fields due to the lack of cost-effective alternatives for straw management.

2.2. *Arthropods and Vector-Borne diseases*

The ecological and epidemiological dynamics of arthropods (e.g., ticks) are closely linked to human populations, as they can transmit a wide range of human diseases.[16] Ticks and many arthropods thrive in warm, wooded areas with leaf litter, tall grasses, and shrub layers. Crop residues left on fields following harvests can serve as reservoirs for pathogens and provide ideal overwintering habitats for ticks. In addition, these residues also support the survival of various pests, including mosquitoes, mites, and flies, across multiple seasons and years.

These creatures not only facilitate the transmission of pathogens among livestock and wild animals but also enable zoonotic transmission to humans. In some cases, they may even contribute to human-to-human transmission.[17] In addition, the increase in arthropod population has been linked to an increase in insect-related allergies and toxicity events, as human exposure to crop residues and arthropods becomes more frequent.

[15] We introduce the construction of policy rollout measures in Section 3.

[16] Insects and arachnids are both classified under the broader group of arthropods, sharing a common characteristic of having segmented bodies and jointed appendages. While insects make up the largest subset of arthropods, distinguished by their six legs and typically three body parts, arachnids, such as ticks, spiders, scorpions, are readily identifiable by their eight legs and two main body sections. Despite these distinctions, insects and arachnids share ecological roles, often serving as predators, prey, or pollinators within various ecosystems. Their intricate relationships contribute significantly to the biodiversity and balance of natural habitats.

[17] Examples of vector-borne diseases that can be transmitted between humans include Dengue fever, malaria, and Zika virus disease.

A Case of Tick-Borne Diseases Ticks are ectoparasites that feed on the blood of mammals, birds, and reptiles. They are vectors of a wide range of pathogens, including bacteria, viruses, and protozoa, which can cause severe diseases in humans and animals. Tick-borne diseases encompass a group of illnesses transmitted to humans through tick bites, including Lyme diseases, rickettsiosis, encephalitis, tick paralysis, and others. When a tick attaches to a host, it begins feeding and may remain attached for several days until it is engorged. Notably, tick bites are often painless, making it difficult for individuals to detect them promptly. This delayed detection has resulted in severe illnesses and even fatalities in numerous cases. To date, vaccines are unavailable for most tick-borne diseases.

For instance, SFTS is a severe tick-borne viral disease caused by the SFTS virus, characterized by high fever, thrombocytopenia, and gastrointestinal symptoms such as vomiting and diarrhea. The disease is primarily transmitted through the bite of infected ticks, with limited potential for human-to-human transmission via contact with infected blood. In May 2022, an elderly individual in Xinyang, Henan Province, developed a persistent high fever and was initially diagnosed with a severe cold at a primary healthcare facility.[18] After several days of ineffective treatment, the patient was transferred to a tertiary hospital, Xinyang Central Hospital, where they were diagnosed with Severe Fever with Thrombocytopenia Syndrome (SFTS). Despite intensive medical intervention, the patient succumbed to the disease. Tragically, three individuals who assisted with the funeral arrangements were also diagnosed with SFTS and subsequently passed away.

Disease Categories for Empirical Analyses To construct our dependent variables, we define tick-borne diseases as a category of illnesses primarily transmitted to humans through tick bites. This category includes Lyme disease, rickettsiosis, encephalitis, tick paralysis, and others (as detailed in Table C2). Recognizing that ticks are not the only arthropod population affected by straw-burning bans, we also investigate the hospitalization impact on vector-borne diseases. These are defined as infectious diseases transmitted by arthropods, as well as arthropod-induced allergies and toxicities. Examples include all tick-borne diseases, in addition to dengue, typhoid, cholera, and others (as outlined in Table C1-C2).[19]

We use hospitalizations and medical expenditures related to vector-borne diseases as our primary health outcome variables. As a robustness check, we also analyze the impact of straw-burning bans on hospitalization outcomes specifically associated with tick-borne diseases. Although tick-borne diseases are much less common than conditions such as cardiovascular diseases, they often result in severe health outcomes that are readily observable in hospitalization datasets. Additionally, ticks are among the most widely recognized pests, which contrasts with the relatively lower public awareness of health risks posed by other arthropods. This disparity

[18] See Sina news for details.

[19] We determine the disease list by consulting books and journal articles specifically focusing on illnesses associated with arthropod bites. Our references encompass a broad range of sources, including but not limited to Fang et al. (2005); Jiang et al. (2011); WHO (2014); Bishopp (1915); Hu (1965); Norval et al. (1983); Wilson and Sutherst (1986); Xue (1988); Xue et al. (1989, 1990); Dryden and Broce (1991); Lawler and Dritz (2005, 2006); Jia and Wu (2008); De Oliveira et al. (2012); Ke et al. (2013); Neoh and Bong (2017); Wang et al. (2017).

may result in less prominent representation of other arthropod-related health impacts in hospitalization data.

2.3. *Changes following the Ban*

Before conducting formal empirical analyses, it is helpful to first examine changes in insect abundance and vector-borne disease indidence following the ban. Alongside the observed decline in cropland fires, data from biodiversity monitoring reveal a substantial increase in insect abundance, as illustrated in Figure E2 in the appendix.

We also analyze public attention to insects and insect bites using Baidu Search Indices, which track search frequency for specific terms across cities over time using an algorithm similar to Google Trends.[20] Figure E3 presents the data pattern for three keyword categories: insect bites, ticks, and pest control. Panels (a), (c), and (e) display the raw search data from 2009 to 2023, showing a clear upward trend. Panels (b), (d), and (f) use an event-time framework, with the policy implementation date as the reference point, showing that search activity was relatively stable before the ban but exhibited a sharp increase afterward. Figure E4 further maps the geographic distribution of these search trends, revealing that insect-related searches are concentrated in eastern and central China, aligning closely with the spatial distribution of the straw-burning ban policy.

Lastly, we present the distribution of vector-borne diseases in Figure E5, which exhibits a high correlation with the Baidu Search Index trends observed earlier. Figure E6 further illustrates the trend in total hospitalizations and medical expenditures for both vector-borne and tick-borne diseases, relative to the event period. Before the ban, case numbers were low and stable, with vector-borne disease hospitalizations averaging around 1,000 per quarter and tick-borne cases below 100. However, following the policy implementation, these numbers increased sharply, reaching nearly 10,000 and over 500 cases per quarter, respectively. This dramatic surge strongly suggests a causal relationship, which this paper seeks to formally identify.

3. Data

We compile multiple datasets to examine the effects of straw-burning ban policies. These datasets include policy archives, medical and hospitalization records, satellite imagery of burned areas, web search trends, land cover and crop planting data, and environmental and agricultural statistics. Table 1 presents summary statistics for our county-level panel dataset, which documents straw burning bans, agricultural fires, insect observations, relevant agricultural and health outcomes, and Baidu search indices. The regression sample excludes counties with no recorded cropland fires during the observation period. Additionally, we restrict the analysis to data from two years (eight quarters) before policy implementation and four years (sixteen quarters) after imple-

[20] Baidu is the largest search engine in China and the most widely used platform for online information retrieval. The Baidu Search Index is one of the most effective indicators of public awareness and concern about specific issues among Chinese internet users.

mentation. Columns (2), (3), and (4) provide the number of unique observations at the county (or city) level, the time span, and the frequency of each dataset. Columns (5) and (6) report the means and standard deviations of key variables. Below, we provide detailed descriptions of each data source.

Table 1 about here.

3.1. *Hospitalization Data*

Our dependent variables are derived from a medical records database of inpatient admissions at public hospitals in China from 2017 to 2022.[21] Each hospitalization record includes key variables such as admission type, admission and discharge dates, primary and secondary diagnoses (uniformly coded using ICD-10), medical expenses, patient demographics (gender, age, insurance type, and occupation), and hospital characteristics (tier, class, and type—general or specialty hospital).[22]

To construct hospital-day-level variables, we follow two steps. First, we extract all hospitalization records where tick-borne or vector-borne diseases are the primary diagnosis, excluding cases with extremely low expenditures (below 100 RMB) or exceptionally high expenditures (exceeding 8 million RMB). [23] We then aggregate the number of hospitalizations and total medical expenditures for tick-borne and vector-borne diseases at the hospital-day level.

Second, some hospital-day observations lack hospitalization counts and expenditure data because no patients were admitted for tick-borne or vector-borne diseases on those days. To address this, we determine whether a hospital has an infectious disease department based on whether it admitted at least one infectious disease patient in a given year. For hospitals with an infectious disease department, we assign a value of zero to hospital-day observations missing hospitalization and expenditure data, provided that at least one all-cause admission occurred on that day. Next, we aggregate hospital-day-level data to the hospital-quarter level. Finally, we aggregate hospital-quarter data to the county-quarter level.

3.2. *Policy Data*

The data for straw-related policy documents in this study was sourced from the Peking University Law Database.[24] The core policy variable is a binary indicator of whether a region had a straw burning prohibition policy in effect during a given period. To systematically classify the varying forms of policy implementation, we categorize them based on their strength, progressing from

[21] Hospitals have a strong incentive to maintain a high-quality database of digital medical records of inpatient admissions. See Appendix A.1 for more details.

[22] In China's healthcare system, hospitals are classified into a three-tier system (tier 1, 2, and 3) and within each tier, there are three classes (A, B, and C), resulting in a total of nine levels (3 tiers $\times$ 3 classes). Tier-3 class A hospitals usually have the best medical resources and most skillful physicians among their lower-level counterparts.

[23] These records are usually recorded incorrectly due to wrong placement of the decimal point.

[24] https://www.pkulaw.com.

weak to strong: (1) straw-related policies, (2) straw burning prohibition policies, and (3) straw burning prohibition policies with assessment measures.

For our benchmark analysis, we use the third category—policies with assessment measures—as they played a crucial role in determining the effectiveness of enforcement. Given the high costs associated with alternative straw disposal methods, local officials had to allocate substantial labor resources to implement the ban.[25] As a result, policies with assessment measures provided stronger enforcement incentives, significantly increasing the likelihood of local officials ensuring compliance. However, for robustness checks, we also incorporate the first two policy categories to verify the consistency of our findings.

Since our baseline analysis is conducted at the county level, we define treatment status as follows: If a city-level policy was in effect, all counties within that city are considered treated. If no city-level policy existed, only the counties explicitly covered by specific policies are treated, while all others are coded as 0.[26] Additionally, the implementation of these policies followed a distinct seasonal pattern, with most policies being introduced in May, June, September, and October, coinciding with harvest seasons, as shown in Figure E7. To account for this seasonal variation, we conduct our benchmark analysis at a quarterly frequency, ensuring alignment with the policy's temporal rollout.

3.3. Straw Burning

To measure straw burning, we use two satellite datasets: the Moderate Resolution Imaging Spectroradiometer (MODIS) Burned Area Product and the Land Cover Type Product (MCD12Q1). These datasets enhance measurement precision and enable the tracking of agricultural fires from 2001 to 2022.[27] Following the methodology of Assunçãoa et al. (2019), we overlay the MODIS burned area data with MCD12Q1 land cover classifications to identify straw burning events as fires occurring on croplands (Appendix A.3). This approach mitigates concerns about measurement errors from forest wildfires. We define straw burning as the occurrence of fire on cropland and aggregate these grid-level observations into county-year straw burning frequencies and burned area measures for analysis.

[25]For instance, an official from a major agricultural county in northeastern China reported that cadres were dispatched to guard fields and prevent farmers from openly burning straw. The cost of providing meals for these cadres alone exceeded 100,000 Chinese Yuan during the enforcement period. For more details, see Xinhua News.

[26]Most regions implemented the policy at the city level, with no separate policies at the county level, except for nine counties in Guangxi Province and one county each in Beijing, Zhejiang, and Chongqing. Our results are robust if we exclude these counties from the sample.

[27]MCD12Q1 provides global land cover data, offering high temporal consistency and annual updates throughout our study period. Compared to other land cover products, MCD12Q1 ensures comprehensive coverage. MODIS is a widely used remote sensing tool for fire detection, recording both fire events and burned areas. Data were sourced from NASA Land Processes Distributed Active Archive Center

3.4. *Supplementary Data*

Web Searches We analyze public awareness of vector-borne diseases and the straw burning ban by tracking search intensity for key terms. To do so, we use Baidu, China's leading search engine, which compiles city-level search frequency data from both desktop and mobile users. The platform has provided these indices since 2011, using a methodology similar to Google Trends. Our analysis focuses on searches for "insect bite," "tick," "paederus," and "straw" to assess how public interest evolves in response to the policy.

Insect observations We obtain data on the number of observations for species across various taxonomic categories (i.e., Arthropoda, Arachnida, Insecta, Coleoptera, and Staphylinidae) from iNaturalist, an online social network and biodiversity platform.[28] iNaturalist enables users to share observations of organisms, contributing to a collaborative database that supports scientific research and public education about nature. This platform serves as a valuable resource for gathering large-scale, community-driven biodiversity data, which we utilize to analyze trends and patterns related to these taxonomic groups.

First, we assess the effect of the policy on the total number of Arthropoda observations. Second, given the heightened awareness of tick-borne diseases, we specifically examine its impact on Arachnida observations.[29] Third, since Insecta comprises the largest number of species within Arthropoda, we investigate changes in the number of Insecta observations. Additionally, among the organisms in Insecta, species related to Paederus-induced diseases are relatively well-known; therefore, we further analyze the policy's impact on Coleoptera and Staphylinidae observations.[30] Finally, we extend our analysis to arthropods from other classes within Arthropoda, excluding Arachnida and Insecta.

Each record in iNaturalist is one observation of a species.[31] From 2011 to 2022, there are 153,933 individual-by-species observations. Since the observation and documentation of other species in natural environments have only gained popularity in recent years, primarily in some major cities across China, the original records are relatively sparse and unevenly distributed. Thus, we aggregate the original records to the county-year level, which allows us to mitigate data scarcity issues while maintaining a meaningful spatial and temporal resolution for our study.

Crop Planting Data on winter wheat planting areas are obtained from the map product provided by Dong et al. (2020). Data on rice planting areas are sourced from map product provided by Han et al. (2022). Corn planting area data are provided by Peng et al. (2023).[32] We aggregate these

[28] The website is https://www.gbif.org.

[29] Ticks belong to the class Arachnida.

[30] Paederus belongs to the order Coleoptera and the family Staphylinidae within the class Insecta.

[31] Note that records of iNaturalist do not include information on the number of each species observed on each trip.

[32] Dong et al. (2020) applied a phenology-based approach to distinguish winter wheat from other crops by comparing the seasonal variations of satellite-based NDVI across all croplands. This product enables large-scale early-season winter wheat mapping and generates high-resolution (30 m) winter wheat maps for 2001–2023, covering 11 provinces that account for more than 98% of China's winter wheat production. Validation based on survey samples indicates

grain crop planting areas to the county-year level by summing grid-level planting area values.

Land Cover We employ the 30m annual land cover datasets provided by Yang and Huang (2021).[33] To capture the changes in cropland and forest, we aggregate the grid-level values in forest and cropland to obtain the county-year level data.

Pollution and Biomass Power Plant Monthly $PM_{2.5}$ concentrations are obtained from the Global Annual $PM_{2.5}$ Grids derived from satellite data by van Donkelaar et al. (2021).[34] To capture the biomass power plant, we obtain the list of registered companies in the biomass power industry from the Industrial and Commercial Firm Registry Database. Based on business scopes, we retain in our sample companies that generate electricity from direct combustion or gasification of agricultural and forestry waste following Cao and Ma (2023). We then calculate the number of new biomass power plants at the county-year level.

Weather and Slope of Land Weather conditions, including temperature and precipitation, were collected from The Global Summary of the Day (GSOD) files.[35] We calculate weighted average weather characteristics using all stations in each county, with the weights being the inverse of the distance between a station and each city's centroid. We aggregate the weather data to the county-by-year-by-month level. To assess the geographical condition for agricultural production, we get measures of land slope with a spatial resolution of 30m from the Chinese Digital Elevation Model (ASTER DEMv3).[36]

3.5. Visualization of Hospitalization and Cropland Fire

Figure 4 presents the spatial distribution of hospitalization and cropland fire. Panel (a) displays county-level data on agricultural fire incidents and province-level vector-borne disease hospitalizations for 2022. In China's eastern and coastal regions, a high level of vector-borne disease

producer and user accuracies of 89.30% and 90.59%, respectively. Han et al. (2022) generated the annual paddy rice planting area maps with a 500m from 2001 to 2021, using improved remote sensing methods incorporating multiple data sources. These maps were further validated using Sen's slope and the Mann–Kendall test. Peng et al. (2023) produced the annual corn planting map with a 30m resolution for 2001–2023 across 22 provinces and municipalities, using a high spatiotemporal resolution fused dataset and a phenology-based method called Time-Weighted Dynamic Time Warping. Validation based on field study samples showed average user and producer accuracies of 77.32% and 80.98%, respectively.

[33] Yang and Huang (2021) built Landsat-derived annual land cover product of China (CLCD) from 1985 to 2023. Land cover was classified into nine major types: cropland, forest, shrub, grassland, water, snow and ice, barren, impervious, and wetland.

[34] van Donkelaar et al. (2021) estimate ground-level $PM_{2.5}$ by combining Aerosol Optical Dept (AOD) retrevals from the NASA MODIS, MISR, and SeaWiFS, which are subsequently calibrated to global ground-based observations of $PM_{2.5}$ using Geographically Weighted Regression (GWR). The raster grids of this ground calibrated $PM_{2.5}$ data have a high grid cell resolution of $0.01° \times 0.01°$. Several studies on air pollution have used this data and verified its validity (Freeman et al., 2019; Yao et al., 2022).

[35] The GSOD database reports detailed daily climatic information by weather station from 1928 to the present for over 9000 stations. Weather variables provided by GSOD include mean temperature, mean dew point, mean station pressure, and total precipitation.

[36] Data source: National Earth System Science Data Center, http://www.geodata.cn

hospitalizations is observed, alongside relatively few agricultural fires. Panel (b) further illustrates the negative correlation between agricultural fires and vector-borne hospitalizations across the country. Specifically, areas with high agricultural fire incidents, such as the central regions, tend to report fewer vector-borne disease hospitalizations. In contrast, regions with lower agricultural fire incidents, including the central, southern, and northwestern parts of China, show higher rates of vector-borne disease hospitalizations. Panel (c) categorizes vector-borne disease hospitalizations by type from 2017 to 2022 in our data. Insect allergies, fly-borne diseases, and insect toxicity rank as the top three types of vector-borne diseases, with tick-borne diseases accounting for approximately 5.6% of all vector-borne diseases. Finally, Panel (d) presents the total number of vector-borne disease hospitalizations by year and quarter from 2017 to 2022. A clear seasonal pattern emerges for tick-borne diseases, insect allergies, and insect toxicity, with higher incidence in the second and third quarters and lower incidence in the first and fourth quarters.

Figure 4 about here.

4. Empirical Strategy

We use a staggered DID regression to estimate the impact of straw-burning ban policy on the number of hospitalizations and medical expenditure of vector-borne diseases. The basic two-way fixed effect (TWFE) regression is as follows:

$$Y_{cyq} = \theta + \beta Ban_{cyq} + \mathbf{X}_{cyq}^{'}\gamma + \eta_{cy} + \delta_{pyq} + \varepsilon_{cyq} \tag{1}$$

c, y, q, and p represent county, year, quarter, and province, respectively. Ban_{cyq} is a dummy variable equal to 1 if county c has implemented a straw burning ban with policy assessment in the q-th quarter of year y. $\mathbf{X}_{cyq}^{'}$ refers to county-level time-varying control variables, including characteristics of hospitals, weather, and forest fires in each county-quarter unit. η_{cy} is county-by-year fixed effects and δ_{pyq} is province-by-year-by-quarter fixed effects. Then β is the key coefficient that captures the treatment effect of straw burning ban policy.

Previous literature demonstrates that the TWFE estimate of β may not provide a straightforward measure of the true treatment effect when the average treatment effect varies across groups and over time (Goodman-Bacon, 2021; Sun and Abraham, 2021; Gardner et al., 2024). Therefore, we employ the two-stage difference-in-differences (2SDD) approach proposed by Gardner et al. (2024). This two-stage procedure reliably identifies the overall average treatment effect on the treated (ATT) even when treatment adoption and average treatment effects vary across groups and periods under the usual parallel trends assumption. The 2SDD method compares treated and untreated outcomes after removing group and period effects, which are first identified through a regression using only untreated observations. As a regression-based approach, 2SDD conducts inference within a conventional GMM asymptotic framework, allowing for the inclusion of time-varying controls and individual or unit fixed effects while also estimating dynamic treatment

effects. More importantly, the 2SDD approach produces standard errors comparable to those of TWFE regressions, regardless of whether treatment effects are homogeneous or heterogeneous. It also outperforms several alternative heterogeneity-robust estimators in terms of both efficiency and computational speed.

To ease understanding, we repeat the basic estimation procedure of the 2SDD method using the syntax of Gardner et al. (2024). We observe Y_{it}, X_{it}, D_{it}, where i indexes individuals or units, t indexes time, and D_{it} is an indicator for treatment status.[37] A general regression expression for Equation 1 is as follows:

$$Y_{it} = \lambda_i + \alpha_t + D_{it}\beta_{it} + \mathbf{X}_{it}^{'}\gamma + \varepsilon_{it}. \tag{2}$$

Here β_{it} is the heterogeneous treatment effect. $\mathbf{X}_{it}^{'}$ is a vector of covariates. The Average Treatment Effect on the Treated (ATT) is defined as:

$$\beta = \mathbb{E}[\beta_{it} \mid D_{it} = 1] \tag{3}$$

where the expectation of β_{it} is taken over all units that receive treatment and all times during which they receive it.

There are several assumptions for implementation of the 2SDD method. First, the parallel trend assumption needs to be satisfied. This assumption takes the form $\mathbb{E}[\varepsilon_{it} \mid D, \mathbf{X}] = 0$, i.e., ε_{it} is mean independent of $\mathbf{X}$ and D. Second, the 2SDD method requires everyone to be untreated for at least one period, i.e., for all i, there exists some t where $D_{it} = 0$, and $\mathbb{E}[\sum_{t=1}^{T} D_{it}] > 0$. Third, it does not require independence across time for a given unit, but requires independence over units. That says, observations $\{Y_{it}, \mathbf{X}_{it}, D_{it}\}_t$ are independent and identically distributed over individuals i.

The general regression-based 2SDD estimation procedure is outlined as follows.

1. Regress Y_{it} on X_{it} and individual fixed effects to obtain $\hat{\gamma}$ and $\hat{\lambda}_i$ for observations with $D_{it} = 0$.
2. Regress adjusted outcomes $Y_{it} - \hat{\lambda}_i - \mathbf{X}_{it}^{'}\hat{\gamma}$ on D_{it}.

Let $T_i^0 = \sum_{t=1}^{T}(1 - D_{it})$ denote the number of periods that individual i is untreated. Define $\tilde{Y}_{it}$ as

$$\tilde{Y}_{it} = Y_{it} - \frac{1}{T_i^0}\sum_{t=1}^{T} Y_{it}(1 - D_{it}). \tag{4}$$

Define $\tilde{\varepsilon}_{it}$ similarly. Let $\tilde{\mathbf{X}}_{it}$ denote the matrix of deviations from individual untreated means.[38] Then the above two-stage procedure is equivalent to the following procedure:

1. Regress $\tilde{Y}_{0i}$ on $\tilde{X}_{0i}$ to obtain $\hat{\gamma}$.
2. Regress adjusted outcomes $\tilde{Y}_{it} - \tilde{\mathbf{X}}_{it}'\hat{\gamma}$ on D_{it} to obtain $\hat{\beta}$.

[37] Since indices i and t are sufficient to determine the group g and period p, the indices g and p are suppressed for simplicity purposes.

[38] Define $\tilde{Y}_{0i} = [\tilde{Y}_{i1}(1 - D_{i1}) \cdots \tilde{Y}_{iT}(1 - D_{iT})]'$, which is a $T \times 1$ vector. In addition, using X_{kit} to denote the kth

The 2SDD estimator of β is:

$$\hat{\beta} = \left(\sum_{i=1}^{N} \sum_{t=1}^{T} D_{it} \right)^{-1} \left(\sum_{i=1}^{N} \sum_{t=1}^{T} D_{it} (\tilde{Y}_{it} - \tilde{\mathbf{X}}_{it} \hat{\gamma}) \right). \tag{5}$$

The estimators provide solution to the following GMM problem:

$$\mathbb{E} \begin{bmatrix} \tilde{\mathbf{X}}_{0i}' (\tilde{Y}_{0i} - \tilde{\mathbf{X}}_{0i} \gamma) \\ \sum_{t=1}^{T} D_{it} (\tilde{Y}_{it} - \tilde{\mathbf{X}}_{it}' \gamma - \beta D_{it}) \end{bmatrix} = 0. \tag{6}$$

The basic intuition behind the 2SDD approach is that group and period fixed effects can be identified using the subset of untreated groups and periods, provided that each group and period contains both treated and untreated observations. By comparing the mean outcomes between treated and untreated groups after removing these fixed effects, the method estimates the overall group-by-period ATT.

We use the 2SDD method in Gardner et al. (2024) to estimating β in Equation 1. The estimation procedure is outlined as follows. Let c index units (e.g., counties) and t index calendar time (e.g., quarters). Based on policy adoption across groups, we partition units and time into treatment groups $g \in \{0, 1, \ldots, G\}$ and periods $p \in \{0, 1, \ldots, P\}$. Group 0 remains untreated in all periods, while only members of group 1 receive treatment in period 1, members of groups 1 and 2 receive treatment in period 2, and so forth. Let D_{gp} be an indicator for whether group g are treated in period p. Define Y_{gpct} as the observed outcome for the c-th observation of group g during time t of period p. The 2SDD approach first estimates the following model

$$Y_{gpct} = \lambda_g + \alpha_p + \mu_{gpct} \tag{7}$$

on the sample of observations for which $D_{gp} = 0$, and save the estimated group and time effects $\hat{\lambda}_g$ and $\hat{\alpha}_p$. Second, regress $Y_{gpct} - \hat{\lambda}_g - \hat{\alpha}_p$ on D_{gp}. We also use the 2SDD approach to analyze the dynamic treament effects.

The two-stage estimator proposed in Gardner et al. (2024) provides identical point estimates as the imputation estimator in Borusyak et al. (2024). In our application, the approach in Borusyak et al. (2024) eliminates too many observations after controlling for all fixed effects and time-varying covariates, which is probably due to the unbalanced data structure in the hospitalization data. In addition, the two papers differ in variance estimators. The asymptotic theory developed in Borusyak et al. (2024) results in an asymptotically conservative default variance estimator.

We conduct two sets of robustness checks employing alternative estimation methods to ensure

regressor for individual i at time t, $\tilde{\mathbf{X}}_{0i}$ is defined as a $T \times K$ matrix of the following form:

$$\tilde{\mathbf{X}}_{0i} = \begin{bmatrix} \left(X_{1i1} - \frac{1}{T_i^0} \sum_{t=1}^{T} X_{1it} (1 - D_{it}) \right) (1 - D_{i1}) & \cdots & \left(X_{Ki1} - \frac{1}{T_i^0} \sum_{t=1}^{T} X_{Kit} (1 - D_{it}) \right) (1 - D_{i1}) \\ \vdots & \ddots & \vdots \\ \left(X_{1iT} - \frac{1}{T_i^0} \sum_{t=1}^{T} X_{1it} (1 - D_{it}) \right) (1 - D_{iT}) & \cdots & \left(X_{KiT} - \frac{1}{T_i^0} \sum_{t=1}^{T} X_{Kit} (1 - D_{it}) \right) (1 - D_{iT}) \end{bmatrix}$$

the reliability of our findings. First, we utilize the CSDID approach (Callaway and Sant'Anna, 2021), a staggered DID method that facilitates the analysis of treatment effects in scenarios featuring multiple time periods and staggered treatment adoption, particularly when time-varying controls are necessary. Second, we apply the high-dimensional Poisson pseudo-maximum likelihood (PPML) model, which is particularly useful in settings with nonnegative outcome variables such as the number of hospitalizations and medical expenditure, to estimate the effect of straw burning ban policy on hospitalizations and medical expenditure of vector-borne diseases (Correia et al., 2020):

$$Y_{cyq} = exp(\beta Ban_{cyq} + \mathbf{X}_{cyq}\gamma + \eta_{cy} + \delta_{pyq}) + \varepsilon_{cyq} \tag{8}$$

We control for county-level time varying characteristics, county-by-year fixed effects, and province-by-year-by-quarter fixed effects. PPML can make use of zero values of the dependent variable and provide consistent and robust estimates in the presence of heteroskedasticity.

4.1. Identification

The key identification assumption for the staggered DID method is that in the absence of the straw-burning ban policy, trends of the hospitalization outcomes of the treated groups would be parallel to those of the untreated groups, even if policy was adopted at different times across counties. This means that any observed differences in outcomes between the treated and untreated groups after treatment adoption can be attributed to the treatment itself, not pre-existing trends. In this section, we further discuss the validity of these assumptions and discuss potential biases in estimation.

Assignment to Straw Burning Ban Policy The primary identification concern in our analysis pertains to the potential correlation between the implementation of the straw-burning ban policy with unobservable influencing factors of the outcome variable, namely vector-borne diseases. This correlation could result in non-parallel trends between treated and untreated groups before treatment. However, we do not consider this concern to be significant mainly for two reasons. First, the straw-burning ban policy is one of the most important policy instruments of *APPC plan*, especially in rural air pollution control. China's effor to combat pollution, such as the Air Pollution Monitoring and Disclosure Program, was widely believed to be a top-down decision based on administrative hierarchies and characteristics determined long before the program (Barwick et al., 2024). Figure 5 illustrates that the straw-burning bans and the Air Pollution Monitoring and Disclosure Program followed similar rollout patterns. The left panel shows a strong correlation between the timing of straw-burning bans and the phases of the monitoring program—regions that adopted the monitoring program later also implemented the ban later. The right panel compares the monitoring program adoption in areas that never implemented the straw-burning ban. It reveals that most of these regions adopted monitoring only in the third wave, highlighting that

regions without a ban were rare and were also late adopters of air pollution monitoring.

Figure 5 about here.

Additionally, Table B1 compares the baseline characteristics of regions that implemented the straw-burning ban at different times. The results show that treated regions generally have higher GDP than untreated ones, and earlier adopters tend to have even higher GDP, aligning with the policy's administrative rollout strategy. Naturally, earlier-adopting regions also tend to have larger populations. Moreover, treated regions have larger cropland areas, suggesting that grain production scale was a factor in policy adoption. However, earlier adopters do not necessarily have larger cropland areas than later adopters, indicating that cropland size was not the primary determinant in the rollout. Some concerns exist regarding whether straw could serve as a household fuel source for farmers, potentially affecting policy adoption. However, the pre-ban practice of onsite straw burning suggests that farmers were unlikely to collect straw for fuel use. To further investigate, we compare electricity consumption between treated and untreated regions. While earlier-adopting regions exhibit higher electricity usage (likely due to greater economic development), we find no significant difference between treated and untreated groups in electricity consumption. Finally, we examine differences in healthcare resources across regions. We find no clear trend in hospital bed availability across different policy adoption periods, nor do we observe significant differences in the number of hospitals between treated and untreated groups.

Although there are differences between treated and untreated regions, these differences do not pose a threat to our identification strategy. This is because our regression includes county-by-year fixed effects and province-by-year-quarter fixed effects, which account for yearly-varying county-level characteristics and quarterly-varying provincial-level factors. These fixed effects absorb the influence of factors such as crop types, industrial structure, transportation importance, medical facilities, and climate policies that vary at the county-year level, as well as air pollution trends that vary at the province-year-quarter level. In addition, we test for parallel pre-treatment trends in the outcome variables between treated and untreated regions. By visually and statistically examining pre-trends, we provide further evidence that the observed effects are not driven by pre-existing differences between these groups.

Another potential concern is that since the straw-burning ban reduces air pollution, our findings could be confounded if air quality is correlated with vector-borne diseases. To address this, we confirm in Table B2 that vector-borne diseases are uncorrelated with PM2.5 levels across various model specifications, further reinforcing the validity of our identification strategy.

Time-varying Factors A violation of this assumption may occur if the policy rollout correlates with county-level quarterly-varying factors that influence our outcome variables. To address this, we control for rich influencing factors of the hospital inpatient admission level. Since the hospital-day level data form an unbalanced panel, we calculate the number of weekdays and weekend days each hospital appears in our dataset per quarter and then aggregate these variables to the

county-quarter level. Recognizing that hospitals with greater capacity can accommodate more patients and handle higher admission volumes, we construct two groups of proxies for hospital capacity. First, we measure the number of hospitalizations for bone fractures and blood diseases at the hospital-quarter level, as these conditions are generally considered unrelated to air pollution (Schlenker and Walker, 2016; Xiao et al., 2024), and then aggregate these values to the county-quarter level. Second, we compute the number of hospitals by tier, class, and type, along with the total number of hospitals, for each county-quarter observation.[39]

The second category of control variables accounts for weather conditions, which can influence both the habitat suitability of arthropods and outdoor labor patterns, potentially affecting hospitalization rates. We control for average temperature and precipitation amount.

The third category pertains to forest fires, which may also affect both the survival of arthropods and hospitalizations. Thus, we include controls for the incidence of wildfires in forested areas.

Placebo Tests for Unrelated Diseases As a placebo test, we examine the hospitalization impact of straw-burning ban policy on diseases that are unlikely influenced by this policy using the same regression framework. The placebo diseases include bone fractures and blood diseases.

Spillover Effects As previously discussed, within-county spillovers from rural to urban areas are captured using aggregated county-level measures of vector-borne disease. However, our estimates may still be subject to two additional sources of bias when spillovers occur across county borders. First, control counties may not serve as valid counterfactuals if treatment counties indirectly affect neighboring controls through insect mobility. Second, outcomes in treated counties may reflect a combination of their own treatment effects and spillover effects from nearby treated counties. Estimating spillover effects in a staggered treatment setting is particularly challenging due to their cumulative nature. A staggered policy adoption complicates the direct application of standard spillover estimation methods. To mitigate these concerns, we isolate direct effects by excluding geographically adjacent counties with non-synchronous policy adoption.

Concurrent Policies Several concurrent agricultural policies were implemented alongside the straw burning ban. However, it is unlikely that these policies bias our results for two key reasons. First, many of these policies were national in scope, for example, the reform to abolish the agricultural tax, while a few were introduced as regional pilot programs, for example, the pilot program for agricultural insurance financial subsidies, and land transfer policy reform. The rollout of these pilot programs was not correlated with the implementation of the straw burning ban, since most of these policies were implemented on a provincial basis, and their operational focus differed significantly from the ban. Second, these policies did not directly affect insects, making it unlikely that they had any significant impact on the health outcomes we study.

[39] Note that our original hospitalization data does not cover all hospitals throughout the entire sample period, so the county fixed effects and year-by-season fixed effects do not absorb the influence of these covariates.

Another threat to our identification is the possibility that other concurrent health policies may contaminate the estimation. We believe this is not a concern since these health policies should have no impact on vector-borne diseases. For example, the drug centralized procurement policy since 2020 mainly lowers the prices of medications for tumors, cardiovascular diseases, and mental illnesses, and has no impact on patients with vector-borne diseases. Similarly, the Diagnosis-Related Group (DRG) payment reform, which pays hospitals based on patients' diagnosis and procedure, primarily affects how hospitals treat and code patients, but does not influence the incidence of vector-borne diseases.

4.2. Heterogeneity Analyses

To further explore the mechanisms behind the policy's impact, we conduct heterogeneity analyses along three key dimensions. First, we examine spatial variation by major grain type, as different crops have distinct straw-burning practices, which may influence the policy's effect. Second, we analyze regional differences in precipitation levels, since humidity plays a crucial role in insect survival and vector-borne disease transmission. Third, we investigate temporal variation, focusing on whether the policy's impact is more pronounced during the harvest season, when increased field activity may heighten human exposure to insect bites.

5. Result

5.1. Straw Burning Ban and vector-borne Diseases

To investigate the impact of straw burning ban policies on vector-borne diseases, we estimate Equation 1 using the two-stage staggered DID model suggested by Gardner et al. (2024). County-year fixed effects, province-year-quarter fixed effects, and hospital controls and baseline controls are included. Table 2 reports the results.

Table 2 about here.

In Column (1), we include county-by-year and province-by-quarter-year fixed effects. The estimated treatment effect is positive and significant at 1% level. In Column (2) we further add control variables for hospital characteristics, weather, and forest fires. The results indicate that the straw burning ban significantly increases hospitalizations for vector-borne diseases by 11.94 cases per county per season. Note that the average number of the hospitalizations is 18.38 in our data. It suggests that the policy increases the hospitalization of vector-borne diseases by around 65%. Columns (3) and (4) analyze the impact on medical expenditures. The policy leads to an increase of 59,128 Chinese Yuan per county per quarter for vector-borne diseases (around 67% of the sample average).

Table 3 examines the treatment effect on tick-borne diseases. Column (2) shows that the treatment affect of the straw-burning ban on tick-borne disease hospitalization is 1.16 cases per quarter

and county, or 110% of the sample average. Column (4) shows that the policy leads to an increase of 8,973 Chinese Yuan for tick-borne diseases (186% of the sample average).

Table 3 about here.

Figure 6 illustrates the dynamic effects of the straw-burning ban on hospital inpatient admissions for vector-borne and tick-borne diseases. We employ an event study approach to test for common trends before policy implementation and to assess its dynamic impacts after implementation. The x-axis represents quarters relative to the treatment, with the vertical dashed line indicating the quarter of policy implementation. The y-axis plots the estimated treatment effects relative to never-treated counties, along with the 95% confidence intervals.

The upper panel and lower panel of Figure 6 display results for vector-borne and tick-borne disease hospitalizations, respectively. It shows that, after policy implementation, the treatment effect is persistengly positive and statistically significant, with the magnitude of impact similar to Column (2) of Table 2. A sharp increase occurs immediately after the ban's introduction, persisting for sixteen subsequent quarters (four years). This suggests a significant and sustained rise in hospitalizations for vector-borne and tick-borne diseases following the policy's implementation. Figure 7 shows similar results for medical expenditures.

Figure 6 about here.

The upper and lower panels of Figure 7 illustrate the dynamic effects of the straw-burning ban on medical expenditures associated with vector-borne and tick-borne diseases, respectively. Consistent with the results for hospital admissions, the pre-treatment coefficients are statistically insignificant, supporting the parallel trend assumption. Following policy implementation, the coefficients increase and remain persistently positive, indicating a sustained rise in medical expenditures related to vector-borne and tick-borne diseases over time.

Figure 7 about here.

A back-of-the-envelope calculation suggests that across 1,404 counties where the ban was implemented during 2011-2022, the annual increase in total medical expenditures for in-hospital vector-borne diseases exceeds 1.95 billion Chinese Yuan (59,564 $\times$ 4 $\times$ 1,404 $\times$ 5.84), approximately 280 million US dollars.[40] Among this, the additional medical burden from tick-borne diseases alone amounts to 298 million Chinese Yuan per year (9,141 $\times$ 4 $\times$ 1,404 $\times$ 5.84). Given that outpatient data is unavailable, the actual cost burden is likely substantially higher than our estimates. Since outpatient data is unavailable, the true economic burden is likely significantly higher, as our estimates only capture hospitalization costs and do not account for outpatient medical expenses.

[40] In 2022, there were 36,976 hospitals across 2,843 counties in China (National Health Commission of the People's Republic of China, 2023), and 2,788 hospitals across 1,252 counties in our health data. Thus, we use (36976/2843)/(2788/1252)=5.48 as a multiplier to extrapolate our estimates to the national sample.

5.2. Heterogeneity

Spatial Heterogeneity by Major Grain Table 4 presents the heterogeneous effects of straw burning ban policies on inpatient admissions for vector-borne and tick-borne diseases by different major grains grown. Specifically, we compare regions where the major grain is one of the two: wheat and corn. All counties are divided into two groups by the grain area of the county during 2011-2022: counties where the planting area of one grain exceeds that of the other grains are defined as “major" counties for that particular grain; otherwise, it is defined as “minor" counties for that grain.

The results indicate significant heterogeneity in the policy’s impact. For wheat-growing counties, the straw burning ban policies lead to an increase of 11.53 inpatient admissions for vector-borne diseases in counties where wheat is a minor crop, but a larger increase of 24.85 in counties where wheat is a major crop, as shown in Columns (1) and (2). In contrast, the results for corn-growing counties show a reversed pattern: the policies significantly increase inpatient admissions by 18.77 cases in counties where corn is a minor crop, while the effect is negligible and statistically insignificant in counties where corn is a major crop, as shown in Columns (3) and (4). The straw burning ban policies also exhibit a similar pattern of heterogeneous effects on tick-borne diseases, as shown in Columns (5)–(8). County-year fixed effects, province-year-quarter fixed effects, and hospital controls and baseline controls are included.

Table 4 about here.

The findings highlight that the straw burning ban policies have a larger impact on vector-borne and tick-borne disease related hospitalizations in regions where the major crop residues of wheats, due to its low value and difficulty in collection, was mainly disposed of by burning on-site before the ban was implemented after harvest. Straw burning in these area are more prevalent and thus the ban are more likely contribute more to ecological or environmental changes. Conversely, the negligible impact in major corn-growing counties suggests that corn residue burning may play a smaller role in altering vector-borne disease dynamics than wheat or rice residues. Since the corn straw is an important agricultural resource in rural areas, with a relatively higher value compared to wheat, it is rarely burned on-site, thus the corn major regions are less affected by this policy.

Heterogeneity by Climate Table 5 presents the heterogeneous effects of straw burning ban policies on hospitalizations related to insect-borne and tick-borne diseases across counties by different precipitation levels. All counties are divided into two groups according to their average precipitation during 2011-2022: counties experiencing precipitation above the median level are categorized as "High Precipitation" counties, while those below the median are classified as "Low Precipitation" counties.

The empirical results indicate significant heterogeneity by precipitation levels. As shown in Columns (1) and (2), the impact of straw burning ban policies on insect-borne disease hospitalizations is considerably stronger and statistically significant in high precipitation counties, increasing

hospitalizations by 14.39 cases. In contrast, the policy effect in low precipitation counties is smaller (6.17 cases) and statistically insignificant. Similarly, Columns (3) and (4) display similar patterns for tick-borne diseases, with the policies significantly increasing hospitalizations by 1.47 cases in high precipitation regions, while the effect is negligible and statistically insignificant in low precipitation regions. County-year fixed effects, province-year-quarter fixed effects, and hospital controls and baseline controls (excluding precipitation) are included.

Table 5 about here.

These findings suggest that the policy-induced habitat changes affecting vectors and ticks are more pronounced in humid environments, where moisture-rich conditions are favorable to vector survival, reproduction, and activity. Consequently, ecological shifts caused by the straw burning bans may interact strongly with climatic factors in humid regions, leading to more substantial changes in vector populations and disease transmission dynamics. In contrast, the relatively dry conditions in low precipitation counties may inherently limit vector abundance and activity, thereby reducing the effects of ecological changes induced by policy implementation.

Temporal Heterogeneity Since straw burning is most prevalent during the autumn harvest season, we analyze temporal heterogeneity to determine whether the policy's effect on hospitalizations for vector-borne diseases aligns with its implementation timing. To do so, we separately estimate the impact of the straw burning ban on hospitalizations for each quarter of the year. Table 6 presents the corresponding results. The dependent variables in Columns (1) to (4) represent the number of hospitalizations for vector-borne diseases in each of the four quarters, with the independent variable capturing the policy's implementation status for that year. The results show that the largest increase in hospitalizations occurs in the third and fourth quarters, which coincide with the autumn harvest season. This suggests that the policy's effects are most pronounced during this period, reinforcing the notion that the ban disrupts ecological conditions at a time when straw burning is typically widespread.

Table 6 about here.

In Table D1, we present quarterly policy-health outcome estimates. Panels A, B, C, and D show the effects of policies implemented in each of the four quarters on vector-borne hospitalizations, respectively. Columns (1)–(4) report the results using total inpatient admissions in each quarter as the dependent variable. The findings highlight two key insights. First, policies implemented during the harvest seasons—the second and fourth quarters—exhibit more pronounced effects, suggesting that straw burning bans have the greatest immediate impact when crop residues are most abundant. Second, the effects persist throughout the year, indicating a lasting ecological shift that continues to influence human health beyond the harvest period. These results underscore the need for year-round straw residue management rather than policies that solely focus on the harvest season.

5.3. *Additional Robustness Checks*

Placebo Tests for Unrelated Diseases: As a placebo test, we examine the hospitalization impact of straw-burning ban policy on diseases that are unlikely influenced by this policy using the same regression framework. The placebo diseases include bone fractures and blood diseases. As shown in Table D2, effects of the straw-burning ban policy on the number of hospitalizations and medical expenditure are insignificant across both placebo disease categories. These results confirm that the estimated hospitalization effects on vector-borne diseases cannot be attributed to common factors that affect hospitalizations for all diseases.

Accounting for Spillover Effects: To mitigate potential contamination from earlier to later treatment waves, we exclude geographically adjacent counties with differing policy implementation timelines. Figure E8 illustrates the spatial and temporal distribution of treatment counties after removing adjacent counties across treatment waves and between treatment and control groups. Using this restricted sample, we re-estimate treatment effects, focusing only on counties not adjacent to previously treated areas. Results in Table D3 show a comparable magnitude to the annual average effects reported in Table 6. Given the persistence of treatment effects over time, potential biases from cross-county spillovers appear limited and unlikely to affect our conclusions.

Alternative Staggered DID Model: We use alternative methods suggested by Callaway and Sant'Anna (2021), the results are robust, as shown in Table D4. We also conduct event study using this framework. The results are shown in Figure D1, confirming the findings in our benchmark model that the policy has persistent impact in up to four years post the ban.

Alternative Empirical Model: Given that both hospitalization counts and medical expenditure data contain a substantial number of zero observations, one may question the appropriateness of using a linear model. To address this concern, we employ a Poisson Pseudo-Maximum Likelihood (PPML) model as a robustness check. The results, presented in Table D5, confirm the robustness of our findings. In the PPML model, we include county-by-year, county-by-quarter, and province-by-year-quarter fixed effects, and separately test the impact of the straw burning ban policy on hospitalization counts and medical expenditures for vector-borne and tick-borne diseases. Consistent with our benchmark results, the ban significantly increases both hospitalization counts and expenditures under both measures. These findings reinforce the robustness of our analysis and validate the policy's unintended health consequences.

Alternative Measures of Policy Implementation: We demonstrate that the results remain consistent when using alternative indicators for the policy. Specifically, we replace the benchmark policy with local official assessment with two alternative measures: (1) policies that explicitly prohibit straw burning and (2) all straw-related policies. The results, presented in Table D6 , show

that the findings are consistent with the benchmark, with coefficients of similar magnitude. However, in some specifications, statistical significance is slightly weaker. This suggests that policies with local official assessment have stronger effects, likely because they provide greater incentives for enforcement.

Alternative Sample Periods We conduct robustness checks using alternative sample periods, as presented in Table D7. Columns (1) and (2) utilize the full sample without restricting the analysis to 8 and 16 quarters before and after policy implementation. Columns (3) and (4) limit the sample to 2017–2022, a period when the data is more balanced. The results remain consistent across all specifications.

6. Pathway of Impact

6.1. Straw Burning

We begin by assessing the impact of the straw-burning ban policy on agricultural fires. Table 7 shows that the straw burning ban policy led to an annual increase of 3 agricultural fires and reduced the agricultural burned areas by 141.667 hectares on average for all counties. These results mirror the direct effects of the ban policy on decreasing in straw burnings. For areas with burning histories, counties observed even fewer straw burnings following the ban, with 4 agricultural fires decreasing per year and 191.418 km^2 less burned areas. Our results proved robust across various measurements of agricultural fires and control setup (see Table D8), measures of policy implementation (see Table D9), and use alternative DID estimation methods (see Table D10). The results are also consistent across counties with different dominant crops (see Table D11). The observed reduction in agricultural fires originates from the assessment-based ban policy, which changed the agricultural ecosystem and agricultural results, intentionally affecting human health by increasing the population of insects.

Table 7 about here.

6.2. Insect Observations

To validate the influencing channel of straw-burning bans on vector-borne and tick-borne diseases through the proliferation of relevant arthropods, we analyze the policy's impact on the number of species observations across various taxonomic categories. Our analysis controls for county fixed effects, year fixed effects, weather characteristics, the number of forest fires, burned forest area, and the number of unique observers. Table 8 presents the results, excluding counties that have never experienced vegetation fires. Following the implementation of straw-burning bans, the number of Arthropoda observations significantly increases, aligning with the observed rise in hospitalizations for tick-borne diseases. The policy also leads to an increase in Coleoptera and

Staphylinidae observations. Although the estimated effects on Arthropoda and Insecta are statistically insignificant, their signs are positive and consistent with expectations. These findings provide supportive evidence for the underlying mechanisms through which the policy affects hospitalizations of vector-borne diseases.

Table 8 about here.

6.3. Web Search for Insect Bites

We have presented evidence based on in-hospitalization data, but since not all insect-related diseases result in hospital admissions, the actual impact may be underestimated. To complement this analysis, we use the Baidu Search Index as a proxy for public awareness and observed incidence of insect bites, as discussed in Section 2.2.

To formally assess this effect, we estimate the DID model using different categories of Baidu Search Indices as dependent variables. Table 9 presents the results. Since the Baidu Index is only available at the city level, the regression is conducted at the city-quarter/year level, incorporating city-year, city-quarter, and province-year-quarter fixed effects to account for regional and seasonal variations.

The results show that the straw burning ban significantly increases Baidu search activity related to all three categories of keywords. Specifically, as reported in Column (1), searches for "Insect Bites" increase by 11.3 (approximately 0.28 standard deviation) following the policy implementation. Column (2) shows that searches for "Ticks" rise by 49.5 (approximately 0.5 standard deviation). Additionally, Baidu also records the search frequency of specific queries, such as "What to do if bitten by a tick?". Column (3) shows that the policy increased this search index by 8.0 (0.15 percentage points), further indicating heightened public concern following the ban. All these effects are statistically significant at the 5% level. These findings suggest that the straw burning ban heightened public awareness and concern regarding insect bites.

Table 9 about here.

6.4. Web Search for Protective Measures and Pest Control

The findings above establish that the straw-burning ban triggered a chain reaction, including a reduction in fires, an increase in insect abundance, and a surge in Baidu searches related to insect bites. A natural response to these changes is that people may adopt protective measures to mitigate the risks of insect-borne diseases. To examine this, we analyze Baidu search indices for relevant keywords. We generate four categories of search terms: (1) Protective measures, such as using mosquito nets, mosquito coils, and insect repellent sprays or lotions. (2) Vaccines for vector-borne diseases, including tick-borne encephalitis, yellow fever, and hemorrhagic fever vaccines. (3) Pest control solutions, such as insecticides and pesticide sprays. (4) Straw management technologies, including straw shredders, straw pellet machines, and straw balers.

Table 10 shows that the policy led to increase equivalent to 0.2 to 0.5 standard deviation in searches for these terms, confirming that people actively sought protective measures in response to heightened insect exposure. This also indicates that the policy imposed additional health-related costs beyond hospitalization expenses. Moreover, since our results show that the policy's impact on disease incidence persists over time, the preventive measures observed are insufficient to fully mitigate the health risks. This underscores the importance of further public health education and government interventions to address long-term disease prevention.

Table 10 about here.

6.5. Additional Results

The straw burning ban policy can generate impacts beyond the above discussions. First, we examine whether the straw burning ban policy has facilitated the changes of agricultural outcomes. As certain crops may incur more health concerns and requires more labor in planting, it is possible that agricultural sectors tend to reallocate labor towards crops less affected by the straw burning ban policy, reducing the health risk while enhancing productivity. Table E1 presents our key findings: Following the assessment-based straw burning ban policy, there was a significant decrease in local cropland, with an average decrease of 1,579 km^2. This cropland changes was particularly pronounced as they did not convert to forest areas which observed insignificant changes. Followng the policy, among the grain outputs, wheat planting decreased by 2.2% annually while the corn planting areas increased by 2.8%. As wheat planting can cause more burden due to straws, these results indicates that the policy not only affect agricultural burnings but also saw a substantial additional changes in agricultural outcomes.

We provide empirical evidence of improvements in air quality using satellite-based annual $PM_{2.5}$ concentration data from 2001 to 2022. Table E2 shows the estimation results. Columns (1)-(2) indicate that the straw burning ban is associated with a reduction in average $PM_{2.5}$ concentration by approximately 1 $\mu g/m^3$, which constitutes about 3% of the average annual concentration. Columns (3)-(4) exclude the county sample with no fire incidence during the study period and still find a reduction in $PM_{2.5}$, albeit to a lesser extent.

We also examine the impact of an alternative to straw burning: biomass power plants (BPPs). These plants use agricultural waste, such as straw, as fuel to generate electricity, thereby internalizing the environmental costs of straw burning. Table E3 shows that approximately two BPPs were established in each county after the straw burning ban, as indicated in Columns (1) and (2). For counties with a history of straw burning, the number of BPPs established was slightly lower, as shown in Columns (3) and (4).

7. Policy Implications

This study examines the ecological and agricultural consequences of straw-burning bans, with a focus on their implications for human health. Our findings carry important policy relevance. While the bans reduce $PM_{2.5}$ concentrations and related health costs, they unintentionally create favorable conditions for arthropods, increasing hospitalization costs associated with vector-borne diseases. These results highlight the need for integrated environmental and public health policies that balance pollution control, ecological stability, and health outcomes, ensuring that interventions do not unintentionally disrupt ecosystems or amplify health risks.

Given the rise in vector-borne diseases — particularly in regions where cropland burning historically suppressed pest populations — policies should promote alternative pest management strategies. Methods such as biological control, crop rotation, and targeted pesticide use can mitigate the unintended health consequences of the ban. These approaches can enhance environmental benefits while minimizing adverse health risks, especially in disadvantaged rural areas. Our findings also provide relevant insights for other countries considering similar air pollution control policies.

Our study does not oppose the straw-burning ban or downplay concerns about air pollution. Rather, it aims to clarify the mechanisms through which such policies affect ecological and health outcomes, offering guidance for minimizing unintended consequences. By examining spatial, crop-type, and seasonal heterogeneity, we underscore the importance of targeted attention to wheat-growing regions, where alternative disposal options are limited. Moreover, due to the overwintering behavior of adult ticks and other arthropods, the policy's effects extend beyond harvest periods, with implications across all seasons. The heterogeneous impacts of the ban by crop type and season suggest that a uniform policy may be suboptimal. Policymakers should consider seasonal or regional exemptions for controlled burning in areas with elevated vector-borne disease risk, while maintaining the ban where alternative disposal methods are viable.

Additionally, we find that the ban has led to an increase in biomass power plants as a viable alternative to recycle crop residues into electricity. Consistent with the literature (Cao and Ma, 2023; Nian, 2023), biomass power plants remunerate farmers for collecting crop straw and internalize the environmental costs of burning practice. Encouraging mechanized straw incorporation, composting, or bioenergy production can reduce reliance on burning while mitigating ecological conditions that promote arthropod proliferation. Providing subsidies and incentives for farmers to adopt sustainable straw disposal techniques could further alleviate unintended consequences.

Moreover, strengthening disease surveillance systems in agricultural regions would enable rural communities to respond proactively to emerging health risks associated with agricultural practices. Such investments would not only protect human health but also enhance agricultural productivity and ensure the long-term equality.

Overall, these insights contribute to the broader empirical literature on straw burning policies, offering guidance on balancing environmental objectives with ecological and public health considerations.

8. Conclusion

This study highlights the unintended health consequences of environmental policies by examining how China's straw-burning ban, originally implemented to reduce air pollution, has altered agricultural ecosystems and increased the prevalence of vector-borne diseases. Our findings reveal that the policy significantly increased hospitalizations and medical expenditures for insect-borne diseases. We further demonstrate that the ban reduced cropland fires while simultaneously heightening public concern about insect-borne diseases, as reflected in increased online search activity.

This paper illustrates the complex and often overlooked interactions between human interventions and ecological systems. Our findings do not suggest that straw burning should continue, but rather that policies targeting environmental improvements must also consider broader ecological and health implications. The negative consequences of the ban can be mitigated by complementary measures such as improved straw disposal methods, public health education, and preventive strategies. More broadly, this study calls for a more integrated approach to environmental policy design, where interventions account for ecosystem feedback loops to avoid shifting health and environmental risks elsewhere.

Tables and Figures

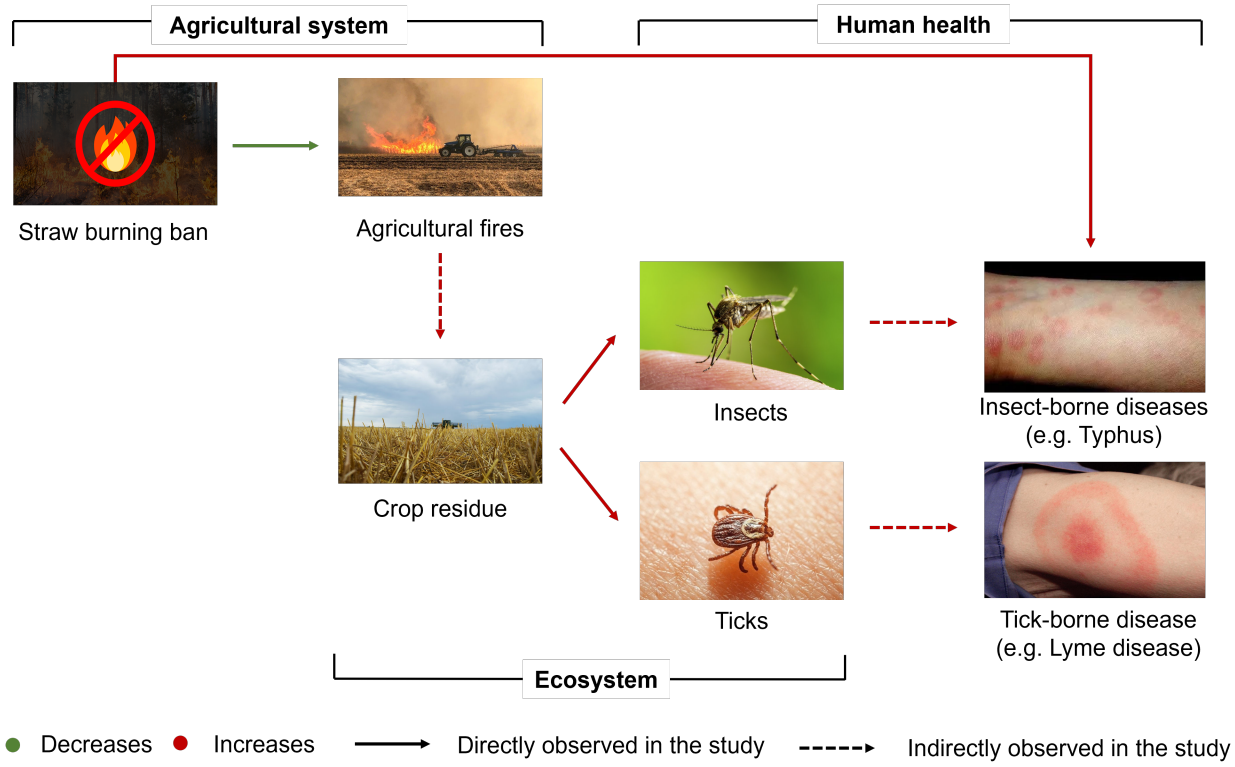
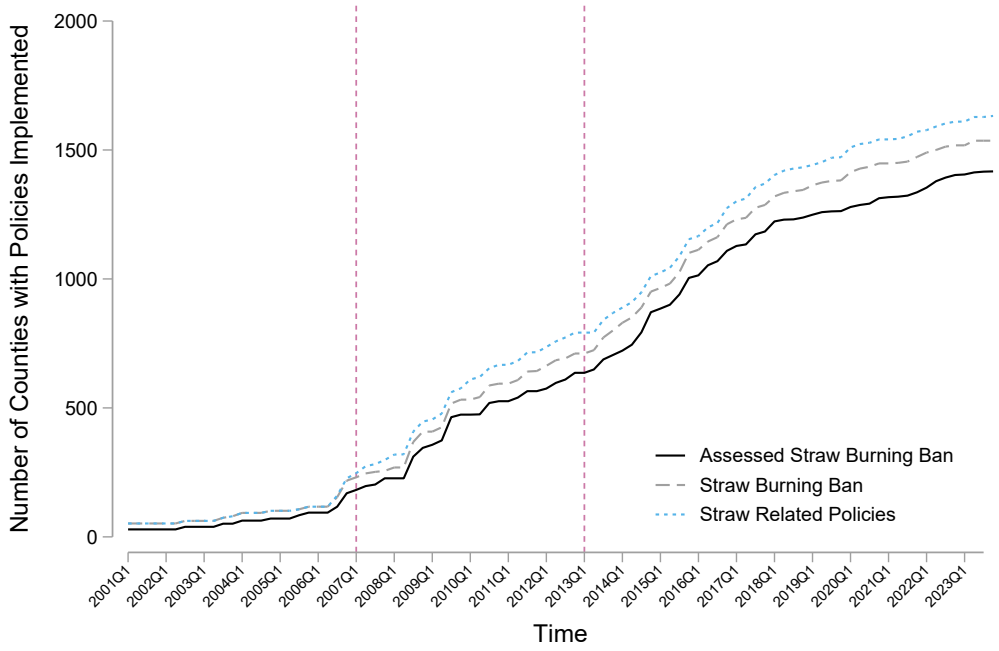


Figure 1. Ecological Framework Linking Straw-Burning Ban with Human Health

Notes: The figure illustrates the key elements of the study and the theoretical predictions regarding how (i) the straw-burning ban policy leads to a decrease in agricultural fire incidence and an accumulation of crop residues; (ii) in turn creating favorable habitats for pests and arthropods, including ticks; and (iii) resulting in negative impacts on human health by causing more vector-borne infectious diseases and insect bite dermatitis through increased exposure.

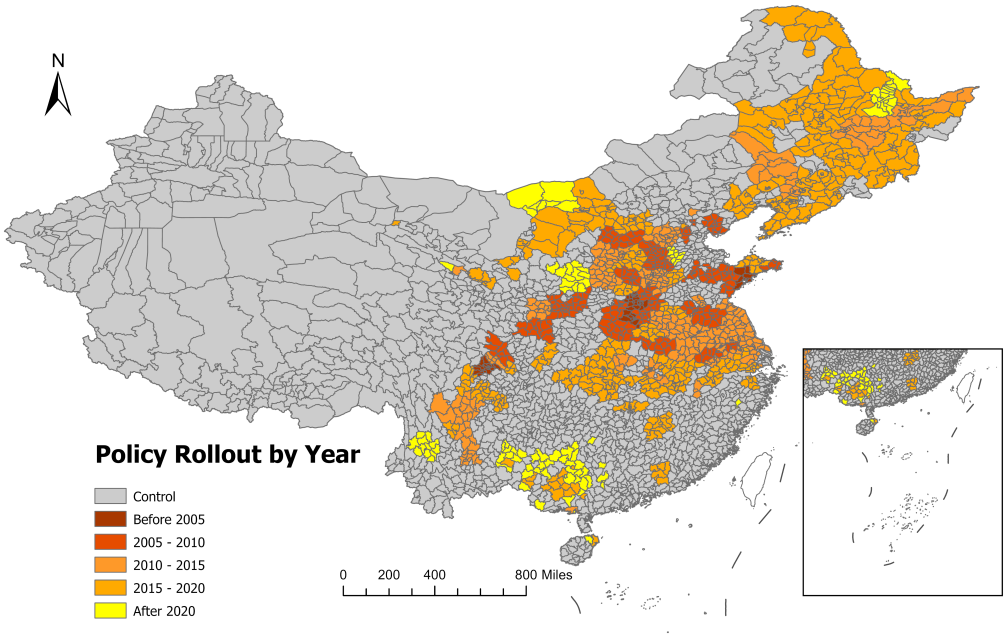
Figure 2. Timeline for China's Straw Burning Policies



Source: The data are obtained from the Peking University Law Database (https://www.pkulaw.com), which are described in detail in Appendix A.2.

Note: This figure illustrates the timeline for the implementation of straw burning policies. As shown in the figure, since 2006, the prohibition of straw burning has been more extensively and deeply implemented in additional counties across China, with a staggered rollout that eventually covered more than half of the counties in the country.

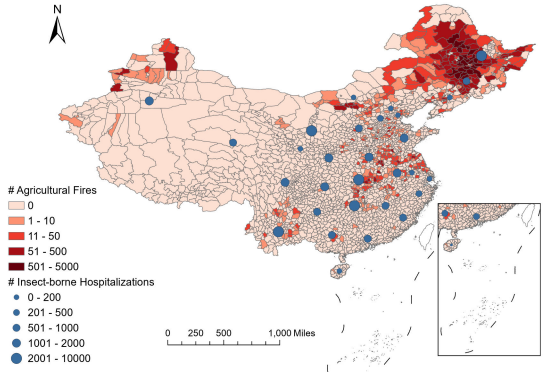
Figure 3. Roll-out of China's Straw Burning Policies



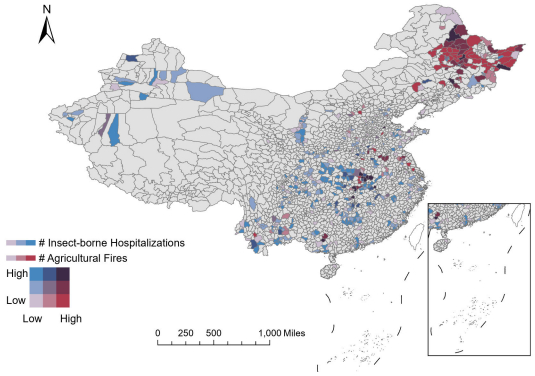
Source: The data are obtained from the Peking University Law Database (https://www.pkulaw.com), which are described in detail in Appendix A.2.

Note: This figure illustrates the distribution of roll-out of straw burning policies.

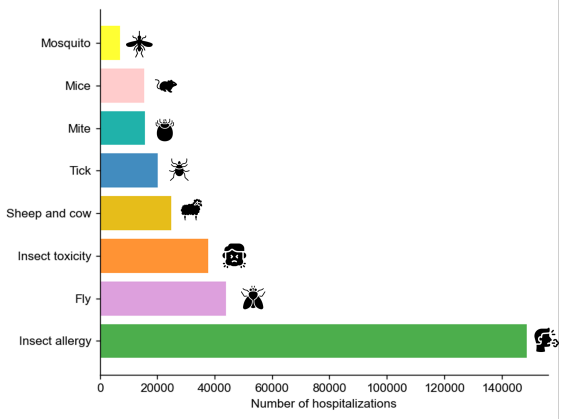
(a) Distribution of agricultural fires and vector-borne hospitalizations



(b) Negative correlation between agricultural fires and vector-borne hospitalizations



(c) Categories of vector-borne hospitalizations



(d) Time trends of vector-borne hospitalizations

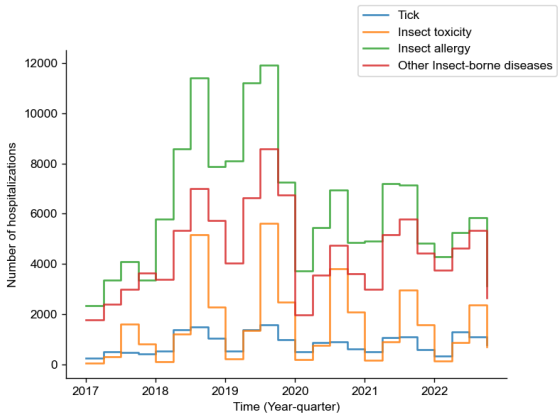
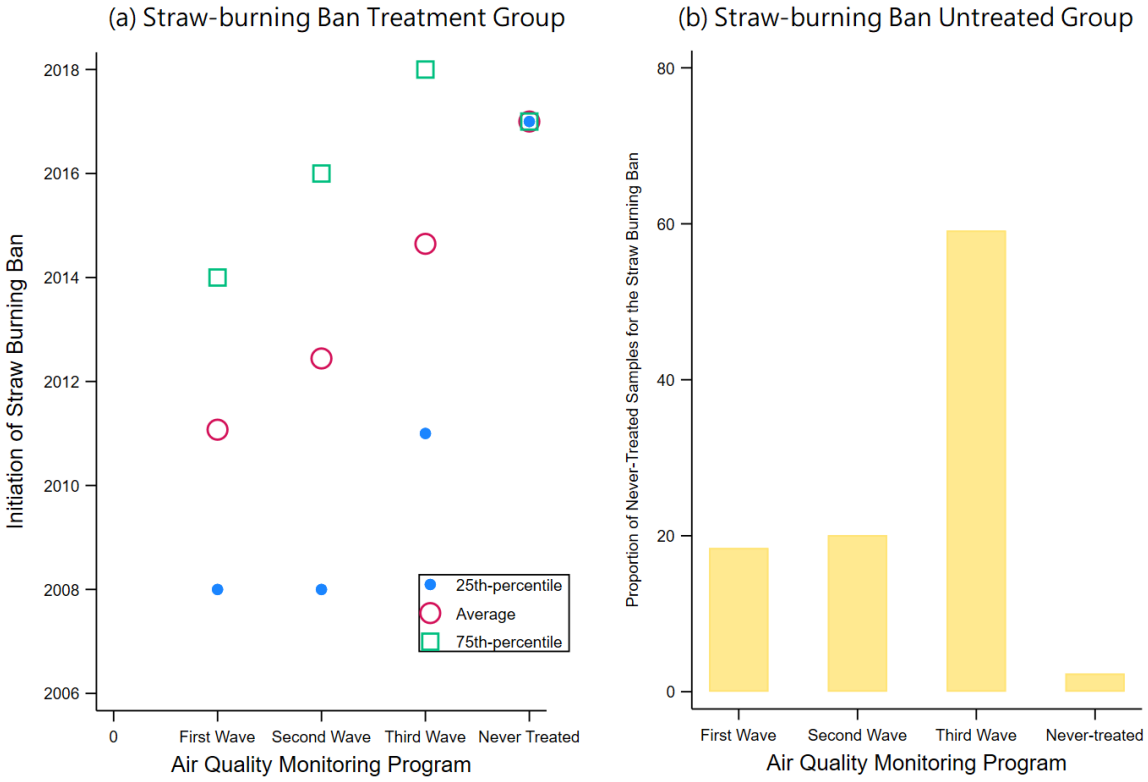


Figure 4. Distribution of Straw Burning and vector-borne Disease Hospitalizations

Notes: Panel (a) presents county-level agricultural fire incidents and province-level vector-borne disease hospitalizations in 2022. Panel (b) illustrates the negative spatial correlation between agricultural fire incidents and vector-borne disease hospitalizations in 2022. Panel (c) categorizes vector-borne disease hospitalizations by type from 2017 to 2022. Panel (d) shows the total number of vector-borne disease hospitalizations by year and quarter from 2017 to 2022.

Figure 5. Straw Burning Ban and Air Quality Monitoring Program Rollouts



Source: The data are obtained from Barwick et al. (2024) and the Peking University Law Database (https://www.pkulaw.com), which are described in detail in Appendix A.2.

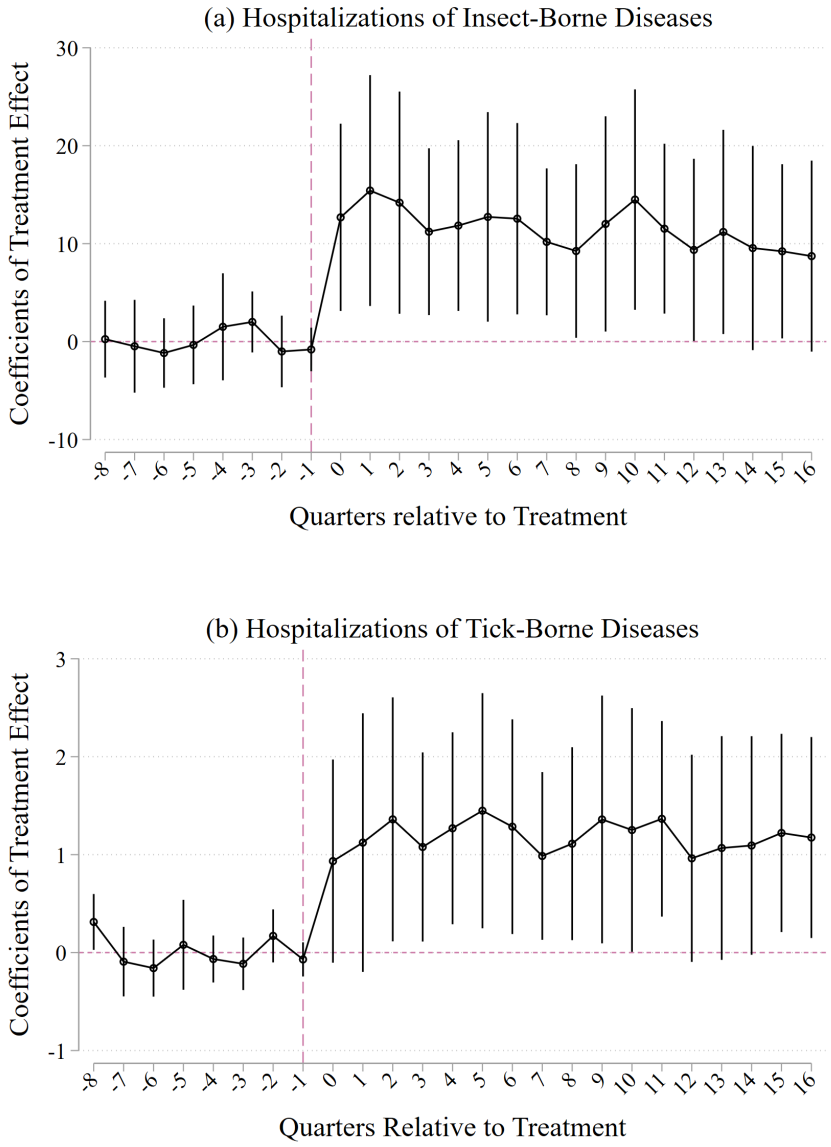


Figure 6. Event Study: Hospitalizations

Notes: This figure illustrates the dynamic effects of the straw-burning ban on hospitalizations using a two-stage difference-in-differences event-study approach (Gardner et al., 2024). Treatment status is set to 1 for counties that implemented a straw-burning ban with policy assessment. The dependent variables are the number of inpatient admissions for vector-borne and tick-borne diseases, with the unit of observation at the county-year-quarter level. The regression sample excludes counties with no recorded cropland fires between 2001 and 2022 (i.e., counties with minimal cropland or crop residues). The analysis includes data from the two years (eight quarters) preceding policy implementation and the four years (sixteen quarters) following implementation. The model incorporates county-by-year fixed effects and province-by-year-by-quarter fixed effects. Control variables include the number of hospitalizations for bone fractures and blood diseases, the total number of hospitals, and the counts of tier-2, tier-3, Class B, Class C, and general hospitals, the aggregated number of weekdays and weekend days at the county-quarter level, the frequency and burned area of forest wildfires in the corresponding quarter, the average temperature, and precipitation. The y-axis presents the estimated treatment effects relative to never-treated counties, with 95% confidence intervals.

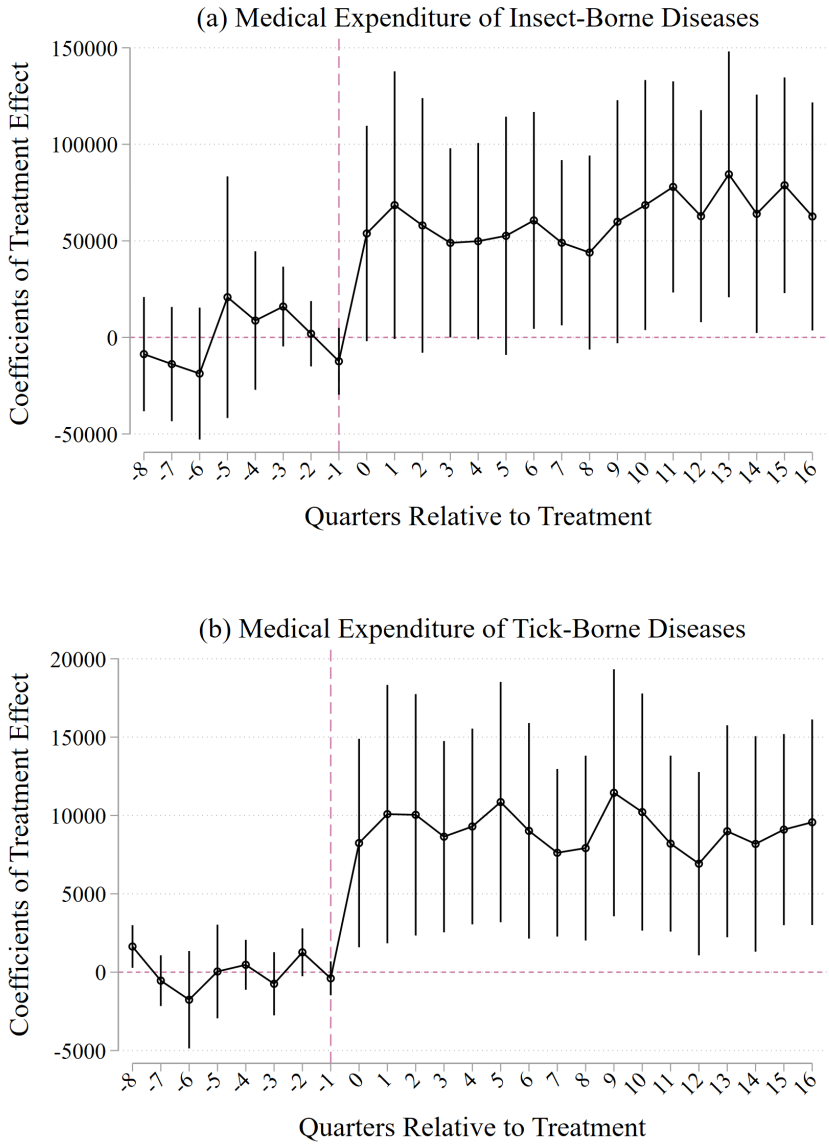


Figure 7. Event Study: Medical Expenditure

Notes: This figure illustrates the dynamic effects of the straw-burning ban on medical expenditure (in Chinese Yuan) using a two-stage difference-in-differences event-study approach (Gardner et al., 2024). Treatment status is set to 1 for counties that implemented a straw-burning ban with policy assessment. The dependent variables are the number of inpatient admissions for vector-borne and tick-borne diseases, with the unit of observation at the county-year-quarter level. The regression sample excludes counties with no recorded cropland fires between 2001 and 2022 (i.e., counties with minimal cropland or crop residues). The analysis includes data from the two years (eight quarters) preceding policy implementation and the four years (sixteen quarters) following implementation. The model incorporates county-by-year fixed effects and province-by-year-by-quarter fixed effects. Control variables include the number of hospitalizations for bone fractures and blood diseases, the total number of hospitals, and the counts of tier-2, tier-3, Class B, Class C, and general hospitals, the aggregated number of weekdays and weekend days at the county-quarter level, the frequency and burned area of forest wildfires in the corresponding quarter, the average temperature, and precipitation. The y-axis presents the estimated treatment effects relative to never-treated counties, with 95% confidence intervals.

Table 1: Summary Statistics

	Counties Available	Years Available	Frequency	Mean	SD
Panel A: Health Data					
Hospitalization: Vector-borne	1,253	2011-2022	Quarterly	20.002	36.661
Hospitalization: Tick-Borne	1,253	2011-2022	Quarterly	1.121	3.424
Medical Expenditure: Vector-borne (CNY)	1,253	2011-2022	Quarterly	105667.562	230831.027
Medical Expenditure: Tick-Borne (CNY)	1,253	2011-2022	Quarterly	5521.088	19412.694
Panel B: Agricultural Data					
# Agriculture Fire	2,751	2001-2022	Monthly	3.265	27.652
Burned Area (*hectare*)	2,751	2001-2022	Monthly	187.019	1825.310
Cropland ($100\ km^2$)	2,689	2001-2022	Yearly	687.443	758.512
Forest ($100\ km^2$)	2,626	2001-2022	Yearly	9.196	19.805
Wheat Plant Area ($100\ km^2$)	2,691	2001-2022	Yearly	77.441	192.956
Crop Plant Area ($100\ km^2$)	2,691	2001-2022	Yearly	117.509	231.436
Rice Plant Area ($100\ km^2$)	2,691	2001-2021	Yearly	102.194	256.855
Panel C: Straw Burning Ban Policy and Institional Reactions					
Policy: straw burning ban policy (with assessment)	2,751	2001-2022	Monthly	0.233	0.423
Policy: straw burning ban policy (ban)	2,751	2001-2022	Monthly	0.260	0.439
Policy: straw burning policy (all)	2,751	2001-2022	Monthly	0.279	0.448
$PM_{2.5}$ ($\mu g/m^3$)	2,691	2001-2022	Monthly	40.371	22.885
Biomass Entry	2,751	2001-2022	Yearly	1.949	8.644
Baidu Index: Insect-bite	329 (cities)	2009-2022	Quarterly	20.67	39.94
Baidu Index: Tick	329 (cities)	2009-2022	Quarterly	71.71	102.66
Baidu Index: Bite-related inquiries	329 (cities)	2009-2022	Quarterly	22.99	53.56
Baidu Index: Protective measures	329 (cities)	2009-2022	Quarterly	33.05	62.92
Baidu Index: Vaccination	329 (cities)	2009-2022	Quarterly	10.26	22.25
Baidu Index: Pest control	329 (cities)	2009-2022	Quarterly	67.17	122.12
Baidu Index: Straw Utilization	329 (cities)	2009-2022	Quarterly	30.94	52.87
Panel D: Insect Population					
# obs. trips of species within Arthropoda	1,989	2011-2022	Yearly	4.801	96.373
# obs. trips of species within Arachnida	1,989	2011-2022	Yearly	0.133	1.705
# obs. trips of species within Insecta	1,989	2011-2022	Yearly	4.296	91.161
# obs. trips of species within Coleoptera	1,989	2011-2022	Yearly	0.558	31.394
# obs. trips of species within Staphylinidae	1,989	2011-2022	Yearly	0.015	0.357
# obs. trips of species within other classes	1,989	2011-2022	Yearly	0.372	9.061

Note: Our data are national representative in scope. Health data are sourced from hospitalization records (see Section 3 and Appendix A.1). Agricultural data are sourced from satellite products including MODIS and MCD12Q1, NDVI and CLCD (see Section 3 and Appendix A.3). Straw-Burning Ban policy data is obtained from the Peking University Law Database (https://www.pkulaw.com). Baidu Search index is sourced from (https://index.baidu.com). Insect population data are sourced from iNaturalist (https://www.gbif.org). Column (2) presents the coverage of our data out of Counties nationwide (for Baidu index, city-level), while Columns (3) and (4) provide their time horizons and frequencies. Columns (5) and (6) show their means and standard deviations. In Panel D, other classes refer to classes in Arthropod phylum excluding Arachnida and Insecta.

Table 2: Effects of Straw-Burning Ban Policies on Vector-Borne Diseases

	Hospitalizations				Medical Expenditure			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment (=1)	16.166***	13.939***	13.182***	10.707**	83941.886***	76327.558***	73196.133***	52023.404**
	(1.357)	(1.450)	(1.321)	(4.218)	(8395.966)	(8891.835)	(8444.935)	(25109.974)
Sample Mean	20.002				105667.562			
Sample SD	(36.661)				(230831.027)			
County-Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Year-Quarter FE		✓				✓		
Province-Year-Quarter FE			✓	✓			✓	✓
Hospital Controls				✓				✓
Baseline Controls				✓				✓
Observations	9047	9047	9047	8951	9047	9047	9047	8951

Note: This table presents the estimated effects of straw-burning ban policies on vector-borne diseases using a two-stage difference-in-differences approach (Gardner et al., 2024). The treatment variable is set to 1 for counties that have implemented a straw burning ban with policy assessment. The dependent variables include the number of inpatient admissions and medical expenditures (in RMB) for vector-borne diseases. The unit of observation is at the county-year-quarter level. The regression sample excludes counties with no recorded cropland fires between 2001 and 2022 (i.e., counties with minimal cropland or crop residues). The analysis includes data from the two years (eight quarters) preceding policy implementation and the four years (sixteen quarters) following implementation. The model incorporates county-by-year fixed effects and province-by-year-by-quarter fixed effects. Hospital controls include the number of hospitalizations for bone fractures and blood diseases, the total number of hospitals, and the counts of tier-2, tier-3, Class B, Class C, and general hospitals, along with the aggregated number of weekdays and weekend days at the county-quarter level. Forest fire controls include the frequency and burned area of forest wildfires in the corresponding quarter. Weather controls include the average temperature and precipitation. Robust standard errors (in parentheses) are clustered at the county level. *** p <0.01, ** p <0.05, * p <0.1.

Table 3: Effects of Straw-Burning Ban Policies on Tick-Borne Diseases

	Hospitalizations				Medical Expenditure			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment (=1)	1.000***	0.902***	0.867***	1.058**	4709.494***	4191.747***	4043.912***	8184.993***
	(0.116)	(0.129)	(0.119)	(0.485)	(642.290)	(742.225)	(661.917)	(2921.422)
Sample Mean	1.121				5521.088			
Sample SD	(3.424)				(19412.694)			
County-Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Year-Quarter FE		✓				✓		
Province-Year-Quarter FE			✓	✓			✓	✓
Hospital Controls				✓				✓
Baseline Controls				✓				✓
Observations	9047	9047	9047	8951	9047	9047	9047	8951

Note: This table presents the estimated effects of straw-burning ban policies on tick-borne diseases using a two-stage difference-in-differences approach (Gardner et al., 2024). The treatment variable is set to 1 for counties that have implemented a straw burning ban with policy assessment. The dependent variables include the number of inpatient admissions and medical expenditures (in RMB) for tick-borne diseases. The unit of observation is at the county-year-quarter level. The regression sample excludes counties with no recorded cropland fires between 2001 and 2022 (i.e., counties with minimal cropland or crop residues). The analysis includes data from the two years (eight quarters) preceding policy implementation and the four years (sixteen quarters) following implementation. The model incorporates county-by-year fixed effects and province-by-year-by-quarter fixed effects. Hospital controls include the number of hospitalizations for bone fractures and blood diseases, the total number of hospitals, and the counts of tier-2, tier-3, Class B, Class C, and general hospitals, along with the aggregated number of weekdays and weekend days at the county-quarter level. Forest fire controls include the frequency and burned area of forest wildfires in the corresponding quarter. Weather controls include the average temperature and precipitation. Robust standard errors (in parentheses) are clustered at the county level. *** p <0.01, ** p <0.05, * p <0.1.

Table 4: Heterogeneous Hospitalization Effects by Different Major Grain Grown

	Vector-Borne Hospitalizations				Tick-Borne Hospitalizations			
	(1) Wheat Minor	(2) Wheat Major	(3) Corn Minor	(4) Corn Major	(5) Wheat Minor	(6) Wheat Major	(7) Corn Minor	(8) Corn Major
Treatment (=1)	11.533**	24.846*	18.767***	-7.242	1.089*	5.659**	2.464***	-0.062
	(5.822)	(14.918)	(4.457)	(11.776)	(0.629)	(2.680)	(0.573)	(1.099)
County-Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Province-Year-Quarter FE	✓	✓	✓	✓	✓	✓	✓	✓
Hospital Controls	✓	✓	✓	✓	✓	✓	✓	✓
Baseline Controls	✓	✓	✓	✓	✓	✓	✓	✓
Observations	7262	1689	5478	3473	7262	1689	5478	3473

Note: This table presents the heterogeneous effects of straw-burning ban policies on vector-borne and tick-borne diseases across counties with different primary grain crops. A "Wheat Major" county is defined as a county where the wheat planting area exceeds that of other grain crops and accounts for more than 5% of the total cropland area. The unit of observation is at the county-year-quarter level. The model includes county-by-year fixed effects and province-by-year-by-quarter fixed effects. We also control hospital characteristics, forest wildfires, and climate characteristics same as that in the baseline model. Robust standard errors (in parentheses) are clustered at the county level. *** p <0.01, ** p <0.05, * p <0.1.

Table 5: Heterogeneous Hospitalization Effects by Different Precipitation Levels

	Insect-Borne		Tick-Borne	
	(1)	(2)	(3)	(4)
	Low Precipitation	High Precipitation	Low Precipitation	High Precipitation
Treatment (=1)	6.174	14.393***	0.595	1.465***
	(6.160)	(3.461)	(0.604)	(0.458)
County-Year FE	✓	✓	✓	✓
Province-Year-Quarter FE	✓	✓	✓	✓
Hospital Controls	✓	✓	✓	✓
Baseline Controls	✓	✓	✓	✓
Observations	4926	4025	4926	4025

Note: This table presents the heterogeneous effects of straw-burning ban policies on vector-borne and tick-borne diseases across counties with different precipitation levels. Counties with an average precipitation above the median are classified as "High Precipitation", while those below the median are classified as "Low Precipitation". The unit of observation is at the county-year-quarter level. The model includes county-by-year fixed effects and province-by-year-by-quarter fixed effects. We also control hospital characteristics, forest wildfires, and climate characteristics (excluding precipitation) same as that in the baseline model. Robust standard errors (in parentheses) are clustered at the county level. *** p <0.01, ** p <0.05, * p <0.1.

Table 6: Heterogeneous Hospitalization Effects by Different Quarters

	Vector-borne Diseases Hospitalization			
	(1)	(2)	(3)	(4)
Quarter =	Q1	Q2	Q3	Q4
Treatment (= 1)	2.063	5.930**	15.144***	17.217***
	(2.088)	(2.643)	(4.098)	(3.531)
County FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Hospital Controls	✓	✓	✓	✓
Forest Fire Controls	✓	✓	✓	✓
Weather Controls	✓	✓	✓	✓
Observations	2231	2276	2327	2394

Note: This table presents the quarterly heterogeneous effects of straw-burning ban policies on vector-borne diseases. The unit of observation is at the county-year level. Columns (1)-(4) use dependent variables measured as hospitalizations in the corresponding quarter. The results indicate that vector-borne hospitalizations are more severe in fall and winter. The model includes county and year fixed effects. Control variables include hospital characteristics, forest wildfire occurrences, and climate factors consistent with the baseline model. Robust standard errors (in parentheses) are clustered at the county level. *** p <0.01, ** p <0.05, * p <0.1.

Table 7: Decreased Straw Burning following the Policy (2001-2022)

	# Straw Burning		Burned Areas	
Straw Burning	(1)	(2)	(3)	(4)
Treatment (= 1)	-2.948***	-3.976***	-141.667***	-191.418***
	(0.791)	(1.060)	(51.086)	(68.415)
County FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓
Grain planting areas	✓	✓	✓	✓
Forest fire	✓	✓	✓	✓
Biomass power plant	✓	✓	✓	✓
Fire History	All Counties	Ever Fire	All Counties	Ever Fire
Observations	56,490	36,141	56,490	36,141

Note: This table presents the effects of straw-burning ban policies on the number of agricultural fires, using a two-stage difference-in-differences method suggested by Gardner et al. (2024). Burned area is measured in hectares, while straw burning is recorded as an event. Agricultural burning during the harvest season (June–December) is used as the measure for straw burning. Column (1) and (3) investigate the policies' effects on all the counties while Column (2) and (4) exclude counties with no recorded cropland fires between 2001 and 2022 (i.e., counties with minimal cropland or crop residues). Control variables include climate factors (temperature, precipitation, and land slope) and agricultural characteristics (grain planting area, forest wildfire occurrence and burned area, and the number of biomass facilities). The model includes year fixed effects and county fixed effects. Robust standard errors (in parentheses) are clustered at the county level. *** p <0.01, ** p <0.05, * p <0.1.

Table 8: Effects of Straw-Burning Ban Policies on Insect Population

	Arthropoda	Arachnida	Insecta	Coleoptera	Staphylinidae	Other
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment (=1)	12.446	0.709**	0.880	4.349*	0.037**	10.857***
	(13.478)	(0.275)	(12.878)	(2.245)	(0.018)	(3.611)
Std. Dev. of Dep. Var.	96.373	1.705	91.161	31.394	0.357	9.061
Weather Controls	✓	✓	✓	✓	✓	✓
Forest fire	✓	✓	✓	✓	✓	✓
Observations	23,412	23,412	23,412	23,412	23,412	23,412

Note: This table presents the effects of straw-burning ban policies on insect population, based on data from 2011 to 2022. The dependent variable is the number of recorded observation trips of species within each taxonomic category at the county-year level. The taxonomic category examined in column (6) comprises Arthropoda, excluding Arachnida and Insecta. The regression sample excludes counties with no recorded fires between 2001 and 2022. The model includes county fixed effects and year fixed effects. Control variables include climate factors (temperature and precipitation), the number and total burned area of forest fires, and the number of unique observers at the county-year level. Robust standard errors (in parentheses) are clustered at the county level. *** p <0.01, ** p <0.05, * p <0.1.

Table 9: Effects of Straw-Burning Ban Policies on Web Searches for Insect Bites (2009-2022)

	Baidu Search Index		
	(1) Insects Bite	(2) Ticks	(3) Bite-related inquiries
Treatment (=1)	11.31***	49.46***	8.035***
	(1.959)	(6.155)	(3.224)
Sample Mean	20.67	71.71	22.99
Sample SD	39.94	102.66	53.56
City-Year FE	✓	✓	✓
City-Quarter FE	✓	✓	✓
Province-Year-Quarter FE	✓	✓	✓
Observations	13,809	13,809	13,809

Note: This table presents the heterogeneous effects of straw-burning ban policies on Baidu Search Index, a proxy for public attention and concern regarding topics including insects bite, tick, and two questions regarding insect bites. The unit of observation is at the city-year-quarter level. Robust standard errors (in parentheses) are clustered at the county level. *** p <0.01, ** p <0.05, * p <0.1.

Table 10: Effects of Straw-Burning Ban Policies on Web Searches for Protective Measures (2009-2022)

	Baidu Search Index			
	(1) Protection	(2) Vaccination	(3) Pest Control	(4) Straw Utilization
Treatment (=1)	22.04***	5.926***	46.78***	25.00***
	(3.251)	(1.359)	(6.796)	(3.720)
Sample Mean	33.05	10.26	67.17	30.94
Sample SD	62.92	22.25	122.12	52.87
City-Year FE	✓	✓	✓	✓
City-Quarter FE	✓	✓	✓	✓
Province-Year-Quarter FE	✓	✓	✓	✓
Observations	13,809	13,809	13,809	13,809

Note: This table presents the heterogeneous effects of straw-burning ban policies on Baidu Search Index, a proxy for public attention and concern regarding topics including protective measures, vaccination, defensive investment, and straw utilization facilities. The unit of observation is at the city-year-quarter level. Robust standard errors (in parentheses) are clustered at the county level. *** p <0.01, ** p <0.05, * p <0.1.

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Appendices

In this online appendix, we provide further information about data sources, the construction of key variables, and robustness checks for the empirical analysis.

Appendix A. Data Cleaning

A.1. Health Data Cleaning Details

Our hospitalization data, obtained from the Data Center for High-Quality Hospital Management at the Institute for Global Health and Development of Peking University, consists of a comprehensive medical record database of inpatient admissions in public hospitals across China. Hospitals have strong incentives to maintain high-quality digital medical records for two main reasons.

First, medical records serve as the foundation for both public and private insurance reimbursements. For example, the National Healthcare Security Administration of China requires that patients be assigned to payment groups based on primary and secondary diagnoses and primary procedures recorded in their medical files. Each group receives standardized medical insurance payments, and hospitals risk financial losses if patients are misclassified due to inaccurate records.

Second, participation in the digital reporting system is mandated by the National Health Commission. Local health commissions conduct regular performance evaluations of hospitals, which include assessments of their digital medical record systems. To ensure accuracy and consistency, medical records are typically completed by attending physicians and verified by clinical coders, who standardize diagnosis and procedure codes. (Huang et al., 2023).

A.2. Policy Data Cleaning Details

The data for the straw-related policy documents in this article were sourced from the Peking University Law Database (https://www.pkulaw.com). First, all local regulatory documents containing the keyword "straw" were retrieved and downloaded, totaling 2,075 policy documents from March 1993 to September 2024. Next, tthe results underwent a second round of review and corrections.hese policy documents were manually reviewed and organized following detailed policy coding guidelines, and the results underwent a second round of review and corrections.

During the organization process, the primary tasks included reading the policy documents and extracting the following key details:

1). The administrative level and the specific province, municipality, or county to which the policy applies,

2). Whether the policy explicitly addresses the implementation of straw burning prohibition, and

3). Whether the policy includes assessment measures or specifies mandatory targets for straw burning prohibition.

Subsequently, the policies were categorized based on their regulatory strength, in accordance with the guidance provided in the policy coding framework. They were grouped into three types: (1) straw-related policies, (2) straw burning prohibition policies and (3) straw burning prohibition policies with assessment measures. These policies were then classified by policy level into three categories: provincial, municipal, and county-level policies. The policies within each category were aggregated by year and month at the corresponding administrative level. Three different types of policy variables were defined: the number of policies in a given month, the cumulative number of policies, and whether a policy existed in the current period.

Finally, to address potential overlaps across provincial, municipal, and county-level policies, policy data were aggregated into county-level indicators using the following principles: Provincial policies, due to their broader scope and weaker effectiveness, were disregarded. Municipal policies were considered applicable to every county within the municipality, while counties with their own independent policies were also regarded as implementing them. For counties or cities not covered by the downloaded policy documents, a value of 0 was assigned, indicating the absence of relevant policies. The key policy variable in this analysis was whether a county had a straw burning prohibition policy with assessment measures in effect during a given period.

National-level policies before 2013 In the early stages, at the *national* level, between 1997 and 2012, the government issued 12 regulatory documents addressing the prohibition of straw burning. In May 1997, the Ministry of Agriculture issued the "Notice on Strictly Prohibiting Straw Burning and Effectively Carrying Out the Straw Returning to the Field Work for Summer Harvested Crops." In June of the same year, the Ministry of Agriculture issued the "Urgent Notice on Strictly Prohibiting Straw Burning and Effectively Promoting the Comprehensive Utilization of Straw." These two documents were the earliest administrative normative documents issued by the Chinese government at the national level concerning the prohibition of straw burning.

In 1999, the National Environmental Protection Agency (NEPA), the Ministry of Agriculture, and four other departments jointly issued the "Regulations on the Management of Straw Burning Prohibition and Comprehensive Utilization," which explicitly defined straw burning prohibition zones. These included a 15-kilometer radius around airports, a 2-kilometer buffer along both sides of highways and railways, and a 1-kilometer buffer along both sides of national and provincial roads. Starting in 2004, the former NEPA began leveraging modern technological methods, such as satellite remote sensing, to monitor straw burning during the summer and autumn seasons nationwide. Daily straw burning data was then published on their website.

A.3. Straw Burning and Forest Wildfire

Satellite imagery is widely used to quantify agricultural burning and forest wildfires. Two remote sensing-based datasets capable of detecting fire and land use in China are the Moderate Resolution Imaging Spectroradiometer (MODIS) Burned Area product and the Land Cover Type

Product (MCD12Q1).[41]

The MODIS Burned Area product is a widely used satellite dataset that records the presence of fire, the date of burning, and burned area extent. The dataset has been validated by comparison with Landsat 8 Operational Land Imager (OLI) imagery. According to the product guide, the standard errors of accuracy metrics are below 6% globally. Errors of omission and commission at the 30 m resolution largely offset each other, as indicated by the coefficient of determination ($r^2 > 0.70$), slope (> 0.79), and intercept (-0.0030) of the regression between the MCD64A1 product and independent Landsat reference data. Full validation details can be found in Boschetti et al. (2016, 2019).

To address a common limitation in burned area products — low confidence in reliably mapping agricultural burning — we refine the identification of agricultural fires by overlaying burned area pixels with land cover classification data. By integrating MODIS burned area data with land cover products, we improve the accuracy of forest fire and agricultural burning estimates. Following the methodology of Assunçãoa et al. (2019) and using ArcGIS, we overlay land cover grid metrics with MODIS burned area data to distinguish between agricultural burning and forest wildfires. This integration enhances the precision of fire detection by associating burning events with specific land classifications.

In our empirical analysis, we control for the annual frequency and burned area of forest wildfires in our regressions. This mitigates measurement errors arising from wildfire expansion and enhances the robustness of our results.

[41] Data sources: Up-to-date information on datasets, formats, and quality is available from the Land Processes DAAC at https://doi.org/10.5067/MODIS/MCD12Q1.006 for MCD12Q1 and https://modis-fire.umd.edu/ for the MODIS Fire and Burned Area products.

2. Additional Tables for Testing Identification Assumptions

Table B1: Characteristics of Counties by Straw-Burning Ban Policy Roll-out Waves

	(1) Before 2011	(2) 2011-2014	(3) 2015-2018	(4) 2019-2022	(5) Ever Treated	(6) Never-Treated
Number of Counties	514	338	366	161	1379	1334
GDP (2013-2021, 10^9 *CNY*)	36.21	24.54	23.20	12.20	27.05	19.79
	(32.38)	(36.79)	(22.50)	(8.56)	(30.44)	(24.11)
Cropland (Before 2011, *100* km^2)	671.10	914.15	930.37	709.09	804.94	575.90
	(522.05)	(1078.51)	(1010.98)	(765.95)	(861.87)	(597.03)
Electricity (Before 2011, 10^6 *kWh*)	1032.53	955.83	873.16	682.95	930.41	931.90
	(860.16)	(1094.67)	(735.72)	(696.25)	(883.75)	(1539.82)
Population (Before 2011, 10^3)	565.51	474.74	466.47	348.60	491.42	431.79
	(327.85)	(300.83)	(278.85)	(249.65)	(307.49)	(379.23)
Hospital Beds (Before 2011)	1242.22	970.15	1052.52	752.58	1067.31	838.37
	(720.61)	(597.66)	(644.69)	(533.33)	(669.48)	(695.13)
Number of Hospitals Observed (2011-2022)	2.65	2.67	2.66	2.61	2.66	2.63
	(0.37)	(0.37)	(0.37)	(0.39)	(0.37)	(0.39)

Note: All characteristics are measured by the 2001-2011 average, except for GDP due to data availability. The table reports the average characteristics of counties in different waves of straw burning ban policy rollout waves. Standard deviations are in parentheses.

Table B2: $PM_{2.5}$ and Vector-Borne Diseases

	Vector-Borne Hospitalizations			
	(1)	(2)	(3)	(4)
$PM_{2.5}$	-0.178	0.153	0.158	0.158
	(0.126)	(0.101)	(0.101)	(0.101)
Hospital Controls		✓	✓	✓
Weather Controls			✓	✓
Fire Controls				✓
County FE	✓	✓	✓	✓
Province-Year-Quarter FE	✓	✓	✓	✓
Observations	15850	15850	15850	15850

Note: This table presents the impacts of $PM_{2.5}$ on vector-borne diseases. The model includes county fixed effects and province-by-year-quarter fixed effects. We also control hospital characteristics, forest wildfires, and climate characteristics same as those in the baseline model, gradually. Robust standard errors (in parentheses) are clustered at the county level. *** p <0.01, ** p <0.05, * p <0.1.

3. Definition of vector-borne and tick-borne diseases

Table C1: ICD-10 codes for insect-borne diagnosis

Disease name	**ICD-10 codes**
Relapsing fever, unspecified	A68.9
Tularemia	A21
Brucellosis	A23
Arthropod-borne viral encephalitis, unspecified	A85.2
Toxic effect of venom of other arthropods	T63.4
Q fever	A78
Bartonellosis	A44
Typhus fever, unspecified	A75.9
Unspecified viral encephalitis	A86
Plague	A20
Unspecified contact dermatitis due to other agents	L25.800x001
Dengue	A90; A91
Malaria	B50; B51; B52; B53; B54
Mosquito-borne viral encephalitis	A83
Chikungunya virus disease	A92.0
Yellow fever	A95
Zika virus disease	A92.8
Myiasis	B87
Onchocerciasis	B73
Mansonelliasis	B74.4
Gongylonemiasis pulchrum	B83.800x002
Acanthocephaliasis	B83.800
Typhus fever due to Rickettsia typhi	A75.2
Teniasis	B68
African trypanosomiasis	B56
Loiasis	B74.3
Leishmaniasis	B55
Sandfly fever	A93.1
Scabies	B86
Acarine dermatitis	B88.000x004
Acarine dermatitis	B88.000x006

ICD-10 codes for other insect-borne diagnosis, cont.

Disease name	**ICD-10 codes**
Rickettsialpox due to Rickettsia akari	A79.1
Hemorrhagic fever with renal syndrome (HFRS)	A98.5
Paederus dermatitis	L24.800x002
Epidemic louse-borne typhus fever due to Rickettsia prowazekii	A75.0
Louse-borne relapsing fever	A68.0
Trench fever	A79.0
Typhoid and paratyphoid fevers	A01
Shigellosis	A03
Other bacterial intestinal infections	A04
Other bacterial foodborne intoxications, not elsewhere classified	A05
Cholera	A00
Anthrax	A22
Acute amebic dysentery	A06.0
Ascariasis	B77
Enterobiasis	B80
Cysticercosis	B69
Hookworm disease	B76
Acute poliomyelitis	A80
Acute hepatitis A	B15
Trachoma	A71
Pruritus	L29
Rubella [German measles]	B06
Allergic contact dermatitis, unspecific cause	L23.9
Urticaria	L50
Conjunctivitis	H10.1
Papule	R23.800x001
Typhus fever due to Rickettsia tsutsugamushi	A75.3
Leptospirosis	A27
Chlamydia psittaci infection	A70

Note: Insect-borne diseases include all diagnosis in this table and tick-borne diseases as listed in Appendix Table C2. This table is obtained from a cross-reference of relevant literature on diseases related to insect bite and the ICD-10 code list (Fang et al., 2005; Jiang et al., 2011; WHO, 2014).

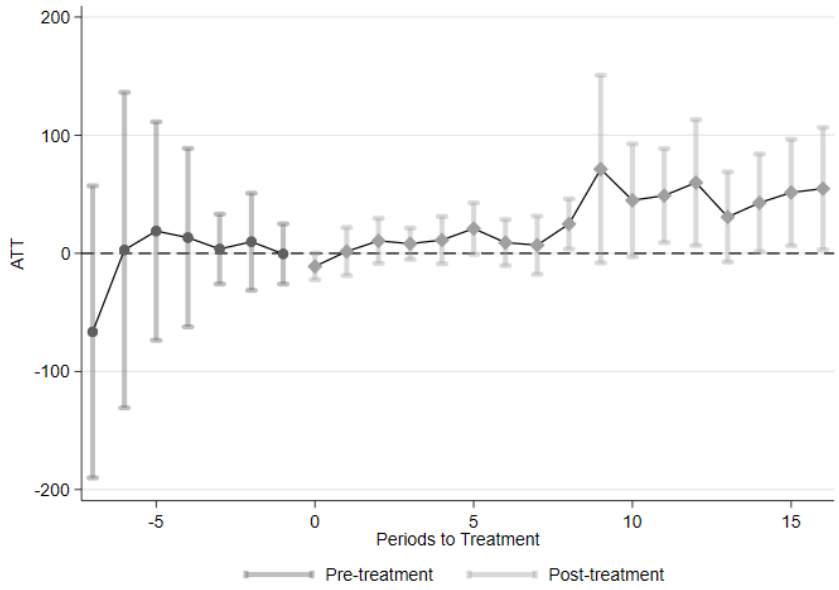
Table C2: ICD-10 codes for tick-borne diagnosis

Disease name	**ICD-10 codes**
Lyme disease	A69.2
Human granulocytic anaplasmosis [HGA]	A93.8
Tick-borne viral encephalitis [TBE]	A84
Severe fever with thrombocytopenia syndrome [SFTS]	A93.8
Crimean-Congo hemorrhagic fever	A98.0
Rickettsiosis	A77; A79.9; A79.8
Babesiosis	B60.0
Omsk hemorrhagic fever	A98.1
Kyasanur forest disease	A98.2

Note: This table is obtained from a cross-reference of relevant literature on tick-borne diseases and the ICD-10 code list (Fang et al., 2005; Jiang et al., 2011; WHO, 2014).

4. Robustness Check

(a) Hospitalizations of Vector-Borne Diseases



(b) Hospitalizations of Tick-Borne Diseases

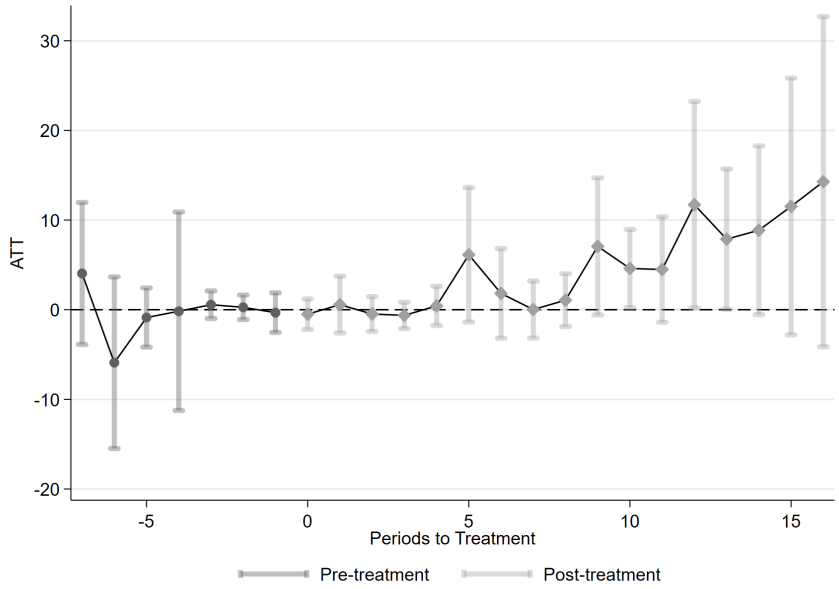


Figure D1. Event Study: Hospitalizations (Callaway and Sant'Anna, 2021)

Notes: This figure illustrates the dynamic effects of the straw-burning ban on hospitalizations using method of Callaway and Sant'Anna (2021). Treatment status is set to 1 for counties that implemented a straw-burning ban with policy assessment. The dependent variables are the number of inpatient admissions for vector-borne and tick-borne diseases, with the unit of observation at the county-year-quarter level. The regression sample excludes counties with no recorded cropland fires between 2001 and 2022. The analysis includes data from the two years (eight quarters) preceding policy implementation and the four years (sixteen quarters) following implementation. We also control hospital characteristics, forest wildfires, and climate characteristics same as those in the baseline model. The y-axis presents the estimated treatment effects relative to never-treated counties, with 95% confidence intervals.

Table D1: Temporal Heterogeneity Effects of Straw-Burning Ban Policies on Vector-Borne Diseases

	(1) Q1	(2) Q2	(3) Q3	(4) Q4
Panel A: Policy in Q1				
Treatment (= 1)	-2.757	5.637	15.505***	19.137**
	(3.325)	(3.969)	(5.739)	(7.534)
Observations	2221	2053	1951	1882
Panel B: Policy in Q2				
Treatment (= 1)	8.327***	11.233***	21.692***	17.444***
	(3.056)	(3.226)	(4.408)	(4.112)
Observations	1998	2209	2031	1936
Panel C: Policy in Q3				
Treatment (= 1)	2.206	6.890**	10.382***	11.652***
	(2.510)	(3.138)	(3.371)	(4.370)
Observations	1873	2004	2236	2092
Panel D: Policy in Q4				
Treatment (= 1)	7.821***	10.174***	17.858***	19.901***
	(2.528)	(3.363)	(5.406)	(4.126)
Observations	1783	1886	2065	2285
County FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Hospital Controls	✓	✓	✓	✓
Baseline Controls	✓	✓	✓	✓

Note: This table presents the quarterly straw-burning ban policies affect vector-borne diseases in the following year (4 quarters). The dependent variable is the number of inpatient admissions for vector-borne diseases within the corresponding quarter. The unit of observation is at county-by-year level. Our sample exludes counties with no recorded cropland fires between 2001 and 2022 (i.e., counties with minimal cropland or crop residues). The results indicate that policies' effects last over a year and the vector-borne hospitalizations are more severe in fall and winter. The model includes county and year fixed effects. Control variables include hospital characteristics, forest wildfire occurrences, and climate factors that are consistent with the baseline model. Robust standard errors (in parentheses) are clustered at the county level. *** p <0.01, ** p <0.05, * p <0.1.

Table D2: Placebo Test on Unrelated Diseases

	Hospitalizations		Medical Expenditure	
	(1) Blood	(2) Fracture	(3) Blood	(4) Fracture
Treatment (=1)	3.032	10.629	-14822.426	-184044.639
	(6.004)	(17.228)	(77094.168)	(386746.999)
Sample Mean	63.198	250.792	503744.766	4760511.450
County-Year FE	✓	✓	✓	✓
Province-Year-Quarter FE	✓	✓	✓	✓
Hospital Controls	✓	✓	✓	✓
Baseline Controls	✓	✓	✓	✓
Observations	8951	8951	8951	8951

Note: This table presents the placebo test of straw-burning ban policies on other diseases. The treatment status equals to 1 when a county has implemented straw-burning ban policies with assessment. Dependent variables include number of inpatient admissions and medical expenditure for blood and fracture. The regression sample excludes counties with no recorded cropland fires between 2001 and 2022. The model includes county-by-year fixed effects and province-by-year-quarter fixed effects. We also control hospital characteristics (excluding the independent variables), forest wildfires, and climate characteristics same as those in the baseline model. Robust standard errors (in parentheses) are clustered at the county level. Robust standard errors (in parentheses) are clustered at the county level. *** p <0.01, ** p <0.05, * p <0.1.

Table D3: Robustness Checks: Accounting for Spillover effect

	(1) Hospitalizations	(2) Medical Expenditure
Treatment (=1)	4.781*	32296.854**
	(2.536)	(16447.124)
County-Year FE	✓	✓
Province-Year-Quarter FE	✓	✓
Observations	3936	3936

Note: This table presents the effects of straw burning ban excluding geographically adjacent counties with non-synchronous policy adoption. The model includes county-by-year fixed effects and province-by-year-by-quarter fixed effects. Robust standard errors (in parentheses) are clustered at the county level. *** p <0.01, ** p <0.05, * p <0.1.

Table D4: Effects of Straw-Burning Ban Policies on Hospitalizations (Callaway and Sant'Anna, 2021)

	Insect-Borne Diseases			Tick-Borne Diseases		
	(1)	(2)	(3)	(4)	(5)	(6)
ATT	20.660***	13.452**	23.077**	3.222*	2.152*	4.551**
	(7.994)	(5.726)	(9.323)	(1.794)	(1.149)	(2.189)
Hospital Controls	✓	✓	✓	✓	✓	✓
Baseline Controls	✓	✓	✓	✓	✓	✓
Aggregations	Simple	Cohort	Calendar	Simple	Cohort	Calendar
Observations	6704	6704	6704	6704	6704	6704

Note: This table presents the impacts of straw-burning ban policies on vector-borne and tick-borne diseases, using method of Callaway and Sant'Anna (2021). The unit of observation is at county-year-quarter level. The regression sample excludes counties with no recorded cropland fires between 2001 and 2022. The analysis includes data from the two years (eight quarters) preceding policy implementation and the four years (sixteen quarters) following implementation. We also control hospital characteristics, forest wildfires, and climate characteristics same as those in the baseline model. Robust standard errors (in parentheses) are clustered at the county level. *** p <0.01, ** p <0.05, * p <0.1.

Table D5: Effects of Straw-Burning Ban Policies on Vector-borne and Tick-Borne Diseases: Fixed-effects PPML Estimation

	Vector-Borne Diseases		Tick-Borne Diseases	
	(1) Hospitalizations	(2) Expenditure	(3) Hospitalizations	(4) Expenditure
Treatment (=1)	0.859**	0.226*	0.803**	0.244**
	(0.376)	(0.119)	(0.352)	(0.122)
County-Year FE	✓	✓	✓	✓
Province-Year-Quarter FE	✓	✓	✓	✓
Hospital Controls	✓	✓	✓	✓
Baseline Controls	✓	✓	✓	✓
Observations	3624	7258	3624	7258

Note: This table presents the impacts of straw-burning ban policies on vector-borne and tick-borne diseases, using method of PPML. The unit of observation is at county-year-quarter level. The regression sample excludes counties with no recorded cropland fires between 2001 and 2022. The model includes county-by-year fixed effects and province-by-year-quarter fixed effects. We also control hospital characteristics, forest wildfires, and climate characteristics same as those in the baseline model. Robust standard errors (in parentheses) are clustered at the county level. *** p <0.01, ** p <0.05, * p <0.1.

Table D6: Effects of Straw-Burning Ban Policies on Vector-Borne and Tick-Borne Diseases: Policy Implementation

	Vector-Borne Diseases		Tick-Borne Diseases	
	(1) Hospitalizations	(2) Expenditure	(3) Expenditure	(4) Hospitalizations
Panel A: straw-burning ban policy with assessment				
Treatment (= 1)	11.963***	59564.089**	1.179**	9140.813***
	(4.620)	(27086.749)	(0.518)	(3202.020)
Observations	8951	8951	8951	8951
Panel B: straw-burning ban policy				
Treatment (=1)	13.006*	30987.424	1.364*	11802.011**
	(7.251)	(41786.866)	(0.805)	(4924.378)
Observations	8497	8497	8497	8497
Panel C: straw burning policy				
Treatment (=1)	10.790*	14340.523	1.168*	9720.729***
	(5.792)	(33335.779)	(0.643)	(3641.941)
Observations	8477	8477	8477	8477
County-Year FE	✓	✓	✓	✓
Province-Year-Quarter FE	✓	✓	✓	✓
Hospital Controls	✓	✓	✓	✓
Forest Fire Controls	✓	✓	✓	✓
Weather Controls	✓	✓	✓	✓
Fire History	Ever Fire	Ever Fire	Ever Fire	Ever Fire

Note: This table presents the impacts of straw-burning ban policies on vector-borne and tick-borne diseases, using different straw burning policy measurements. Panel A presents estimates with treatment defined using straw-burning ban policies with assessments. Panel B provides estimates with treatment defined as straw-burning ban policies. Panel C uses all policies related to straw burnings. The regression sample excludes counties with no recorded cropland fires between 2001 and 2022. The model includes county-by-year fixed effects and province-by-year-quarter fixed effects. We also control hospital characteristics, forest wildfires, and climate characteristics same as those in the baseline model. Robust standard errors (in parentheses) are clustered at the county level. *** p <0.01, ** p <0.05, * p <0.1.

Table D7: Effects of Straw-Burning Ban Policies on Vector-Borne and Tick-Borne Diseases: Alternative Sample Periods (2017-2022)

	Hospitalizations		Medical Expenditure	
	(1)	(2)	(3)	(4)
	Vector-Borne	Tick-Borne	Vector-Borne	Tick-Borne
Treatment (=1)	12.853***	1.393***	22018.828	9302.432***
	(4.920)	(0.522)	(27988.353)	(3121.534)
County-Year FE	✓	✓	✓	✓
Province-Year-Quarter FE	✓	✓	✓	✓
Hospital Controls	✓	✓	✓	✓
Baseline Controls	✓	✓	✓	✓
Sample	2017-2022	2017-2022	2017-2022	2017-2022
Observations	8218	8218	8218	8218

Note: This table presents the impacts of straw-burning ban policies on vector-borne and tick-borne diseases, using samples from 2017 to 2022, which includes the major portion of hospitalization observation data. The regression sample excludes counties with no recorded cropland fires. The model includes county-by-year fixed effects and province-by-year-quarter fixed effects. We also control hospital characteristics, forest wildfires, and climate characteristics same as those in the baseline model. Robust standard errors (in parentheses) are clustered at the county level. *** p <0.01, ** p <0.05, * p <0.1.

Table D8: Robustness Check: Straw Burning by Season

	Straw Burning			Fire Season	
				Spring & Summer	Fall & Winter
Annual Frequency	(1)	(2)	(3)	(4)	(5)
Treatment (= 1)	-4.345*	-4.555*	-4.397*	-2.193	-2.948***
	(2.508)	(2.500)	(2.502)	(2.361)	(0.791)
County FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓	✓
Grain planting areas	✓	✓	✓	✓	✓
Forest fire		✓	✓	✓	✓
Biomass power plant			✓	✓	✓
Observations	56,490	56,490	56,490	56,490	56,490

Note: This table presents the impacts of straw-burning ban policies on the number of agricultural fires and burned area, using different straw burning measurements and controls. In Columns (1) and (2), agricultural burning throughout the entire year is used as the measure for straw burning. In Columns (3) and (4), agricultural burnings are further categorized into Spring and Summer and Fall and Winter for robustness checks. Control variables include climate factors (temperature, precipitation, and land slope) and agricultural characteristics (crop planting area, forest wildfire occurrence and burned area, and the number of biomass facilities). The model includes year-fixed effects and county-fixed effects. Standard errors, clustered at the county level, are reported below the coefficients. *** p <0.01, ** p <0.05, * p <0.1.

Table D9: Robustness Check: Policy Implementation

	#Straw Burning		Burned Area	
	(1)	(2)	(3)	(4)
Panel A: straw-burning ban policy with assessment				
Treatment (= 1)	-2.948***	-3.976***	-141.667***	-191.418***
	(0.791)	(1.060)	(51.086)	(68.415)
Panel B: straw-burning ban policy				
Treatment (= 1)	-2.424***	-3.279***	-108.107**	-146.465**
	(0.773)	(1.023)	(51.815)	(68.652)
Panel C: straw burning policy				
Treatment (= 1)	-2.351***	-3.241***	-106.835**	-147.673**
	(0.795)	(1.060)	(53.528)	(71.468)
County FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓
Grain planting areas	✓	✓	✓	✓
Forest fire	✓	✓	✓	✓
Biomass power plant	✓	✓	✓	✓
Fire History	All Regions	Ever Fire	All Regions	Ever Fire
Observations	56,490	36,141	56,490	36,141

Note: This table presents the impacts of straw-burning ban policies on the number of agricultural fires and burned area, using different straw burning policy measurements. Panel A presents estimates with treatment defined using straw-burning ban policies with assessments. Panel B provides estimates with treatment defined as straw-burning ban policies. Panel C uses all policies related to straw burnings. The model includes county and year fixed effects. We also control hospital characteristics, forest wildfires, agricultural and climate characteristics same as those in the baseline model. Robust standard errors (in parentheses) are clustered at the county level. *** p <0.01, ** p <0.05, * p <0.1.

Table D10: Robustness Check: Straw Burning (Callaway and Sant'Anna, 2021)

	# Straw Burning	Burned Areas	Cropland	% Wheat Area
	(1)	(2)	(3)	(4)
Treatment (= 1)	-4.519***	-265.092*	-15434.826*	-0.278**
	(1.856)	(136.236)	(8,982.049)	(0.123)
County FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓
Forest fire	✓	✓	✓	✓
Observations	40,950	40,950	40,803	15,129

Note: This table presents the impacts of straw-burning ban policies on agricultural outcomes, using method of Callaway and Sant'Anna (2021). The sample of land cover changes excludes counties with no recorded cropland fires between 2001 and 2022 (i.e., counties with minimal cropland or crop residues). The sample of crop changes excludes counties have the corresponding crop planted less than 5%. Control variables include climate factors such as temperature, precipitation, and land slope. The model accounts for year-fixed effects and county-fixed effects. Robust standard errors (in parentheses) are clustered at the county level. *** p <0.01, ** p <0.05, * p <0.1.

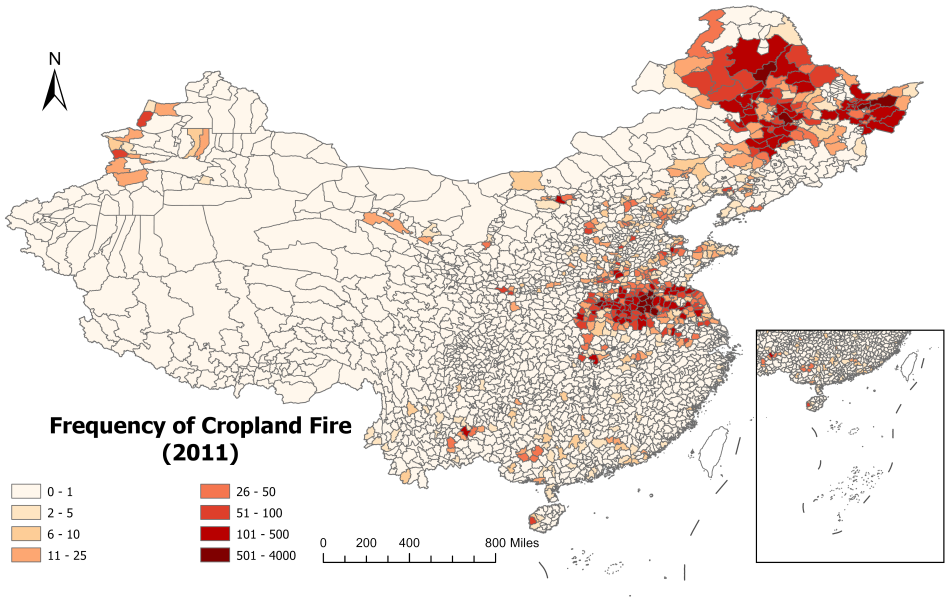
Table D11: Heterogeneity Effects on Straw Burning by Different Major Grain Grown

	# Straw Burning			
	(1) Wheat Major	(2) Wheat Minor	(3) Corn Major	(4) Corn Minor
Treatment (=1)	-5.332***	-3.716***	-2.435	-3.598***
	(1.788)	(1.326)	(1.869)	(1.191)
County FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓
Grain planting areas	✓	✓	✓	✓
Forest fire	✓	✓	✓	✓
Biomass power plant	✓	✓	✓	✓
Observations	7,156	28,985	14,114	22,027

Note: This table presents the heterogeneous effects of straw-burning ban policies on the number of agricultural fires with different primary grain crops. A "Wheat Major" County is defined as a county where the wheat planting area exceeds that of other two grain crops. The unit of observation is at the county-year level. The regression sample excludes counties that do not cultivate all three major grain crops and counties with no recorded cropland fires between 2001 and 2022. Control variables include climate factors (temperature, precipitation, and land slope) and agricultural characteristics (grain planting area, forest wildfire occurrence and burned area, and the number of biomass facilities). The model includes year fixed effects and county fixed effects. Robust standard errors (in parentheses) are clustered at the county level. *** p <0.01, ** p <0.05, * p <0.1.

5. Other Tables and Figures

(a) Distribution of Cropland Fire in 2011



(b) Distribution of Cropland Fire in 2021

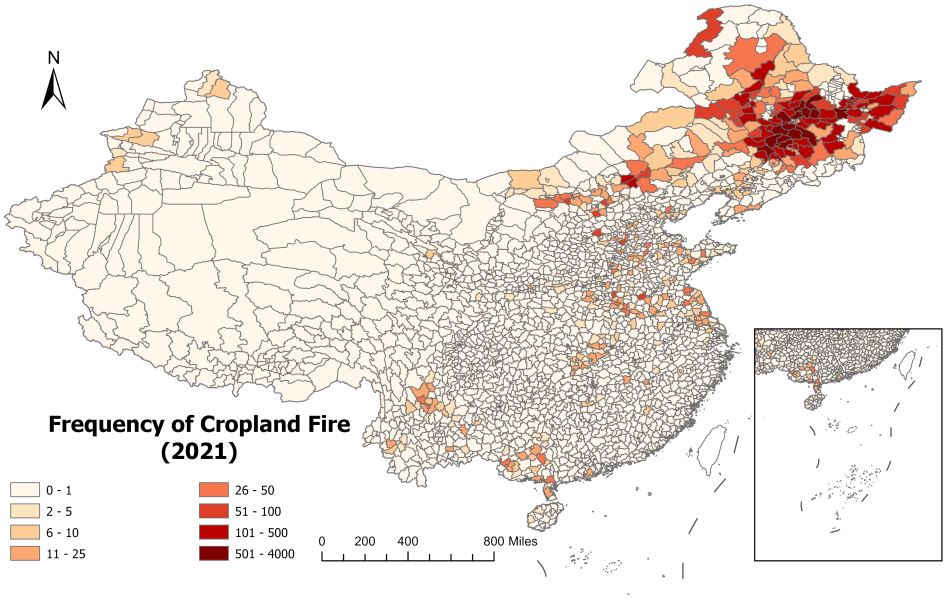
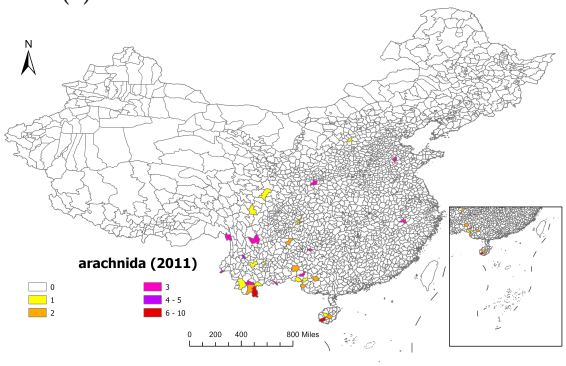
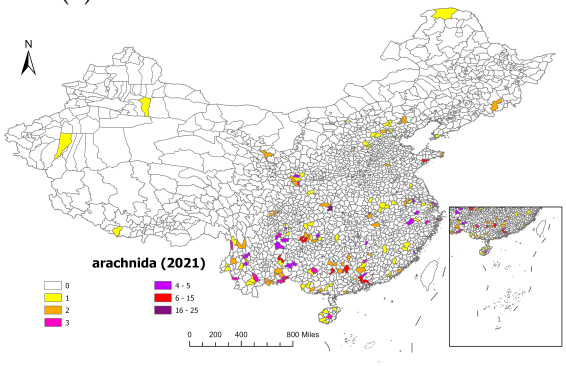


Figure E1. Changes in Cropland Fire 2011-2021

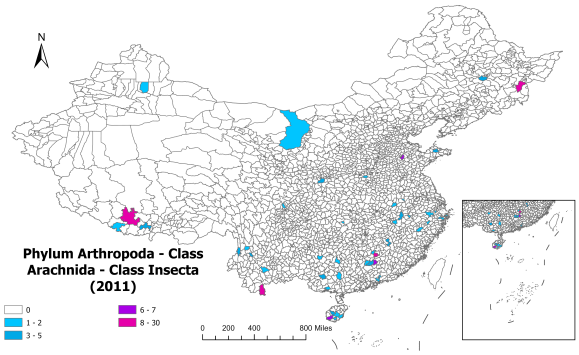
(a) Distribution of Arachnida in 2011



(b) Distribution of Arachnida in 2021



(c) Distribution of Other Arthropods in 2011



(d) Distribution of Other Arthropods in 2021

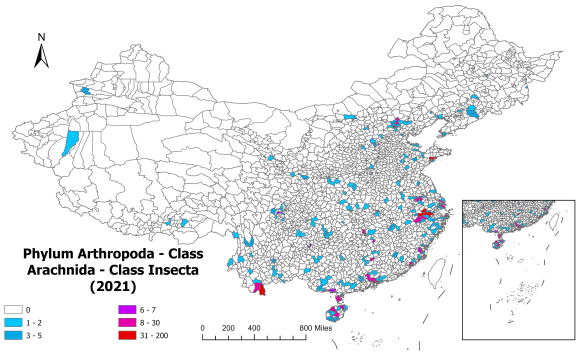
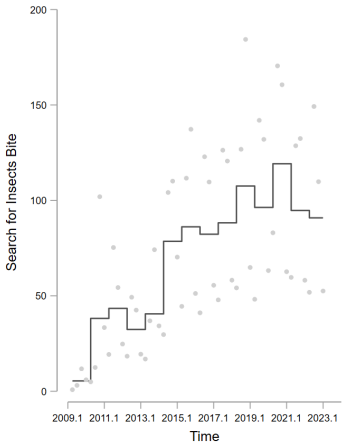


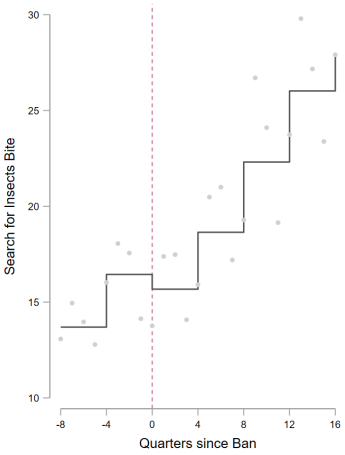
Figure E2. Changes in Insect Abundance 2011-2021

Notes: This graph illustrates the spatial distribution of observations of species within various taxonomic categories in 2011 and 2021. Other arthropods refer to species within Arthropoda, excluding Arachnida and Insecta.

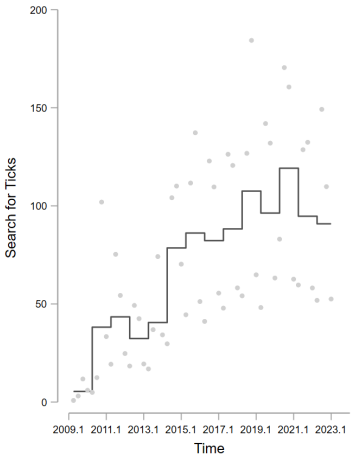
(a) Searches for Insect Bites at the national level



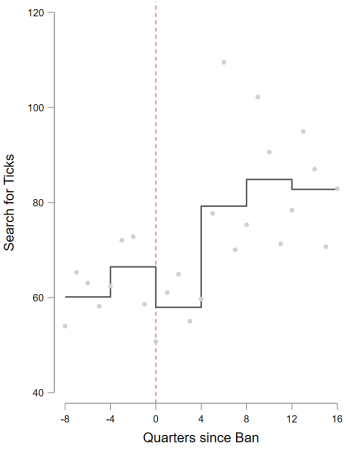
(b) Searches for Insect Bites by event time



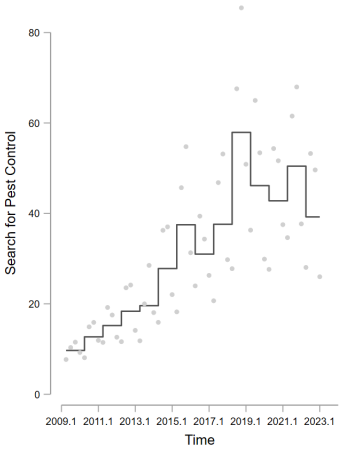
(c) Searches for Ticks at the national level



(d) Searches for Ticks by event time



(e) Searches for Pest Control at the national level



(f) Searches for Pest Control by event time

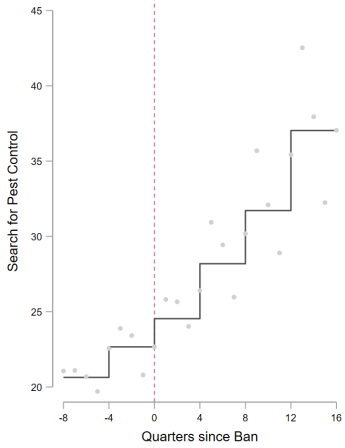
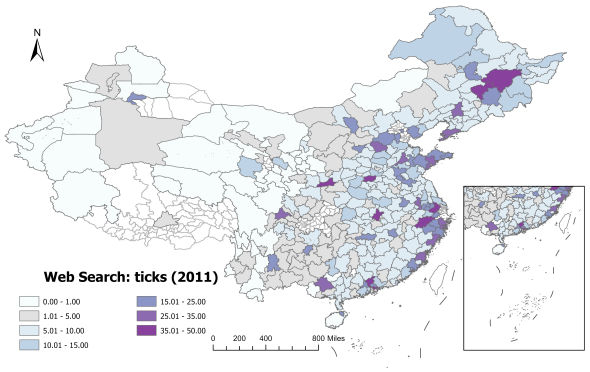


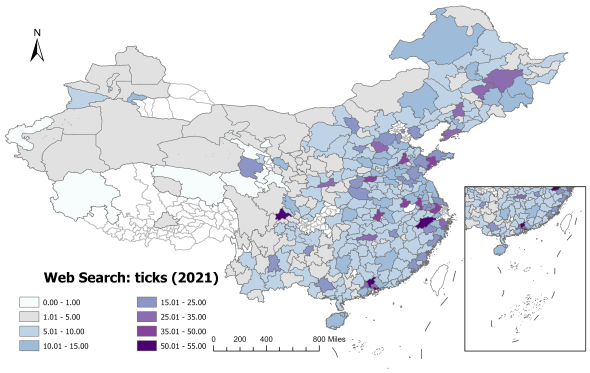
Figure E3. Web Search Indices

Notes: This graph illustrates the trends of Baidu Search Indices regarding Insect Bites and Ticks. Similar to Google Trends, the Baidu Search Index captures the frequency of searches for specific terms across cities over time, providing insights into public interest and awareness patterns.

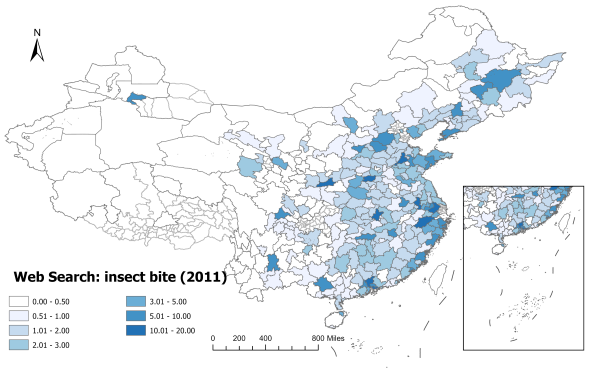
(a) Searches for Ticks (2011)



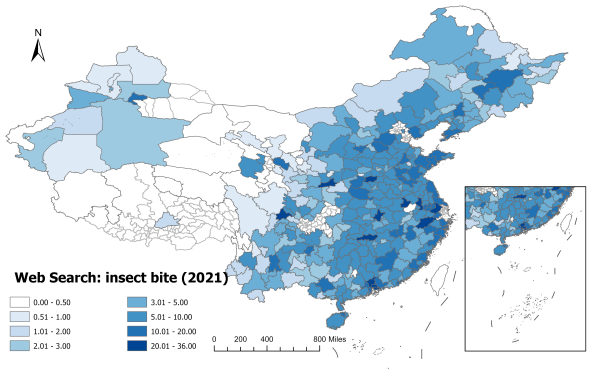
(b) Searches for Ticks (2021)



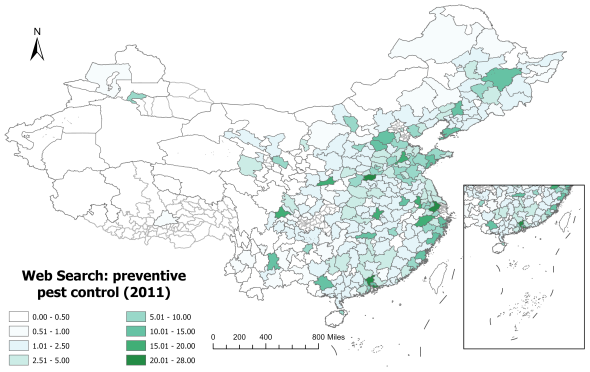
(c) Searches for Insect Bites (2011)



(d) Searches for Insect Bites (2021)



(e) Searches for Pest Control (2011)



(f) Searches for Pest Control (2021)

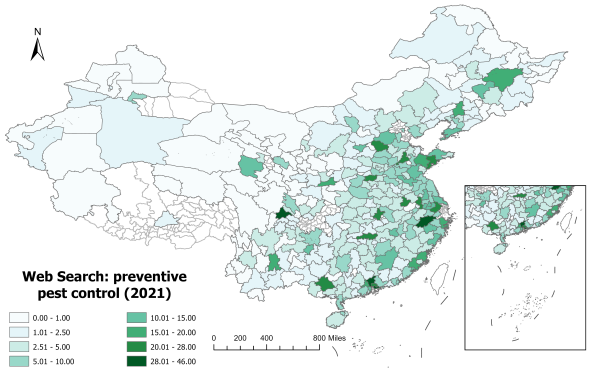
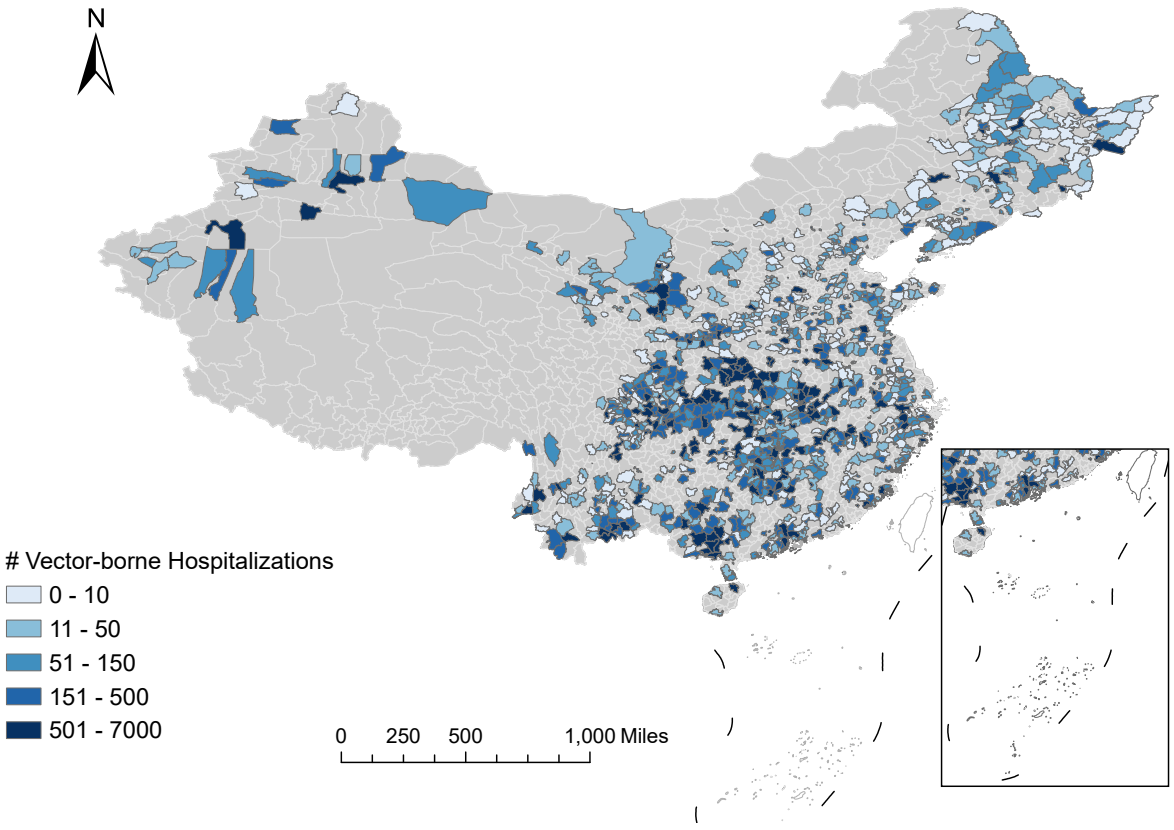


Figure E4. Distribution of Web Search Indices

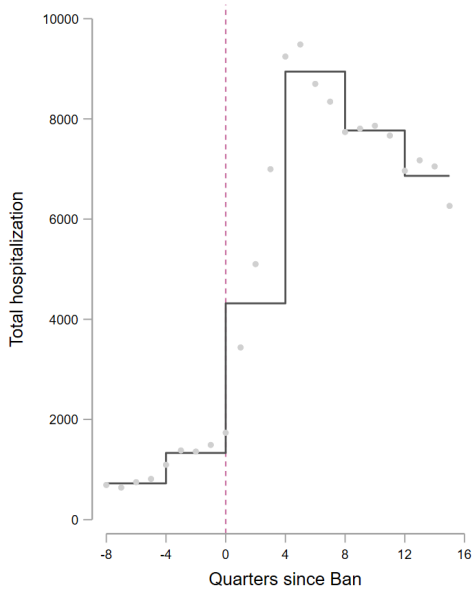
Notes: This graph illustrates the distribution of Baidu Search Index, tracking search frequencies for Chinese terms related to "Ticks," "Insect Bites," and "Pest Control" Similar to Google Trends, the Baidu Search Index captures the frequency of searches for specific terms across cities over time, providing insights into public interest and awareness patterns.



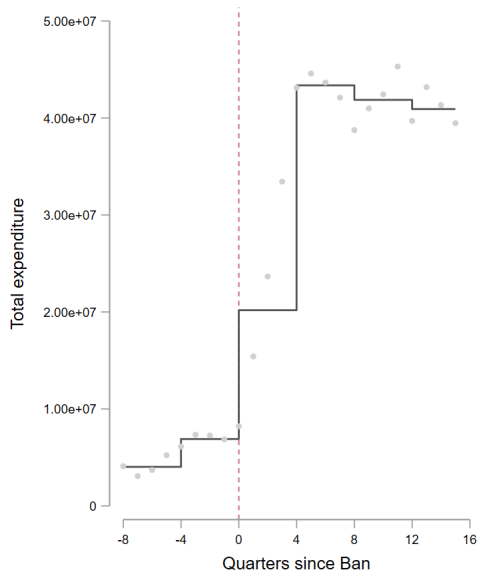
Source: .

Figure E5. Distribution of Vector-borne Diseases (2011-2022)

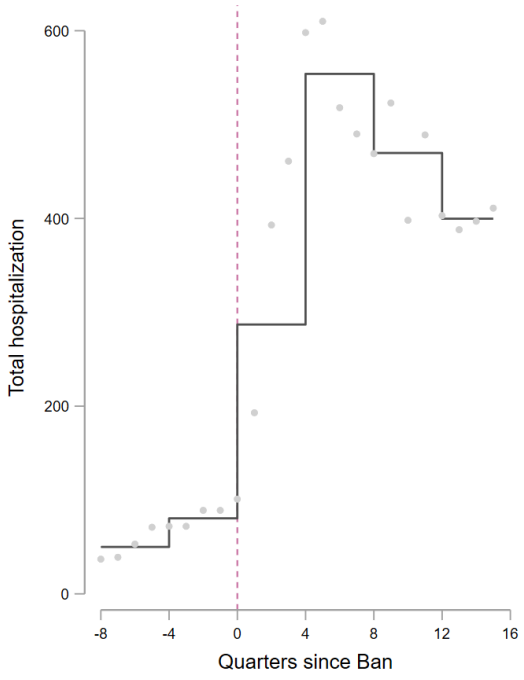
(a) Hospitalization for vector-borne diseases



(b) Medical expenditure for vector-borne diseases



(c) Hospitalization for tick-borne diseases



(d) Medical expenditure for tick-borne diseases

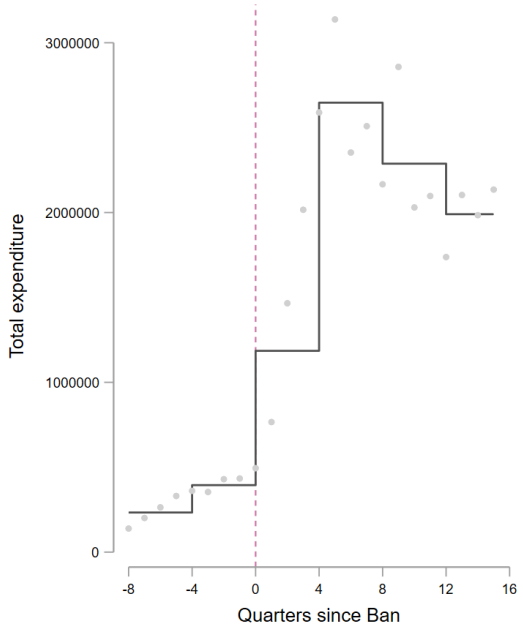


Figure E6. Trends in Hospitalization and Medical Expenditure

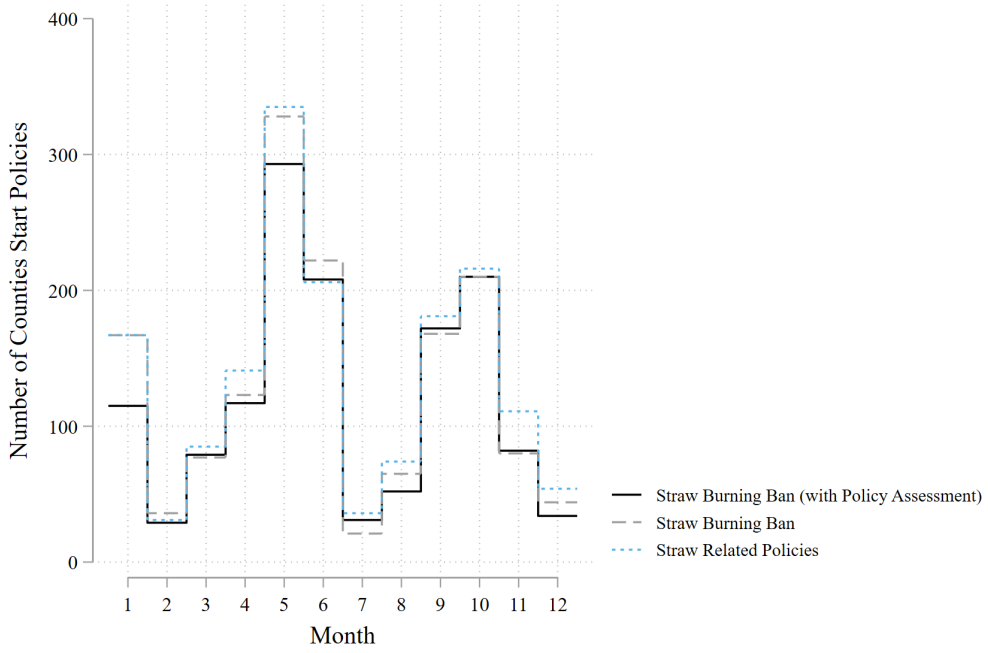


Figure E7. Temporal Pattern of Straw Burning Ban Polices

Source: The data are obtained from the Peking University Law Database (https://www.pkulaw.com), which are described in detail in Appendix A.2.

Note: This figure illustrates that the county-level straw-burning ban was primarily implemented during May–June and September–October, coinciding with the major harvest periods for crops in China. Based on this observation, our primary empirical analysis is conducted at the quarterly level, as detailed in Sections 4 and 5.

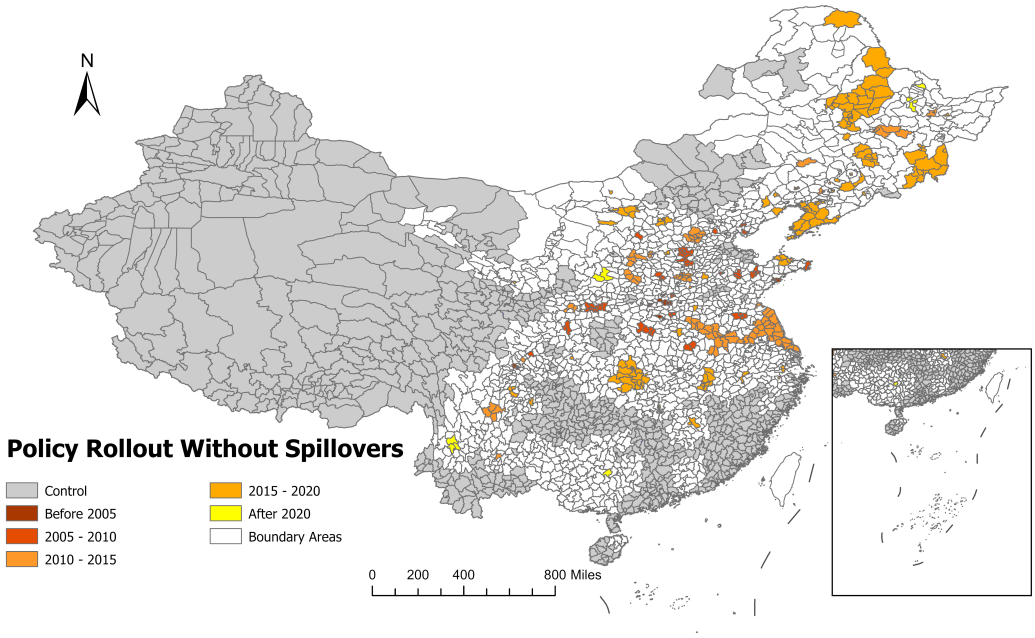


Figure E8. Roll-out of China's Straw Burning Policies without Spillovers

Source: The data are obtained from the Peking University Law Database (https://www.pkulaw.com), which are described in detail in Appendix A.2.
Note: This figure illustrates the distribution of roll-out of straw burning policies excluding geographically adjacent counties with different policy implementation timelines.

Table E1: Effects of Straw-Burning Ban Policies on Agricultural Outcome (2001 - 2022)

	Land Cover		Planting	
	Cropland	Forest	%Wheat Planting	%Corn Planting
	(1)	(2)	(3)	(4)
Treatment (= 1)	-1,578.659***	-5.129	-0.022**	0.028***
	(369.248)	(3.564)	(0.009)	(0.005)
County FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓
Land Slope	✓	✓	✓	✓
Observations	37,862	35,352	15,464	31,216

Note: This table presents the effects of straw-burning ban policies on agricultural outcomes including size of cropland and forest, and percentages of wheat and corn planting. The unit of measurement for cropland and forest is in km^2 (equivalent to 100 hectares), while the percentages of wheat and corn planting are defined as the percentage of wheat and corn planting area to the total cropland. The sample of land cover changes excludes counties with no recorded cropland fires between 2001 and 2022 (i.e., counties with minimal cropland or crop residues). The sample of crop changes excludes counties have the corresponding crop planted less than 5%. Control variables include climate factors such as temperature, precipitation, and land slope. The model accounts for year fixed effects and county fixed effects. Robust standard errors (in parentheses) are clustered at the county level. *** p <0.01, ** p <0.05, * p <0.1.

Table E2: Decreased $PM_{2.5}$ Concentration following the Policy (2001-2022)

	$PM_{2.5}$			
	(1)	(2)	(3)	(4)
Treatment (= 1)	-1.162***	-1.165***	-0.395**	-0.400**
	(0.193)	(0.193)	(0.179)	(0.179)
County FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓
Grain planting areas	✓	✓	✓	✓
Forest fire		✓		✓
Fire History	All Counties	All Counties	Ever Fire	Ever Fire
Observations	56,511	56,511	36,141	36,141

Note: This table presents the effects of straw-burning ban policies on $PM_{2.5}$. Column (1) and (2) investigate the policies' effects on all the counties while Column (3) and (4) exclude counties with no recorded cropland fires between 2001 and 2022 (i.e., counties with minimal cropland or crop residues). Control variables include climate factors (temperature, precipitation, relative humidity and cloud gray) and agricultural characteristics (grain planting area, forest wildfire occurrence and burned area). We account for year fixed effects and county fixed effects. Robust standard errors (in parentheses) are clustered at the county level. *** p <0.01, ** p <0.05, * p <0.1.

Table E3: Increased Biomass Power Plant Entry following the Policy (2001-2022)

	Biomass Power Plant Entry			
	(1)	(2)	(3)	(4)
Treatment (= 1)	1.738***	1.738***	1.335***	1.335***
	(0.301)	(0.301)	(0.430)	(0.430)
County FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Weather controls	✓	✓	✓	✓
Grain planting areas	✓	✓	✓	✓
Forest fire		✓		✓
Fire History	All Counties	All Counties	Ever Fire	Ever Fire
Observations	56,511	56,511	36,141	36,141

Note: This table presents the effects of straw-burning ban policies on Biomass facilities. Column (1) and (2) investigate the policies' effects on all the counties while Column (3) and (4) exclude counties with no recorded cropland fires between 2001 and 2022 (i.e., counties with minimal cropland or crop residues). Control variables include climate factors such as temperature and precipitation, agricultural characteristics such as grain planting area, forest wildfire occurrence and burned area. We account for year fixed effects and county fixed effects. Robust standard errors (in parentheses) are clustered at the county level. *** p <0.01, ** p <0.05, * p <0.1.