Essays in Natural Resources and Environmental Economics



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Abstract

This dissertation examines how innovative market mechanisms and policy interventions can mitigate critical environmental challenges and conflicts in low- and middle-income countries (LMICs). The first chapter presents evidence from a randomized controlled trial in Thailand that tests a novel market-based solution to crop residue burning by connecting farmers to biogas markets. The intervention reduces crop burning by 32% and generates spillover effects on neighboring farms and large-scale farm owners. The second chapter explores related issues and estimates the effects of opening biogas power plants on crop residue burning. Leveraging the staggered timing of biogas plant openings—which purchase crop residues from farmers as feedstock for renewable energy production—and satellite imagery from 2001 to 2023, I find that plant openings reduce agricultural fires by 8.5% within a 5 km radius of the plants. These effects extend beyond direct reductions in agricultural fires to reduce PM2.5 pollution by 2.5% in rural areas, nearby urban centers, and in the downwind areas. The third chapter examines the effects of a mining moratorium in Myanmar and finds that contracting resource extraction reduces civil conflict by 69%, with larger effects in poorer, remote, and ethnic regions. In contrast to existing literature, which shows that mining expansion increases conflict, this chapter demonstrates that a mining ban can promote peace. Collectively, the three chapters highlight the importance of innovative market-based interventions and the role of policy in generating spatially diffuse environmental and social benefits.

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Introduction

Air pollution, environmental degradation, and mismanagement of natural resources are critical development challenges in low- and middle-income countries. These problems have far-reaching consequences for human health, economic development, and social stability. Crop residue burning, a common agricultural practice, generates severe seasonal air pollution. Natural resource extraction, particularly mining, can trigger or intensify civil conflict in resource-rich regions.

This dissertation addresses these challenges by examining how innovative market-based interventions and policy reforms alter incentives in agriculture and resource extraction, and how these changes affect both environmental quality and conflict dynamics. It does so through three chapters. The first chapter tests a novel market-based solution that connects farmers to biogas markets to reduce crop residue burning. The second examines how contracting resource extraction, rather than expanding it as in prior studies, affects civil violence. The third evaluates whether biogas market infrastructure can reduce agricultural burning at scale and improve air quality.

Chapter 1: What a Terrible Thing to Waste: Providing a Market-based Alternative to Crop Residue Burning

Crop residue burning significantly contributes to air pollution in low- and middle-income countries (LMICs). Instead of burning, farmers can sell their crop residues in the biogas market—an underexplored avenue that could reduce crop residue burning while generating income. However, farmers need compression technology to manage and sell their residues, which most smallholder farmers cannot afford. Therefore, this study tests a novel market-based alternative to crop residue burning by connecting smallholder farmers to the biogas

market for their crop residues. I involve 1,024 farmers in a field experiment with two arms: a control arm and a treatment arm. Using high-resolution satellite imagery, I find that the intervention reduces crop residue burning by 32%. The effects are concentrated among farmers who faced high financial constraints, but not among those who faced information constraints about the technology at baseline. Crop residue burning also decreases among neighbors, indicating that green technology can generate significant spillover effects within villages. The results indicate that the intervention is a highly cost-effective policy for mitigating negative externalities in agriculture. The benefits, measured in terms of CO_2 emissions averted, are approximately 54 times greater than the program cost.

Chapter 2: Market Incentives for Environmental Protection: Evidence from Biogas Plants in Thailand

Agricultural burning is a significant contributor to air pollution and health costs in low- and middle-income countries. This chapter examines whether creating markets for agricultural residues reduces farmers' burning behavior by exploiting the staggered timing of biogas plant openings across Thailand from 2001 to 2023. Biogas plants buy crop residues from farmers as feedstock for the production of renewable energy, providing an economic alternative to open burning. Using agricultural fires from MODIS satellite imagery, I compare agricultural fires near operational plants with those near plants not yet operational within a 5-km radius. I find that plant openings reduce agricultural fires by 8.5% with effects concentrated during the burning season. These reductions are only observed within a 30-km radius of the plants. The reductions translate into substantial air quality improvements that extend well beyond the immediate vicinity of biogas plants. PM2.5 concentrations decrease by 2.5% in local areas, but the effects are amplified in nearby urban centers, reaching 6.5% reductions. I find that only plants offering high residue prices or operating at high capacity reduce fires, suggesting that market mechanisms drive the estimated effects. Alternative explanations are ruled out, including enhanced fire enforcement, labor reallocation, and regulatory changes. These findings demonstrate that rural industrial policy that promotes renewable energy can mitigate urban air quality challenges in developing economies.

Chapter 3: Mining Policy Reform and Civil Conflict: Evidence from Myanmar This chapter inverts the standard resource-conflict paradigm by examining how resource contrac-

tion, rather than expansion, affects civil violence. Exploiting a 2016 moratorium in Myanmar that halted new mining licenses, I implement a difference-in-differences strategy using a novel spatially disaggregated database linking mining activity with geo-coded conflict events from 2011–2020. The contraction led to a 69% reduction in conflict incidents—particularly violent and fatal events—in previously licensed townships. The estimated effect is larger and remains persistent in the long term. As the reform is a "license ban", the treatment effect intensifies over time as more licenses expire and mining activity declines. The effects were stronger in ethnic homelands, poorer areas, and remote regions. Strikingly, the analysis uncovers positive spatial spillovers: conflict also declined in neighboring non-mining areas, suggesting that reduced resource extraction diffuses peace rather than displacing violence. Evidence supports three mechanisms: (1) lower mineral rents constrained armed group financing; (2) labor reallocation to productive sectors increased the opportunity cost of violence; and (3) reduced elite rents mitigated local inequality, dampening grievance-based mobilization. This chapter was recently published in the ***Journal of Development Economics***.

Contributions

This dissertation contributes to several strands of literature across environmental and development economics. The three chapters collectively advance our understanding of how innovative market mechanisms and policy interventions affect environmental and conflict outcomes.

First, this dissertation contributes to the literature on market-based solutions to environmental externalities. A large body of work examines how creating property rights or markets can address environmental externalities (Holland & Yates 2015, Hernandez-Cortes & Meng 2023, Jayachandran et al. 2017, Ayres et al. 2021). Recent studies on agricultural fires employ payment-for-ecosystem schemes, such as upfront payments to reduce burning (Jack et al. 2022, Lopes et al. 2023). This dissertation extends this literature in three ways. First, it tests an innovative market-based alternative that connects farmers to biogas markets for their crop residues, finding it is more cost-effective than payment for ecosystem services. Second, it shows how industrial policy can indirectly create environmental markets by promoting biogas, which increases demand for agricultural residues and generates economic incentives that reduce burning without direct environmental regulation. Third, by comparing

the two chapters, it reveals the spatial limits of market-based solutions: while biogas plant openings only reduce burning within 30 km (Chapter 2), providing compression technology that overcomes market access barriers enables farmers located an average of 80 km from plants to access biogas markets (Chapter 1). These findings demonstrate that while industrial policy creates valuable market opportunities, complementary interventions addressing market failures extend geographic reach beyond what market forces alone achieve and offer a more cost-effective and sustainable alternative to direct payment schemes.

Second, the dissertation contributes to the literature on the economics of air pollution. A substantial body of work documents the economic costs of air pollution, including reduced worker productivity (Chang et al. 2019, Hansen-Lewis 2025, He et al. 2020, Zivin et al. 2020) and increased mortality and medical costs (Deryugina et al. 2019). Given these costs, researchers have examined mitigation strategies including environmental regulations (Greenstone & Hanna 2014) and information provision (Barwick et al. 2024). Agricultural fires contribute substantially to air pollution (He et al. 2020), and recent studies find that biogas plants can reduce local PM2.5 concentrations (Nian 2023, Cao & Ma 2023). However, the literature has largely examined local impacts on rural residents, while spatial spillovers to urban populations remain unexplored. This dissertation extends the literature by providing the first evidence that rural biogas promotion reduces PM2.5 pollution in nearby urban and downwind locations, with effects amplified in urban centers (6.5% reduction) compared to local rural areas (2.5% reduction). This finding has important implications for understanding whether rural interventions can mitigate urban air quality challenges in developing economies.

Lastly, this dissertation contributes to the literature on natural resources and conflict. Specifically, it contributes to research that exploits exogenous variation in resource extraction to identify causal effects on conflict. Previous studies have leveraged both market-driven and policy-driven shocks. Market-based studies using commodity price fluctuations consistently find that resource booms increase local conflict through rent-seeking mechanisms (Dube & Vargas 2013, Berman et al. 2017, Denly et al. 2022). Policy-based studies find that mining reforms promoting investment increased local conflict in the Philippines (Crost & Felter 2020). However, what happens to conflict when the state attempts to reduce mining remains unclear. This dissertation directly addresses this gap by investigating the causal impact of

state-induced reductions in mining activity through moratoriums, finding that a mining ban reduces conflict by 69%—a decline comparable in magnitude, but opposite in direction, to the 60% increase associated with mining expansions in Crost & Felter (2020).

The remainder of this dissertation is organized as follows. Chapter 1 presents the randomized controlled trial that tests an innovative market-based solution to crop residue burning in Thailand. Chapter 2 analyzes the long-run impacts of biogas plant openings on agricultural burning and air quality in Thailand. Chapter 3 examines the effects of the mining ban on civil conflict in Myanmar.

Chapter 1

What a Terrible Thing to Waste: Providing a Market-based Alternative to Crop Residue Burning

Abstract Crop residue burning significantly contributes to air pollution in low- and middle-income countries (LMICs). Instead of burning, farmers can sell their crop residues in the biogas market—an underexplored avenue that could reduce crop residue burning while generating income. However, farmers need compression technology to manage and sell their residues, which most smallholder farmers cannot afford. Therefore, this study tests a novel market-based alternative to crop residue burning by connecting smallholder farmers to the biogas market for their crop residues. I involve 1,024 farmers in a field experiment with two arms: a control arm and a treatment arm. Using high-resolution satellite imagery, I find that the intervention reduces crop residue burning by 32%. The effects are concentrated among farmers who faced high financial constraints, but not among those who faced information constraints at baseline. Crop residue burning also decreases among neighbors, indicating that green technology generates significant spillover effects within villages. The results indicate that the intervention is a highly cost-effective policy for mitigating negative externalities in agriculture. The benefits, measured in terms of CO_2 emissions averted, are approximately 54 times greater than the program cost.

Keywords: crop burning, biogas market access, green technology, and field experiment

JEL Classification: O13, Q01, Q56, Q16, Q13, C93

1.1 Introduction

Air pollution is a pressing environmental concern in low- and middle-income countries (LMICs). In these countries, the levels of PM2.5 pollution far exceed the World Health Organization (WHO) guideline of 5 $\mu g/m^3$. Although high-income countries typically maintain levels of PM2.5 below this threshold, LMICs face alarmingly high levels of PM2.5 pollution, exceeding 50 $\mu g/m^3$ (Washington University in St. Louis 2022). The impact of air pollution is staggering, with approximately 9 million deaths per year attributed to it, accounting for one in every six deaths worldwide. Notably, LMICs bear the brunt of these pollution-related deaths, accounting for 92% of the total (Fuller et al. 2022).

At certain times of the year, crop residue burning significantly contributes to air pollution in rural areas and neighboring urban areas. PM2.5 pollution peaks during crop harvest time in South and Southeast Asia (Vadrevu et al. 2021*a*). Various factors drive the burning of crop residues. As the global population grows, the demand for agricultural production increases, leading farmers in LMICs to transition from growing one crop to two crops per year. With limited time between harvesting the first crop and planting the next, crop residue burning has become an efficient method for managing crop residues. Additionally, the migration of workers out of the agricultural sector compels farmers to resort to low labor-saving technology, such as fire, to clear their agricultural land (Garg et al. 2023). Moreover, when the social costs of burning residues are not internalized, farmers facing higher private costs than private benefits tend to over-burn residues and undersell them in the market (Krishna & Mkondiwa 2023).

In this study, I test a novel market-based alternative to crop residue burning by connecting smallholder farmers with the biogas market for their crop residue. Farmers need to use modern compression technology to manage and sell their residues on the market. With this technology, crop residues on the ground can be easily collected, compressed, and transported to the biogas market. However, the cost of renting this equipment is not affordable for smallholder farmers, leading them to undersell their residues on the market and overburn their residues.[1] This paper aims to address market failure by focusing on an innovative market-based solution that offers economic incentives to sell crop residues for biogas production, potentially reducing the need to burn and promoting sustainable energy production from crop resides.

[1]The cost of modern compression technology, amounting to USD 14,200, poses a significant financial burden for smallholder farmers.

In collaborating with compressor rental firms and one of the largest biogas power plants in Thailand, I conducted a randomized control trial to explore whether crop residue burning can be mitigated with an incentive scheme to cover rental costs for modern compression technology, potentially relaxing capital constraints and enhancing access to the biogas market.[2] This study targeted small farmers cultivating less than 15 rai (6 acres) of farmland.[3] Farmers in the treatment group were provided with scratch cards that offered a discount on the rental of modern compression technology from compressor rental firms. The voucher was conditional upon selling crop residues in the biogas market. The validity of the voucher spanned from October 2023 to December 2023, covering the burning season for rainfed cultivation.

Using high-resolution satellite imagery from PlanetScope (3 meters resolution), I find that the capital rental subsidy leads to a 32% drop in crop residue burning in the treatment group. Estimates are robust across multiple checks, including alternative data sources (i.e., Sentinel-2 satellite imagery and ground-field verification), alternative spectral indices for detecting burned plots, alternative burning detection thresholds, and various model specifications with or without baseline outcomes and sociodemographic controls.

I next examine whether the capital rental subsidy had persistent effects on crop burning in the subsequent agricultural season, when farmers no longer received the intervention. I find no statistically significant impact on crop burning in this follow-up period, indicating that the behavioral changes were temporary and reverted after the withdrawal of the subsidies. These findings contrast with learning-by-doing models that predict persistent effects from temporary technology subsidies. The lack of persistence suggests that learning effects were insufficient to overcome structural barriers, including credit constraints and thin rental markets for agricultural machinery.

The capital rental subsidy reduces crop residue burning through enhancing the production of crop residues and increasing their sales in the biogas market. Using data from the biogas power plant, I explore market access, measured by whether farmers sell their rice residues on the biogas market. I find that the capital rental subsidy increases biogas market access by 69% compared to the control mean. Using survey data, I also find that the treatment is

[2]Open-field burning emits more CO_2 and CO than the biogas power plant. For 6.157 million tons of rice residues, the emission savings of the biomass-fired power plant compared to open-field burning are 0.61 million tons of CO_2 and 0.02 million tons of CO in Cambodia (Sokrethya et al. 2023).

[3]On average, Thai farm households have 14.3 rai of land holding. Only 20% of Thai farm households have more than 20 rai (Attavanich et al. 2019)

associated with an increase of 0.329 tons of rice residues among farmers and leads to an increase in the self-reported agricultural income of farmers in treated villages.

Next, I explore heterogeneous treatment effects based on four baseline characteristics: financial constraints, distance constraints, information constraints, and farmer age. I find that crop burning significantly reduces crop burning among farmers who faced high financial constraints at baseline. However, I do not observe significant effects among farmers facing greater distance and information constraints. This suggests that farmers who are closer to the biogas markets, roads, and the capital are more likely to take advantage of the subsidy. Interestingly, older farmers respond more strongly to treatment, challenging conventional assumptions about age and technology adoption when financial barriers are removed. These findings remain robust across alternative datasets, including Sentinel-2 satellite imagery and ground-field verification data.

I further explore the spillover effects of modern compression technology and find that the treatment reduces crop burning among neighbors. To examine these effects, I map the boundaries of rice plots cultivated by all neighbors at the endline. The total number of neighbors' rice plots is 2,996, with respondents having one to five rice-cultivating neighbors. I find that burning decreases among the neighbors of the respondents, indicating that the new technology generates significant spillover effects within the village. Specifically, farmers in treated villages were 20% more likely to have a neighbor adopting the technology compared to farmers in control villages. The results barely change when I restrict the sample to neighbors' plots that do not overlap with treated plots. The results consistently demonstrate that the treatment induces significant within-village adoption among neighbors, even when I use the alternative Sentinel-2 dataset. When accounting for this externality, the cost of the intervention drops from USD 14 to USD 2.777 per additional acre.

Beyond immediate neighbors, I also examine spillover effects on large-scale rice fields by identifying all rice plots greater than 2.4 hectares within the 60 study villages. In total, there are 380 large plots across these villages, each assigned to the nearest main respondent plot. The results show that the treatment reduces crop burning on these larger plots by approximately 3.6%. While this percentage reduction is smaller than for other neighbor categories, this finding is particularly notable given that large-scale plots have substantially higher baseline burning rate (90%). These findings suggest that spillover effects extend beyond immediate neighbors to influence broader agricultural practices within villages, includ-

ing commercial-scale operations. The result remains consistent when using the alternative Sentinel-2 satellite.

After presenting the impact of the capital rental subsidy on crop residue burning, the cost of the intervention is compared to the damage caused by PM2.5 pollution from rice field burning. I first calculate the cost per additional acre not burned using PlanetScope satellite data, which amounts to USD 28. Comparatively, the damage caused by PM2.5 pollution from rice field burning is estimated to be USD 4,673 per acre.[4] Therefore, the damage from PM2.5 pollution from rice field burning is over 166 times higher than the cost of reducing crop residue burning per acre.

Next, I compare the cost of the intervention with the benefit of averting CO_2 emissions. Drawing from a study conducted by Junpen et al. (2018) in Thailand, I calculate CO_2 emissions per acre, which amounts to 2.81 tons. On the intervention cost per ton of delayed CO_2 emissions for the study area, I divide the total cost of the intervention, accounting for spillover effects, by the total CO_2 emitted. The cost per ton of CO_2 averted is USD 1.42. Given that the price of the European carbon market is around EUR 70/tCO_2 ($\approx$77 USD), the benefit of averting CO_2 emissions is approximately 54 times higher than the cost of the intervention.

Lastly, I estimate farmers' willingness to pay (WTP) for clean air by conducting a choice experiment at the endline. The experiment included three attributes: PM2.5 pollution, technology cost, and transport cost. These attributes are based on the costs of managing and selling rice residues in the market to reduce PM2.5 pollution from crop residue burning. Farmers were presented with six different choice sets. Each choice set offered three options for farmers to consider: the status quo and two alternatives with varying attributes. I find that on average farmers have a significant negative marginal utility for PM2.5 pollution and estimate that there is a positive willingness to pay for compression technology per acre of approximately USD 10.13. This suggests that, for farmers without binding credit constraints, the capital rental subsidy for farmers could potentially be reduced from USD 36.12 to USD 25.99 per acre.

This paper contributes to several strands of literature. It first speaks to the literature exploring the importance of market access and linking farmers to value chains for agricultural

[4]To calculate the damage caused by PM2.5 pollution from rice field burning per acre, I divide the damage from premature deaths related to PM2.5, which amounts to USD 21.12 billion by 4.49 million acres of burned rice fields.

productivity and profitability. Bold et al. (2022) find a significant increase in productivity and profitability for farmers when they are presented with access to the market and training. Similarly, Macchiavello & Miquel-Florensa (2019) find that linking domestic suppliers with multinational buyers leads to an increase in the quality of farmers' coffee products and higher farm gate prices. Existing studies focus their attention on traditional agricultural markets and products. Pushing forward the existing knowledge frontier, this study focuses on market access for crop residues and attempts to address agricultural waste market failure that produces environmental pollution by connecting farmers to the biogas market.

Second, this paper contributes to the literature that explores the impact of capital intensification. Caunedo & Keller (2021) have explored the role of capital intensification for agricultural productivity. Caunedo & Kala (2021) have provided causal evidence on how mechanization affects productivity, labor demand, and labor allocation. While existing studies focus on the impacts of capital intensification on agricultural productivity, labor demand, and labor allocation, this paper provides the first available evidence of how modern compression technology impacts crop residue burning and market access for crop residues.

Third, this study relates to the literature that explores technology to address the environmental externalities of agriculture. For example, Emerick et al. (2016) study flood-tolerance rice seeds. BenYishay & Mobarak (2018) explore sustainable farming practices that reduce soil erosion and improve soil fertility through crop residue management. Aker & Jack (2023) study the Rainwater Harvesting (RWH) technique that helps reduce land degradation and restore soil fertility. While previous research has focused on specific agricultural technologies, this study uniquely combines technological intervention with access to the biogas market to address crop burning and increase the supply of alternative energy from crop residues.

Lastly, the nascent literature explores the effects of incentives on crop residue burning. Edwards et al. (2020) evaluate the impact of a bundled intervention that includes awareness training and payments to village governments and find no effect on agricultural fires. Kramer & Ceballos (2018) find that conditioning agricultural insurance payouts on not burning residues reduces crop residue burning in India. Jack et al. (2022) tests the impact of conditional cash transfers on stubble burning in India. They find that financial rewards with upfront payments significantly reduce crop burning, but standard financial rewards with no upfront payments have null effects, possibly due to the distrust of standard financial rewards. In contrast to these studies, which often focus on payment for ecosystem services, my study

adopts an innovative market-based alternative to crop residue burning by connecting farmers to the biogas market for their crop residues. I find that this market-based solution to crop residue burning is more cost-effective compared to payment for ecosystem services. For example, the cost per acre of not burning is USD 28 for a market-based alternative to crop residue burning, while it costs USD 55 per acre of not burning for the payment for ecosystem (Jack et al. 2022).

The remainder of the article is organized as follows. The next section provides an overview of the rice sector in Thailand. Section 3 discusses the experimental design, while Section 4 presents data collection and survey instruments. Section 5 presents the results, and Section 6 summarizes the findings.

1.2 Context

1.2.1 Rice Sector in Thailand

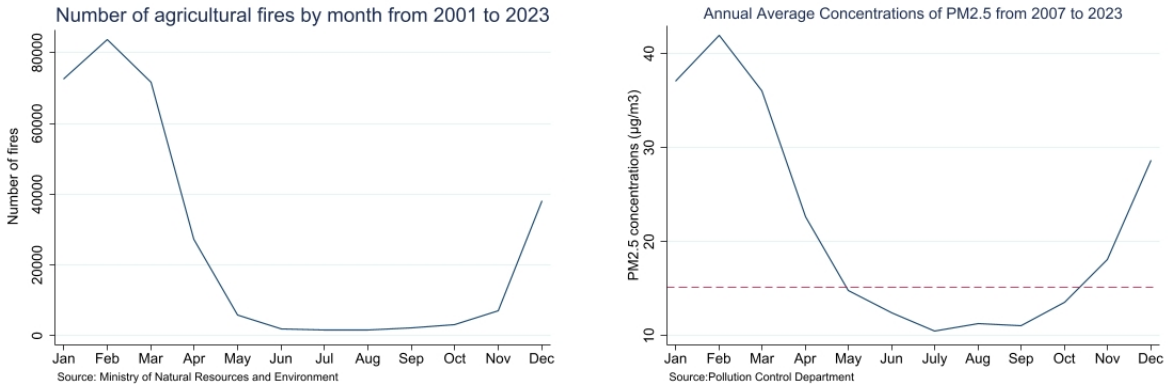
The rice industry in Thailand is of substantial significance, given that the nation is the second largest exporter of rice globally. Rice is cultivated on half of Thailand's agricultural land by more than 20 million farmers (see Appendix Figure A1 for rice growing areas). Thailand, like other low- and middle-income countries, commonly practices crop residue burning (see Appendix Figure A2 for the agricultural fires across Thailand). Annually Thailand generates around 61.87 million tons (Mt) of rice residues, of which 14.23 million tons (23%) are burned within the fields after harvest (Junpen et al. 2018). This leads to a loss of potential electricity generation of 9,243 GWh annually.[5]

Crop residue burning releases greenhouse gas emissions, such as carbon dioxide (CO_2) and particulate matter (PM2.5), which have detrimental effects on air quality, climate change, and human health (Krishna & Mkondiwa 2023). Thailand is ranked 19th in the world for agricultural emissions, with a total emission of 1.1 million tonnes CO_2 equivalent in 2020 (FAOSTAT 2023). The levels of PM2.5 exceed the World Health Organization (WHO) target of 5 μg/m3, particularly during the agricultural burning season in Thailand (Appendix Figure A3). Figure 11 shows that there is a significant increase in PM2.5 pollution as the

[5] Delivand, Barz & Gheewala (2011) estimates that 1.54 tons of rice residues are required to generate 1 MWh of electricity in Thailand. Given that 14.23 million tons (Mt) of rice residues are burned, this could potentially produce 9,243 GWh of electricity annually.

number of agricultural fires increases between November and February. In 2019, approximately 32,200 premature deaths were associated with PM2.5 pollution, resulting in a cost of more than USD 32 billion, equivalent to 6% of Thailand's GDP (World Bank Group 2023).

Why is there an underselling of rice residues in the biogas market? Biogas markets that purchase residues for alternative energy are not well developed in low- and middle-income countries (Shaikh 2022). Limited access to these markets may explain why farmers resort to burning their crop waste (Tippayawong et al. 2020). The cost analysis shows that farmers fail to sell their production (i.e., crop residues) to biogas markets due to high capital rental costs, which account for over 90% of the total costs involved (see Appendix Table A1 for cost and benefit analysis).



(a) Number of agricultural fires by month

(b) Annual average concentrations of PM2.5

Figure 11: Agricultural fires and annual average PM2.5 concentrations

There are several alternatives to rice residue burning, each with its challenges. First, farmers can remove rice residues from fields and sell them in the biogas market for energy production. However, farmers need costly compression technology to prepare residues for sale, which most smallholders cannot afford. Second, farmers can incorporate residues into the soil using rotavator or Happy Seeder. However, this method requires multiple rounds of equipment use to ensure a thorough shredding and integration into the soil for the next crop. While this approach may promote long-term fertility, it is also the most expensive among the alternatives.[6] Third, farmers can leave rice residues in the field, allowing them to decompose over a period of 60 to 90 days (Sarma et al. 2022). However, many farmers cultivate multiple

[6]Discussions with farmers in Khon Kaen Province indicate that the equipment costs (e.g., Happy Seeder machine) a minimum of $28.5 per rai. This suggests a cost of approximately USD 72 per acre, while the machine used in my study cost USD 36.12 per acre.

crops per year, leaving them with limited time between harvesting and planting the next crop (see Appendix Figure A4 for the farming calendar). Finally, farmers can use rice residues as feed for livestock. The feasibility of this option depends on how farmers perceive the nutritional quality of the residues and the availability of ruminant livestock in the local area (Krishna & Mkondiwa 2023).[7]

1.2.2 Government Policies in Addressing Crop Residue Burning

Crop residue burning generates a significant negative externality, prompting various levels of government to implement policies and initiatives to address this problem. However, despite these efforts, a substantial amount of rice residues continues to be burned annually (Newton 2023).

At the national level, the government has introduced the Pollution Management Plan, which provides guidelines for managing crop residue burning and encourages alternative practices (Junpen et al. 2018). Additionally, the government has established the Alternative Energy Development Plan (AEDP) for 2015-2036. Under this plan, subsidies, loans, and tax incentives are offered to promote the adoption of biogas technology and the utilization of crop residues for energy generation (Chaiprasert 2011).

In response to AEDP policy, biogas power plants have been established, purchasing agricultural waste such as rice straws, sugarcane leaves, and corn husks from farmers. The electricity generated from these plants is used for manufacturing processes or sold to the national grid. Thailand is estimated to have the potential to generate approximately 64,594 GWh of electricity annually from 174.1 million tons of waste materials, including bagasse, rice husk, wood residue, palm fiber, palm shell, sawdust, etc. (Department of Alternative Energy Development 2024, Jusakulvijit et al. 2021). However, despite this significant potential, the total renewable energy generated in Thailand was limited to approximately 21,000 GWh in 2021 (Ministry of Energy 2024).

At the local level, provincial governments have implemented a combination of rewards and penalties. For example, in 2019, farmers who burn their fields face fines up to 14,000 Baht and/or a maximum of seven years of imprisonment, while those who report burning events

[7]The cost of supplying rice residues to livestock markets is similar to that of compressing residues for the biogas market (i.e., USD 36.12 per acre). Although livestock markets offer higher prices, they cannot absorb the total volume of rice residues produced throughout the country.

are rewarded with 5,000 Baht in Ratchaburi province (Bangkok Post 2019, Thaitrakulpanich 2019).

1.2.3 Challenges of 2023 Agricultural Seasons

Thailand is the 9th country in the category of 'extreme risk', making it highly vulnerable to the impacts of climate change over the next three decades (UNFCCC 2022). The country has witnessed an increase in severe extreme weather events such as floods, droughts, and heatwaves in recent years (UN Office for Disaster Risk Reduction 2020).

The rice sector, in particular, is exceptionally susceptible to climate change, especially changes in rainfall and temperature patterns (Muehe et al. 2019). In the first half of 2023, Thailand experienced record-breaking temperatures attributed to El Niño, resulting in reduced rainfall during the initial stages of rainfed rice cultivation in June-July 2023 (Bank of Thailand 2023). Insufficient rainfall and water availability hindered the full maturation of rice plants, leading to a decrease in rice production and residues in 2023 (Office of Agricultural Economics 2023). On average, farmers in Northeast Thailand produce about 750 kilograms of rice residues per acre. However, in my sample, farmers produced only approximately 250 kilograms of rice residues per acre in 2023.

Furthermore, heavy rainfall during the late 2023 rice harvest season led to wide-spread flooding across Thailand. Satellite data reveal that on October 14th, 2023, floods affected 67,972 hectares (167,926 acres) of agricultural land, predominantly rice fields (The Nation 2023). The floods also affected some rice fields within my sample, preventing farmers from harvesting their rice and managing rice residues.

1.3 Experimental Design

1.3.1 Treatment

I collaborated with Khon Kaen University, compressor rental firms, and one of the largest biogas power plants in Thailand to implement the intervention. In August 2023, before the rainfed rice cultivation harvest season, farmers in the treatment group were offered a voucher that covers the full cost of crop residue management equipment (equivalent to USD 36.12 per acre). This did not impact farmers' planting decisions, as they had already commenced

planting their crops in late June or early July 2023.

The value of the voucher was based on the rice cultivation area of the farmers (see Appendix Figure A10 for the sample of a voucher).[8] The voucher was contingent on farmers selling their rice residues in the biogas market. We communicated this condition to the farmers when we distributed the vouchers in the treatment villages. To ensure compliance, we signed a contract with compressor rental firms, specifying that the payment would only be made upon receiving two documents: farmer vouchers at compressor rental firms and sales receipts from the biogas power plant.[9]

For treated farmers who wanted to use their vouchers, they contacted the compressor rental companies directly, as contact details were provided on the voucher.[10] Farmers and firms would then schedule a suitable time for rice residue compression. After the residues were compressed, farmers handed over their vouchers to compressor rental companies. Using trucks from these firms, farmers sold their residues at the biogas power plant in Chaiyaphum Province. Upon receiving payment from the biogas market, farmers paid transport fees to compressor rental companies, amounting to an average of USD 2.19 per acre.[11] Every week, compressor rental firms provided the research team with a list of farmers who had compressed rice residues and sold them on the biogas market. The research team cross-verified this information with the administrative data from the biogas market before proceeding with payments for the technology to compressor rental firms.

The farmers in the sample harvested their rice between October 28th and November 25, 2023. As the harvest approached in October 2023, the research team contacted all farmers in the treatment group to remind them of their vouchers. For a detailed timeline of the intervention and data collection activities, along with an agricultural calendar, please refer to Appendix Figure A11.

[8] Data on rice cultivation area were obtained during the baseline survey and cross-checked with farm registration books issued by the government.

[9] Farmers gave their vouchers to compressor rental firms after they finished managing their rice residues. Farmers sold their residues at the biogas factory using capital-rental firms' trucks. The factory sent weekly sales receipts to our research team. We paid the compressor rental firms for the technology costs once we received the farmers' vouchers and the factory sales receipts.

[10] Compressor rental firms also had the contact details of all the farmers in the treatment group.

[11] Transport costs were cheaper as farmers used the trucks of compressor rental firms and organized carpooling to get rice residues to the biogas factory.

1.3.2 Sample and Randomization

Using fire hotspot data from Thailand's Ministry of Natural Resources and Environment, I selected three districts (Khon Kaen, Nam Phong, and Chom Phae), which had the highest number of agricultural fires in Khon Kaen province (Appendix Figure A5). From these districts, I selected 300 out of 406 villages, based on their high rates of burning from 2001 to 2023, for further screening.

Initial village eligibility screening was conducted by phone. Villages were considered eligible if they had at least 30 households that burned rice residues and cultivated rice on or less than 5.93 acres of farmland. The first criterion means that my sample has higher rates of burning than the average for statistical power. I focused on smallholder farmers with less than 5.93 acres of farmland since the average Thai farm household owns 6 acres of land (Attavanich et al. 2019). After the phone screening, 64 villages remained out of 300 villages (see Appendix Figure A6 for the study area).

To screen farmers' eligibility, I used administrative data from village authorities, specifically whether farmers cultivate rice on or less than 6 acres of farmland. From each of the 64 villages, I randomly selected 16 households, resulting in a final sample of 1,024 respondents.

I randomly assigned the villages into two groups following a baseline survey: a control group and a treatment group. Specifically, 32 villages were assigned to the treatment group, while the remaining 32 villages were assigned to the control group. As a result, I have a total of 512 farmers in the treatment group and 512 farmers in the control group (see Appendix Figure A9 for the sample size per arm).

1.3.3 Interpreting the Magnitude of the Intervention

The subsidy covers the rental cost of modern compressing technology from compressor rental firms, at USD 36.12 per acre. Given an average farm size of 2.11 acres in the sample, the total subsidy per farmer is approximately USD 76.21, representing approximately 8.71% of the average annual agricultural income of the household.

Farmers in the sample earn approximately USD 9.79 per acre from selling rice residues in the biogas market. For the average farmer (2.11 acres), this translates into an additional income of USD 20.65, representing 2.36% of the average annual agricultural income. Although this may seem modest, the significance of this revenue stream is more apparent for

larger landholders. For example, a farmer with 5.93 acres would earn approximately USD 58, representing 6.64% of annual agricultural income. It is important to note that these figures likely represent a lower bound; residue production was low (approximately 250kg/acre) in the study year due to an El Niño event that caused severe heatwaves and drought. Under normal weather conditions, both residue yields and potential profits from the biogas market could be substantially higher.

1.4 Data Collection and Survey Instruments

1.4.1 Timeline and Survey Instruments

Baseline survey I conducted the baseline survey in March and April 2023. The survey collected data on demographics, assets, income, credit access, social networks, agricultural production, and crop residue management practices. Additionally, I collected data on key outcomes such as self-reported crop burning, access to the biogas market for crop residues, crop residue production, and income from crop residues. Using this baseline data, I constructed three baseline constraints to explore heterogeneity: finance, distance from the biogas market, and information (Section A.3).

During the baseline survey, I mapped the boundaries of all rice plots of the respondents using the farm registration book. This document provides crucial information, including plot registration numbers, ownership details, crop types, and annual production for each plot. Using the plot registration numbers, I extracted the spatial boundaries of the rice plots of the respondents from the Ministry of Agriculture and Cooperatives (Appendix Figure A7). As this study primarily focuses on smallholder farmers, on average, they cultivate rice on a single plot. I then merged these plot boundaries with satellite data to measure crop burning outcome at the plot level.

Endline survey In January 2024, I conducted the endline survey to measure the impact of the program on various outcomes, including access to the biogas market, crop residue production and income generated from residues. I also added a new question asking whether the rice fields had been affected by floods, since some rice fields within my sample were affected by floods during the intervention. Furthermore, a choice experiment was incorporated to elicit farmers' willingness to pay (WTP) for clean air.

During the endline survey, I mapped the rice plots of all the respondents' neighbors to explore the potential spillover effects of the capital rental subsidy (Appendix Figure A8 shows some treated plots, control plots, and neighbors' plots). In total, there were 2,996 neighbor plots. The endline attrition rate was approximately 0.5%. Appendix Table A2 shows no differential attrition between the treatment group and the control group.

1.4.2 Main Outcome Variables

Crop Residue Burning One of the main outcomes of interest in this study is crop residue burning. The objective is to identify plots that were burned during the burning season by detecting bare and charred soil. I use high-resolution PlanetScope satellite to measure crop residue burning. To validate the accuracy of this measure, I cross-referenced it with alternative measures, including data from the Sentinel-2 satellite and ground-field verification data.

For ground field verification data, we collaborated with the village committee in each sample village to conduct all field visits at the end of the harvest season in January. The village committee is well-informed about the village situation, including the agricultural practices of the villagers. As part of their official responsibilities, the village committee also maintains records of everyone in the village, including the locations of farms, ownership, and agricultural practices.

Regarding satellite data, I utilized high-resolution satellite imagery from PlanetScope to measure crop burning.[12] PlanetScope, with its 3-meter resolution, captures data at a higher frequency, approximately every day. Therefore, it is less likely to miss the burning events. I downloaded the four-band surface reflectance product of PlanetScope for both the baseline (December 2022) and endline (December 2023). These images were then stacked to create a time-series data cube for each study plot. To detect burned areas at the pixel level, I used the Bare Soil Index (BSoI) (Saei Jamalabad & Abkar 2008, Walker et al. 2022).[13] The BSoI

[12]Researchers studying agricultural burning commonly use satellite data from MODIS and VIIRS, which have resolutions of 375 meters and 1 kilometer, respectively. However, I cannot use these sensors because my study focuses on small plots.

[13]The Bare Soil Index (BSoI) is designed to detect areas with low or no vegetation by contrasting the combined reflectance in the near-infrared (NIR) and green bands, which are typically higher for bare soil, against the red and blue bands, which are more strongly absorbed by vegetation. High BSoI values correspond to exposed soil, while low values indicate dense vegetation cover. In post-fire landscapes, vegetation removal leaves bare or charred soil, which results in increased BSoI values.

index generated features, and I aggregated the output at the plot level by taking the mean. The classification threshold for differentiating between burned and unburned plots was set at the 75th percentile. Any value above this threshold was classified as burned (for details of the methodology of the BSoL index, please refer to Section A.2).

In addition to the PlanetScope satellite, I used high-resolution Sentinel-2 satellite imagery to identify burned plots during the burning season. Sentinel-2 offers a 20-meter resolution. I downloaded level-1C products from USGS, specifically selecting images that covered my study area in the three districts. To generate features at the pixel level, I used the Burned Area Spectral Mixture Analysis (BASMA) (Daldegan et al. 2019, Walker et al. 2022).[14] This index has demonstrated accuracy in mapping fire scars in Brazil (Daldegan et al. 2019). To convert data from the pixel level to the plot level, I aggregated the BASMA outputs by calculating the mean value for each plot. Any value above the 75th percentile of these plot-level values was considered as indicating a burned plot (for detailed methodology on the BASMA index, see Section A.2).

To ensure the robustness of the burned plot detection, additional spectral indices were computed for both satellite imagery datasets: Burn Area Index (BAI) from PlanetScope imagery and Mid Infrared Bispectral Index (MIRBI) from Sentinel-2 imagery.[15] The MIRBI has demonstrated strong performance in distinguishing fires in landscapes as diverse as the Peruvian Amazon (Barboza Castillo et al. 2020). These indices provide complementary measures of burned areas and enable cross-validation of the Bare Soil Index (BSoI) from PlanetScope imagery and Burned Area Spectral Mixture Analysis (BASMA) from Sentinel-2 imagery. Pixel-level values were aggregated to the plot level using the 75 percentile threshold, with plots exceeding this threshold classified as burned. Detailed methodologies for BAI and MIRBI calculations are provided in Section A.2).

Market Access I explore whether farmers sell their rice residues on the biogas market, looking at both the quantity sold and the revenue earned from these transactions. This data was collected through baseline and endline surveys. I also verified these data with

[14]The Burned Area Spectral Mixture Analysis (BASMA) models each pixel as a mixture of burned material, vegetation, and soil, estimating the fractional abundance of charred material. Higher BASMA values indicate greater proportions of burned material within the pixel.

[15]Burn Area Index (BAI) identifies burned areas using red and near-infrared (NIR) spectral bands. Fire-affected surfaces exhibit low NIR reflectance and moderate red reflectance, resulting in higher BAI values that correspond to burned areas. Similarly, Mid Infrared Bispectral Index (MIRBI) detects burned areas by exploiting the distinct reflectance patterns of charred surfaces in SWIR1 and SWIR2 bands. High MIRBI values indicate burned surfaces. (Walker et al. 2022)

administrative data obtained from the biogas market and compressor rental firms involved in transportation and found that more than 90% of the data were accurate.

1.4.3 Experimental Validity

Table 11 provides a summary of statistics from the baseline survey and the results of a balance test comparing the treatment and control groups. The p-value of the joint F-test is 0.35 for the comparison between the treatment and control groups. This outcome indicates that the characteristics of the treatment and control groups are well balanced.

There are a few key points to highlight with respect to the characteristics of farmers in Table 11. The average age of farmers in my sample is 61 years, which reflects the broader demographic trend of Thailand's aging agricultural sector.[16] The farmers in the sample had significant experience in agriculture, with an average of 38 years in the sector. However, the level of education among the farmers in the sample was relatively low, with only 13% completing secondary education. This is consistent with national averages for the agricultural sector.[17]

The average annual household income in the control group was approximately 118,074 Baht, with one-third of that income coming from agriculture. The farmers' annual household and agricultural incomes closely aligned with farmers in the region.[18] On average, the farmers cultivated rice on 0.75 hectares of farmland. The average annual rice yield is around 5.54 tons per hectare, similar to the national average.[19] Land ownership was high, with 93% of farmers cultivating rice in their fields, consistent with the national trend (National Statistical Office 2019).[20] In terms of crop burning at the baseline, 32% of farmers burned their rice fields according to the PlanetScope satellite, while the Sentinel-2 satellite shows a slightly higher percentage of 33%.

[16] Thailand is facing an aging farming population, and the average age of farmers increased from 54 years in 2008 to 58 years in 2018 (Attavanich et al. 2019).

[17] In 2018, the secondary education completion of farmers was 19% across Thailand (National Statistical Office 2019).

[18] The average annual agricultural income is 35,332 Baht while the average non-agricultural income is 82,876 Baht in northeast Thailand (Khon Kaen University 2022)

[19] The yield per rai is around 413 kilograms for rain-fed rice cultivation, and the yield per rai is around 643 kilograms for dry-season rice cultivation. Therefore, the annual yield per hectare is approximately 6.36 tons per hectare. (Office of Agricultural Economics 2023).

[20] Approximately 11% of farmers cultivate crops under non-owned lands.

Table 11: Summary Statistics and Balance

	N	Control (Mean)	Control (SD)	Treatment vs Control
Household size	1024	4	0.50	-0.242
				(0.455)
Respondent age	1024	61.42	2.44	0.014
				(0.047)
Total experience in agriculture(years)	1024	38.26	4.24	-0.0007
				(0.043)
Secondary education completed=1	1024	0.13	0.09	0.592
				(1.098)
HH income(Baht)	1024	118074	34805	0.000005
				(0.0000147)
Agriculture income(Baht)	1024	30608	13772	0.000001
				(0.00001)
Total number of plots	1024	1.14	0.11	1.488
				(1.255)
Total plot size(hectare)	1024	0.75	0.12	1.879
				(1.321)
Own the plot=1	1024	0.93	0.08	0.101
				(1.254)
Production per hectare for two crops over the past 12 months (ton)	1024	5.54	2.06	0.024
				(0.081)
Use CRM equipment for managing residues=1	1024	0.28	0.45	-0.597
				(0.640)
Access 4,000 Baht from saving for baler=1	1024	0.19	0.11	-1.394
				(1.100)
Know where to rent CRM equipment=1	1024	0.09	0.21	-0.318
				(0.557)
CRM technique is better for long-term soil health than burning=1	1024	0.79	0.11	-0.757
				(1.132)
Distance from farm to biogas power plant(km)	1024	33.5	27.65	-0.009
				(0.006)
Crop burning(PlanetScope satellite)=1	1024	0.32	0.21	-0.003
				(4.147)
Crop burning(Sentinel-2 satellite)=1	1024	0.33	0.22	-0.812
				(4.094)
P-value of joint F-test				0.21

Note:* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Column 5 displays the coefficient from regressing the baseline variable on a treatment dummy (taking value 1 if the village was in the treatment group). Regression includes strata fixed effects. Standard errors clustered at the village level are in parentheses. There are 1,024 observations:512 observations for the control group and 512 observations for the treatment group. Columns 3 and 4 show the summary statistics for the control group in the baseline. 1 USD is equal to 35 Thai Baht.

1.5 Results

1.5.1 Estimation Strategy

I estimate the effects of the capital rental subsidy on crop residue burning using the following equation:

$$Y_{iv}^{1} = \beta_0 + \beta_1 Incentive_{iv} + \gamma Y_{iv}^{0} + \delta X_{iv} + \varepsilon_{iv} \tag{1.1}$$

where Y_{iv}^{1} is the relevant outcome for individual i in village v. I control for the baseline value of the outcome variable Y_{iv}^{0} in an analysis of covariance (ANCOVA) specification following McKenzie (2012). δX_{iv} is a vector of sociodemographic controls selected via double-selection least absolute shrinkage and selection operator (LASSO) to maximize precision (Belloni et al. 2014). ε_{iv} is an error term clustered at the village level. My coefficient of interest is β_1, the impact of capital rental subsidy (intent-to-treat).

1.5.2 Program Take-up

The program achieved a high take-up rate: 69% of farmers in the treatment villages (353 out of 512) took up the capital rental subsidy. Since the subsidy was conditional on farmers selling their residues in the biogas market, this directly translated to market participation. Consequently, sixty-nine percent of the treatment group sold their crop residues, while no farmers in the control group participated in the market.[21]

During the intervention period, heavy rain caused flooding in various regions (The Nation 2023). The government also had to release water from nine major reservoirs that had exceeded their maximum storage levels, resulting in flooding of many fields in downstream areas (Bangkok Post 2023). To better understand whether this flooding prevented farmers in the treatment group from taking up their subsidies, the endline survey included a question regarding whether their rice fields were flooded. Across the entire sample of 1,024 farmers, 79 farmers experienced field flooding. This exogenous shock had a direct impact on compliance

[21] PlanetScope satellite imagery shows that 34 out of 353 farmers who used vouchers in treated villages burned their rice fields. This is because some parts of the rice fields have uneven topography, making it difficult to manage rice residues with modern compression technology. As a result, farmers burn rice residues only in these hard-to-manage areas. Appendix Figure A12 shows that burning is limited to certain areas of the rice field rather than occurring over the entire field.

within the treatment group. Specifically, 48 farmers in the treatment villages were affected by floods, which prevented harvesting and made it impossible to use the subsidy. As a result, the take-up rate was 0% among these flooded farmers. In contrast, the take-up rate among the 464 non-flooded farmers was 76% (353 out of 464 farmers). This very high take-up rate among non-flooded farmers suggests that when the intervention was logistically feasible, the vast majority of farmers chose to participate.

1.5.3 Main Effect

Average Treatment Effects. The main results of the paper are presented in Table 12. Here I examine the treatment coefficient of Equation (2.1) for crop burning outcomes using three different data sources: PlanetScope satellite, Sentinel-2 satellite, and ground-field verification data. All columns control for the baseline measure of crop burning using Analysis of Covariance (ANCOVA). Sociodemographic controls are included based on a double-selection LASSO procedure (Belloni et al. 2014). Columns (1) to (3) examine the entire sample, while columns (4) to (6) restrict the sample to the non-flooded plots.

Table 12: Effects of capital rental subsidy on crop burning

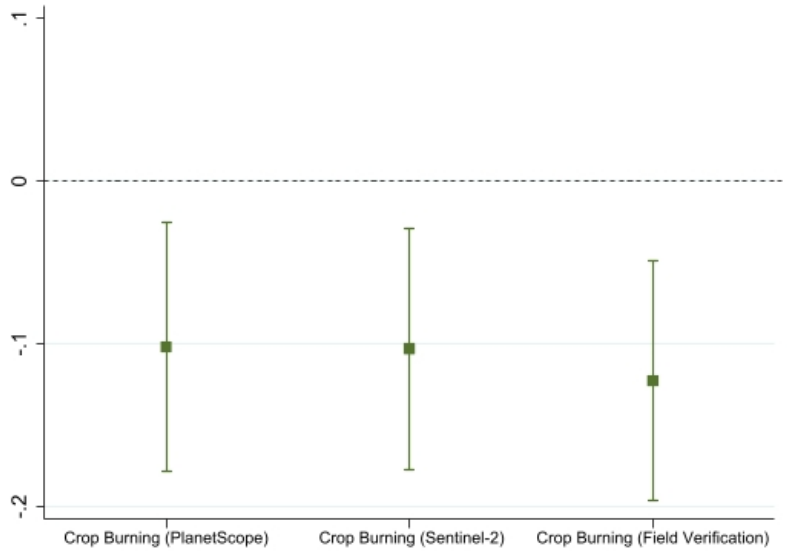
	Crop Residue Burning					
	Full sample			Non-flooded sample		
	PlanetScope	Sentinel2	Verification	PlanetScope	Sentinel2	Verification
Treatment	-0.100**	-0.101**	-0.123***	-0.119***	-0.121***	-0.142***
	(0.041)	(0.041)	(0.037)	(0.042)	(0.042)	(0.040)
Control mean	0.31	0.32	0.37	0.33	0.34	0.38
Observation	1024	1024	1024	945	945	945

Note: This table presents the effect of the capital rental subsidy on crop burning from three data sources: PlanetScope satellite; Sentinel-2 satellite; and ground field verification. Each column displays the Ordinary Least Squares (OLS) estimates derived from Equation (1), which incorporates treatment arm indicator and controls for baseline measures of the respective dependent variables using Analysis of Covariance (ANCOVA). Sociodemographic controls are based on a double-selection LASSO procedure (Belloni et al. 2014). Columns (1)-(3) report results for the full sample, whereas columns (4)-(6) restrict the analysis to non-flooded rice fields. Standard errors in parentheses are clustered at the village level. *, **, and *** indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

Using PlanetScope satellite, column 1 shows that the capital rental subsidy reduces crop burning. Farmers in the treatment group burn 10 percentage points less than those in the

control group. Relative to the control mean (0.31), this estimate suggests a 32% decrease in crop burning in the treatment group. The result remains consistent when using crop burning data from the Sentinel-2 satellite as the outcome of interest (column 2). The estimate shows a larger and statistically significant reduction in crop burning when using ground-truth verification data (column 3). Specifically, the treatment indicator is - 0.123, indicating a 33% reduction in crop burning within the treatment group compared to the control mean (0.37). Figure 12 presents a visual representation of the treatment effects relative to the control group across three data sources.

Figure 12: Treatment Effects Relative to Control



To account for rice fields that had been flooded during the intervention period, I restrict the sample to non-flooded fields in columns (4) - (6). The estimated effects become larger in magnitude and remain statistically significant when the flooded fields are excluded from the sample. In column (4), using the PlanetScope satellite, the treatment indicator is – 0.119 and statistically significant at the 1% level, suggesting a 36% drop in crop burning in the treatment group. The observed effect remains consistent when using an alternative Sentinel-2 satellite (column 5). The effect is somewhat larger when using ground-truth verification data as the outcome of interest (column 6). The coefficient is - 0.142 and statistically significant at the 1% level, corresponding to a 37% reduction in crop burning in the treatment group relative to the control mean (0.38).

Effects on Crop Residue Production and Market Participation. The capital rental subsidy

was designed to reduce crop residue burning by conditioning the subsidy on farmers selling their residues in the biogas market rather than burning them. This section examines whether treatment successfully induced the intended behavioral changes: increased crop residue production, improved market participation, and higher income from residues—changes that should, in turn, reduce crop residue burning. Table 13 presents the results.

Table 13: Effects on Crop Residue Production and Market Participation

	Produc. residues(ton)	Market access	Income from residues
Treatment	0.328***	0.688***	12.94***
	(0.027)	(0.050)	(0.819)
Control Mean	.09	0	0.32
Observations	1019	1019	1019

Note: This table presents the effect of the capital rental subsidy on various outcomes: the production of crop residues (ton), biogas market access for crop residues (equal to 1 if farmers sell their residues in the biogas market), and income from selling crop residues (USD). Each column displays Ordinary Least Squares (OLS) estimates derived from Equation (1), which incorporates treatment arm indicator and controls for baseline measures of the respective dependent variables using Analysis of Covariance (ANCOVA), while sociodemographic controls are included based on a double-selection LASSO procedure (Belloni et al. 2014). Standard errors in parentheses are clustered at the village level. *, **, and *** indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

Using survey data, column (1) of Table 13 shows that the capital rental subsidy significantly increased crop residue production. The coefficient for the treatment indicator is 0.329 and statistically significant at the 1 percent level. This finding indicates that the treatment is associated with an increase of 0.329 tons of rice residues for farmers in the treated villages. The production of crop residues could even be higher in the treated villages if farmers had not been adversely impacted by record breaking temperatures associated with El Nino, which resulted in less rainfall during the initial stages of rainfed rice cultivation in 2023.[22] Farmers in control villages produced an average of 0.09 tons of residues but did not have access to the biogas market (column 2), suggesting that they manage their residues for other markets, probably the livestock market.

Column (2) of Table 13 explores the effects of the capital rental subsidy on access to the biogas market using data from the biogas market. The subsidy was conditional on farmers

[22] Farmers usually produce over 300 kilograms of rice residues per rai in Northeast Thailand; however, in my sample, farmers only produced around 100 kilograms of rice residues per rai in 2023.

selling their rice residues at the biogas power plant. To measure market access, I construct a binary variable that takes the value 1 if farmers sell their rice residues at the biogas power plant. I then estimate the main specification in Equation (2.1), substituting market access as the main outcome of interest. I find that the capital rental subsidy has a positive (i.e., 0.69) and significant effect on biogas market access. This finding indicates that the subsidy leads to an increase in access to the biogas market by 69% in the treated villages.

Column (3) of Table 13 explores the impact of the capital rental subsidy on self-reported income from crop residues using survey data. The assumption is that farmers' income would increase if they choose to produce crop residues for the biogas market rather than burning them. Consistent with this expectation, I observe an increase in self-reported income from crop residues. The coefficient is 12.94 and statistically significant at the 1 percent level, indicating that treatment increases the income from crop residues by $12.94. The estimated effects could be higher if farmers had not been affected by extreme weather events, such as extreme heatwaves and floods, in 2023.

In summary, the evidence in Section 1.5.3 shows that the capital rental subsidy leads to a 32% reduction in crop residue burning relative to the control group. This finding is robust across multiple data sources, including Sentinel-2 satellite imagery and ground verification. The results suggest that the subsidy reduces crop residue burning by increasing crop residue production, access to the biogas market, and income from crop residues.

1.5.4 Mechanisms

This section examines three potential mechanisms that underlie the observed reduction in crop residue burning. First, I examine whether the intervention operates through a financial cost channel by relaxing credit constraints that limit farmers' access to compressor technology required for residue collection and market participation. The capital rental subsidy may allow constrained farmers to overcome the upfront costs of equipment rental, facilitating entry into the residue market. Second, I test a transaction cost channel in which the subsidy reduces search costs and coordination failures by organizing equipment providers to deliver services directly to villages. If transaction costs are the barrier, the intervention should generate positive spillovers to untreated farmers within treated villages. Third, I assess the role of information acquisition and learning. If the subsidy provides new knowledge about market

value or logistics that reduces perceived uncertainty, its effects should persist after the subsidy is removed.

Financial Costs

I first examine whether financial constraints drive the observed reduction in crop burning. If credit constraints are the barrier preventing farmers from participating in residue markets, the subsidy's impact should be stronger among farmers who are more likely to be financially constrained. To test this mechanism, I examine the heterogeneous treatment effects across different farmer baseline characteristics, including financial constraints, distance to markets, and information access. I also explore heterogeneous effects by farmer age, given Thailand's aging agricultural population and potential differences in technology adoption across age cohorts (see Section A.3 for survey questions).

Column (1) of Table 14 presents the effect of heterogeneous treatment by financial constraints, which is the main barrier that motivates me to test this intervention. I construct a binary variable for high financial constraint that equals 1 if a farmer's baseline savings are at or below the sample mean. The coefficient for "treatment × high finance constraint" is -0.117 and statistically significant at the 5% level. This result suggests that the incidence of crop burning is lower among treated farmers who faced high financial constraints at baseline.

Column (2) of Table 14 examines how the effects vary with distance constraints. I construct the binary variable, high distance constraint, which equals 1 if the average distance from the farm to the biogas market, main road, and capital city is greater than or equal to the sample mean, and 0 otherwise. The coefficient for the treatment indicator is -0.104 and statistically significant, while the coefficient for the "treatment × high distance constraint" is 0.009 and statistically insignificant (column 2). These results indicate that the subsidy significantly reduces crop burning among farmers with low distance constraints (i.e., closer to markets, roads, and the capital), whereas no significant effect is observed for farmers facing higher distance constraints. Farmers who are closer to the biogas markets, roads, and the capital are more likely to take advantage of the subsidy, highlighting the significance of proximity. Remote participants may face higher effective costs, and the size of subsidy may not be enough to shift them to profitability. These results are consistent with previous studies that have shown how distance or remoteness can impact market access (Fafchamps &

Gabre-Madhin 2006), agricultural productivity (Khandker et al. 2009), and farmer well-being (Jacoby 2000).

Table 14: Heterogenous Impacts

	Crop Residue Burning			
	PlanetScope	PlanetScope	PlanetScope	PlanetScope
Treatment	-0.003	-0.104**	-0.094**	-0.056
	(0.057)	(0.044)	(0.043)	(0.050)
High finance constraint	0.082**			
	(0.040)			
Treatment × High finance constraint	-0.117**			
	(0.054)			
High distance constraint		0.001		
		(0.064)		
Treatment × High distance constraint		0.009		
		(0.074)		
High information constraint			0.012	
			(0.044)	
Treatment × High information constraint			-0.022	
			(0.052)	
High age group				0.010
				(0.028)
Treatment × High age group				-0.084*
				(0.044)
Control Mean	0.31	0.31	0.31	0.31
Observations	1024	1024	1024	1024

Note: This table presents heterogeneous treatment effects of the capital rental subsidy on crop burning using PlanetScope satellite data, with each column displaying Ordinary Least Squares (OLS) estimates incorporating treatment arm indicators and controls for baseline measures of the respective dependent variables using Analysis of Covariance (ANCOVA), while sociodemographic controls are included based on a double-selection LASSO procedure (Belloni et al. 2014). High financial constraint equals 1 if a farmer's baseline savings are at or below the sample mean. High distance constraint equals 1 if the median baseline distance from the farm to the factory, road, and capital city is at or above the sample mean. High information constraint equals 1 for farmers with knowledge gaps at or above the sample mean regarding CRM practices and equipment rental locations. High age group equals 1 if the respondent's age is greater than or equal to the sample mean, and 0 otherwise. Standard errors in parentheses are clustered at the village level. *, **, and *** indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

Column (3) of Table 14 presents the heterogeneous treatment effect based on information

constraints. In low and middle-income countries, there may be significant search costs and information friction. Fafchamps & Gabre-Madhin (2006) show that the presence of information asymmetry along the value chains severely limits the efficiency of agricultural markets in developing countries. Nakasone et al. (2013) find that the lack of information on prices limits farmers from maximizing their profits. Camacho & Conover (2019) find that smallholder farmers who receive price information through text messages make more informed planting decisions, while larger farmers explore new markets and engage in conversations with other producers.

I construct a high information constraint index based on two variables: farmers' knowledge about crop residue burning and whether farmers know where to rent crop residue management equipment. High information constraint is 1 if the average score of these two variables is greater than or equal to the mean. In column (3) of Table 14, I do not observe a significant effect for those with high information constraints. This differs from the findings of Lopes et al. (2023), suggesting that, in this context, information constraints may not be the primary driver of crop residue burning.

Column (4) of Table 14 presents heterogeneity by farmer age, given that Thailand's farming population is relatively old, which could influence adoption behavior. Interestingly, the coefficient for the "treatment $\times$ high age group" is -0.084 and statistically significant, suggesting that the effects are stronger among older farmers. This finding contrasts with existing studies which suggest that aging has a significant negative impact on farmers' adoption behavior of conservation technology (Huang et al. 2019). One possible explanation is that older farmers might be more financially constrained, and therefore more responsive to subsidies. Their greater farming experience could also increase their openness to alternatives once the financial obstacles are removed.

In summary, the evidence in Section 1.5.4 suggests that crop residue burning is driven by financial constraints. Effects are stronger among financially constrained farmers, while no statistically significant effects are observed for farmers facing information constraints. The results are robust when using alternative datasets from the Sentinel-2 satellite and ground-field verification (Appendix Table A6).

Transaction Costs

In this section, I test whether transaction costs explain the reduction in crop residue burning. The subsidy coordinates compressor rental firms and reduces search frictions, which should lower transaction costs for farmers in treated villages. If transaction costs are the binding constraint, the intervention should generate positive spillovers within treated villages. To test this mechanism, I examine whether untreated farmers in treated villages also reduce burning, particularly those neighboring treated farmers and those with larger plots.

To measure potential spillovers within villages, I first mapped the boundaries of rice plots belonging to the neighbors of the respondents at the endline. I identified respondents' rice-cultivating neighbors (ranging from one to five per respondent). For each neighbor, I obtained the plot identification numbers from their farm registration book, which contains crucial information about plot ownership, cultivated crops, and production values. The plot identification numbers were then merged with the Department of Land Development data to extract the boundaries of the 2,996 rice plots belonging to the neighbors. Second, I identified all large-scale rice plots (more than 2.4 hectares) within the 60 villages in my study. In total, there are 380 large plots in these villages. Each large plot was assigned to the nearest main plot (respondent). When multiple large plots were located near the same main plot, I averaged their burning values to create a single observation per respondent.

Table 15 presents evidence of substantial geographical spillovers consistent with the transaction cost mechanism. Column (1) examines the main neighbor plots, which are defined as the closest neighbors with whom the respondents engage in frequent conversations on various topics, including agriculture. The coefficient is - 0.082 and statistically significant, indicating a 26% reduction in crop burning among these main neighbors relative to the control mean (0.31). Column (2) expands the analysis to all neighbors' plots and finds a 22% reduction in crop burning. To address potential concerns about overlaps with treated plots, column (3) restricts the sample to neighbors' plots that did not overlap with treated plots. The results barely change.

Column (4) examines spillover effects on large-scale rice plots (greater than 2.4 hectares). The coefficient is -0.032 and statistically significant, indicating that the capital rental subsidy reduces crop burning on these larger plots by approximately 3.6% compared to the control mean of 0.90. While the percentage reduction is smaller than for other neighbor categories,

this finding is notable given that large-scale plots have substantially higher baseline burning rates (90% versus 30-31% for other neighbor plots), suggesting that spillover effects extend beyond immediate neighbors to influence broader agricultural practices within the village. These results are robust to alternative Sentinel-2 satellite imagery, consistently demonstrating spillover effects across all neighbor categories (Appendix Table A7).

Table 15: Spillover Effect

	PlanetScope satellite			
	Burn (main neighbors plots)	Burn (all neighbors' plots)	Burn (nonoverlap plots)	Burn (big plots)
Treatment	-0.082**	-0.069*	-0.082*	-0.032**
	(0.039)	(0.041)	(0.044)	(0.016)
Control Mean	0.31	0.31	0.30	0.90
Observation	1024	1024	973	1024

Note: This table presents the effect of the capital rental subsidy on crop burning of respondents' neighbors, displaying OLS estimates from Equation (1) with treatment arm indicator, baseline measures of the respective dependent variable (ANCOVA), and sociodemographic controls selected through a double-selection LASSO procedure (Belloni et al. 2014). Main neighbors' plots are those with whom respondents interacted most often, including on agricultural matters. Non-overlap plots refer to neighbors' plots that were not recipients of the intervention. Big plots or large-scale rice plots are defined as those with a cultivation area greater than 2.4 hectares. Standard errors in parentheses are clustered at the village level. *, **, and *** indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

The prevalence of compression technology adoption among neighbors suggests that the intervention reduced village-level transaction costs. While I lack survey data on neighbors, qualitative evidence indicates a cost reduction channel.[23] Neighbors and other villagers paid approximately USD 22.77 per acre for compression technology—significantly lower than the USD 36.12 per acre baseline cost in this study.[24] This cost reduction likely reflects the program's coordination of equipment providers, which eliminated search costs and improved service availability at the village level.

Neighbors may choose to sell their rice residues in livestock markets, which are more

[23] I did not survey neighbors at endline. Only neighbors' plot identification numbers were obtained to merge with the Department of Land Development's data for the boundaries of the plots. The cost reduction channel is based on qualitative interactions with neighbors and village heads.

[24] Instead of paying per acre, neighbors and villagers chose to pay for the technology based on packs of residues. One pack of residues costs around USD 0.9 (weighing 12 kilograms). On average, farmers produced about 25.30 packs per acre. Therefore, they paid USD 22.77 per acre.

widespread compared to biogas markets. The price of rice residues in these livestock markets ranged between USD 1 and USD 1.4 per pack, suggesting that farmers could potentially earn between USD 25.30 and USD 35.42 per acre by selling their rice residues at these livestock markets.[25] The livestock market channel, while offering higher prices, faces structural limitations in terms of absorption capacity. Demand depends on local livestock markets, which vary significantly across regions. These markets cannot feasibly absorb the total volume of rice residues produced across the country, suggesting that biogas markets may offer more scalable solutions for residue utilization.

In summary, the evidence in Section 1.5.4 provides strong support for the transaction cost channel. By organizing equipment providers and reducing search frictions, the intervention created a village-level market infrastructure that benefited neighbors and owners of large-scale rice plots in treated villages, not just direct recipients. The compression technology became more accessible once coordination mechanisms were established, allowing others to access services at lower costs and participate in residue markets. These results remain robust even when I use an alternative Sentinel-2 satellite (Appendix Table A7).

Learning Effects

In this section, I examine whether the intervention generates learning effects that persist beyond the subsidy period. The capital rental subsidy may provide farmers with new information about residue collection costs, market logistics, and potential returns. If farmers learn that residue sales are profitable through experimentation, they should continue to participate after the subsidy ends. Therefore, treatment effects should remain significant in the medium term after subsidy removal, as shown in other contexts where learning leads to sustained adoption (Conley & Udry 2010, Beaman & Dillon 2018).

To test this mechanism, I examine whether the capital rental subsidy had persistent effects on crop burning behavior in the subsequent agricultural season (April 2024), when farmers no longer received the intervention. Table 16 presents estimates of the medium-term effects. I find no statistically significant impact of the capital rental subsidy on crop burning in the subsequent season, suggesting that the behavioral changes induced by the intervention were temporary.

[25] Among farmers who sell residues in the sample, the average income from selling residues at the biogas market is USD 9.79 per acre.

Table 16: Effects of Capital Rental Subsidy on Crop Burning in Subsequent Agricultural Season

	Crop Residue Burning	
	PlanetScope	Sentinel-2
Treatment	0.091	-0.100
	(0.068)	(0.066)
Control mean	0.23	0.31
Observations	1024	1024

Note: This table presents the medium-term effect of the capital rental subsidy on crop burning from two satellite sources: PlanetScope and Sentinel-2. Each column displays the Ordinary Least Squares (OLS) estimates derived from Equation (1), which incorporates the treatment arm indicator and controls for baseline measures of the respective dependent variables using Analysis of Covariance (ANCOVA). Sociodemographic controls are based on a double-selection LASSO procedure (Belloni et al. 2014). Standard errors in parentheses are clustered at the village level. *, **, and *** indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

These findings contrast with learning-by-doing models that predict persistent effects of temporary technology subsidies (Arrow 1962, Foster & Rosenzweig 1995). Instead, my results are consistent with studies documenting that behavioral changes often revert after intervention withdrawal (Kremer & Miguel 2007, Cohen & Dupas 2010, Duflo et al. 2011). The lack of persistence suggests that learning effects were insufficient to overcome structural barriers to sustained technology adoption, including credit constraints limiting equipment access and thin rental markets for agricultural machinery.

In summary, the evidence in Section 1.5.4 shows no persistent effects in the medium term. This finding suggests that learning effects were insufficient to overcome structural barriers, such as credit constraints and thin equipment rental markets, that prevent the sustained adoption of alternative crop residue management practices.

1.5.5 Robustness Checks

The main results are robust to alternative model specifications, burning detection thresholds, using different data sources (PlanetScope, Sentinel-2 and ground verification), and with alternative spectral indices for detecting burned plots.

Appendix Table A3 shows that the estimated effects are robust to various model specifications with or without baseline outcomes and socioeconomic controls. The capital rental sub-

sidy significantly reduces crop burning without any controls (columns 1-3), when controlling only for baseline burning using ANCOVA (columns 4-6), and when including socioeconomic covariates (columns 7-9). The magnitude and significance of the treatment effects remain stable across all specifications.

I also find that the results are not sensitive to the choice of burning classification thresholds. For the PlanetScope satellite, a plot is classified as burned if its average predicted score from the Bare Soil Index (BSoI) exceeds the 75th percentile threshold. Similarly, for the Sentinel-2 satellite, I average the predicted score from the Burned Area Spectral Mixture Analysis (BASMA) index across pixels in a plot and classify fields as burned using the same 75th percentile threshold. Appendix Figures A13 and A14 show that the treatment effects remain stable across alternative thresholds.

Crop residue burning measure from the PlanetScope satellite performs well compared to alternative satellite data (Sentinel-2 satellite) and ground-truth observations. Appendix Table A4 shows that crop burning from the Sentinel-2 satellite correlates highly and statistically significantly with the crop burning measure from the PlanetScope satellite (column 1). Additionally, crop residue burning from ground-truth data shows strong and statistically significant correlations with measures from the PlanetScope satellite (column 2) and the Sentinel-2 satellite (column 3).

The results are also not driven by the specific choice of spectral indices. I estimate Equation (2.1) using alternative indices: the Burn Area Index (BAI) for PlanetScope imagery and the Mid Infrared Bispectral Index (MIRBI) for Sentinel-2 imagery, the latter of which has shown strong performance in distinguishing fires across diverse landscapes (Barboza Castillo et al. 2020). Even when using alternative indices to detect crop burning, I consistently find that the capital rental subsidy reduces crop residue burning.

1.5.6 Cost Effectiveness

In this section, I compare the program cost to the benefits of reducing PM2.5 pollution from crop residue burning and averting CO_2 emissions.

Compare the Program Cost to the Benefit of Reducing PM2.5 Pollution from Crop Residue Burning In Table 17, I explore the cost-effectiveness of the intervention across

two data sources: PlanetScope satellite and ground field verification.[26] In column (1), the "Amount Paid per Acre " represents the payment in USD that farmers received in the treated villages. This amount is calculated by multiplying the original subsidy per acre by 0.7, which represents a 70% adoption rate among farmers in the treated villages. It is then divided by 9 to account for the effect across nine plots (four main plots and five neighbor plots). I do not include the monitoring costs, as they can vary greatly depending on program size and monitoring procedures.

In columns (2) and (4), the variable "No burn" takes the value 1 if a farmer did not burn any of their plots and 0 otherwise, consistent with the estimates in columns (1) and (2) of Table 12. The "Cost per Unburned Acre" in columns (3) and (5) is the "Amount Paid per Acre" in column (1) divided by the "No Burn" estimates in columns (2) and (4). The standard errors in columns (3) and (5) are calculated using the Delta method. The cost per additional unburned acre is approximately USD 28.10 when using PlanetScope satellite data (column 3). On the other hand, the cost is slightly lower at USD 22.845 when utilizing the ground-field verification data (column 5).

Table 17: Cost Effectiveness

		PlanetScope satellite		Field verification	
	Amount Paid Per Acre	No Burn	Cost per Unburned Acre	No Burn	Cost per Unburned Acre
Treatment	2.810***	0.100***	28.100	0.123***	22.845
	(0.000)	(0.041)	(1.160)	(0.037)	(0.856)
Observations	1024	1024		1024	

Note: Sociodemographic controls are included based on a double-selection LASSO procedure (Belloni et al. 2014). Amount Paid per Acre (column 1) is the payment in USD that the farmer received. This amount is calculated by multiplying the original subsidy per acre by 0.7, which represents a 70% adoption rate among farmers in the treated villages. It is then divided by 9 to account for the effect across nine plots (four main plots and five neighbor plots). In columns (2) and (4), the variable "No burn" takes the value 1 if the farmer did not burn any of their plots and 0 otherwise, consistent with the estimates in columns 1 and 3 of Table 12. The "Cost per Unburned Acre" in columns (3) and (5) is the "Amount Paid per Acre" divided by the "No Burn" estimates (i.e., column 1 divided by column 2, and column 1 divided by column 4, respectively). The standard errors in columns (3) and (5) are calculated using the Delta method. Standard errors in parentheses are clustered at the village level. *, **, and *** indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

[26] I do not report the cost-effectiveness of Sentinel-2 satellite because the cost per unburned acre is similar to that of the PlanetScope satellite.

The cost of the intervention is then compared with the benefits of reducing crop residue burning. In 2019, PM2.5 pollution contributed to 32,211 premature deaths in Thailand (World Bank Group 2023).[27] Using a median Value of Statistical Life (VSL) of $0.66 million , these deaths translate into an annual damage of $21.12 billion (Witvorapong & Komonpaisarn 2020).[28] Given that 1.82 million hectares (4.49 million acres) are burned annually, the damage caused by PM2.5 pollution from rice field burning is approximately US$ 4,673 per acre.[29] When comparing these damages with the cost of reducing crop burning, the damage caused by PM2.5 pollution is more than 66.8 times higher than the cost per acre of implementing measures to reduce burning. This underscores the significant economic benefits that can be achieved by investing in interventions aimed at mitigating crop burning and reducing PM2.5 pollution.

Compare the Program Cost to the Benefit of Averting CO_2 Emissions I further calculate the monetary value of the averted CO_2 emissions and compare it to the program cost. I first calculate the amount of delayed CO_2 emissions from the study area. Using the PlanetScope satellite, I estimate the areas of crop burning in the study villages. At the endline, the total area that was not burned amounted to 1,565 acres. Following the methodology used in a study by Junpen et al. (2018) in Thailand, I calculate the CO_2 emission per acre. The result shows that the averted CO_2 emission per acre is 2.81 tons.[30]

Next, I calculate the program cost per ton of delayed CO_2 emissions for the study area. After accounting for the spillover effects, the average payment per acre is USD 4.1 (column 1 of Table 17).[31] I do not include monitoring costs due to their significant variation based on program size and monitoring protocols. The total cost for the study area is USD 6,262 (USD 4.1 per acre * 1,565 acres), while the total CO_2 emission for the study area is 4,400 tons (2.81

[27] While Mueller et al. (2021) estimates approximately 50,000 premature deaths per year from PM2.5 pollution, I adopt a more conservative figure of 32,000 in this analysis.

[28] Witvorapong & Komonpaisarn (2020) estimate the Value of a Statistical Life (VSL) in Thailand using nationally representative labor market data, including the 2012–2014 Labour Force Survey (N = 109,947) and records from the Social Security Office, and applying the standard hedonic wage approach.

[29] To estimate burned areas, I use data from Cheewaphongphan et al. (2018). I divide the total volume of rice straws subjected to open-burning (6.13 million tons) by the average rice straw density (3.37 tons per hectare), resulting in approximately 1.82 million hectares of burned area. The damage caused by PM2.5 pollution from rice field burning may be somewhat lower than US$ 4,673 per acre, as I do not have data on deaths specifically attributed to rice field burning and therefore rely on general PM2.5 mortality costs.

[30] Junpen et al. (2018) estimate the air pollution emission from rice residue open burning in Thailand using the MCD64A1 burned area product and emissions from air quality monitoring station sites from 2010-2017.

[31] I multiply the subsidy per acre by 0.7% (70% adoption rate among farmers in treated villages) and then divide it by 9 to account for the effect across nine plots (four main plots and five neighbor plots).

tons per acre * 1565 acres). Therefore, the cost per ton of CO_2 averted for the study area is USD 1.42.

Finally, I compare the program cost with the benefit in terms of averting CO_2 emissions. To do so, I compare the amount paid to avert carbon emissions with the European carbon market price, which is around 70/tCO_2 (≈ USD 77).[32] With a program cost of USD 1.42 per averted ton of CO_2, the benefit is approximately 54 times the cost (see Appendix Table A9 for a detailed analysis of the cost-effectiveness of the intervention in terms of averting CO_2 emissions).

1.5.7 Willingness to Pay for Clean Air

To explore farmers' willingness to pay for clean air, I designed a discrete choice experiment (DCE) at the endline. The DCE is specifically designed to assess the willingness to pay for each attribute that describes the choice options (Louviere et al. 2000). In the DCE, three options are typically presented: the status quo and two alternative options. Each option is characterized by different levels of attributes. By varying the levels of these attributes among the options, the DCE provides valuable insights into the trade-offs that farmers consider when making decisions (Chèze et al. 2020).

For this study, the chosen attributes are based on the costs associated with managing and selling rice residues in the market, as well as the environmental implications of reducing PM2.5 pollution. These attributes include both the monetary contributions of the respondents (such as technology cost and transport cost) and the environmental benefits (such as reduction in exposure to PM2.5 pollution).

The first attribute is the cost of modern compressing technology per rai (1 rai = 0.395 acres), with values of 250 Baht, 350 Baht, and 450 Baht.[33] The second attribute is the transportation cost per rai per kilometer, with values of 2 Baht, 4 Baht, and 6 Baht. The third attribute represents the reduction in exposure to PM2.5 pollution, which exceeds the Thai government standard during the burning season.[34] The levels for this attribute are 70 days,

[32] Instead of relying on a single Social Cost of Carbon (SCC) estimate, which varies widely in the literature (USD 50–300 per ton), I benchmark against the European Union Emissions Trading System (EU ETS), where the carbon price has recently traded around EUR 70 (≈ USD 77) per ton of CO_2 (EU Emissions Trading System 2025).

[33] 1USD = 35 Thai Baht

[34] The Thai government has set the annual mean concentration of PM2.5 at 25 μg/m3, while the World Health Organization (WHO) standard is 5 μg/m3.

80days, and 90 days (see Appendix Table A10 for a detailed description of the attributes and levels).[35]

Using a full factorial design, I obtained a statistically optimal subset of the possible combinations. In the endline survey, I presented six choice sets to farmers (see Appendix Figure A15 for an example of the choice set). The farmers were then asked to choose their preferred option out of a total of j =3 alternative options (the status quo and two alternative options) in t = 6 choice sets. I then estimate the following specification to analyze the farmers' preferences and their willingness to pay for the different attributes:

$$U_{njt} = \beta_0 \text{SQ}_{njt} + \beta_1 \text{PM25}_{njt} + \beta_2 \text{Tech}_{njt} + \beta_3 \text{Transport}_{njt} + \varepsilon_{njt} \tag{1.2}$$

where U_{njt} is the utility that farmer n derives from choosing alternative j in choice set t. SQ_{njt} is an alternative-specific constant for the status quo option. β displays the effect on the utility from changes in the attribute. When we divide the β of PM2.5 by the β of technology, we can get a monetary estimate of the willingness to pay for reducing PM2.5 pollution. Therefore, the willingness to pay for the technology fee to avoid an additional day of PM2.5 pollution exceeding the standard level is given by:

$$\frac{\partial U_{njt}/\partial \text{PM25}_{njt}}{\partial U_{njt}/\partial \text{Tech}_{njt}} = \frac{\beta_1}{\beta_2} \tag{1.3}$$

Table 18 presents the estimation results, based on the specification in Equation (1.2). Column (1) shows the results from the conditional logit model. The coefficient for PM2.5 is negative and statistically significant at the 1% level. This finding suggests that, on average, farmers have a significant negative marginal utility toward PM2.5 pollution.

To further explore farmers' willingness to pay for the technology fee, I examine the amount they are willing to pay to reduce an additional day of PM2.5 pollution that exceeds the standard set by the Thai government, as prescribed by Equation (1.3). I find that there is a positive willingness to pay approximately 1.56 Baht per rai (equivalent to USD 0.004 per rai) or 4 Baht per acre (equivalent to USD 0.01 per acre) in technology fees to avoid an additional day of PM2.5 pollution. Considering that farmers are exposed to PM2.5 levels exceeding the standard for approximately 90 days per year, their willingness to pay for the technology 140

[35] PM2.5 pollution exceeds the Thai government standard for a total of 90 days during the burning season (Khon Kaen University 2022).

Baht per rai (equivalent to USD 4 per rai) or 354 Baht per acre (equivalent to USD 10.13 per acre) (Khon Kaen University 2022). Therefore, the capital rental subsidy can be reduced from USD 36.12 to USD 25.99 per acre.

Table 18: Willingness to pay estimates

	(1)
	Conditional logit
Number of days PM2.5 exceeds the standard level	-0.007***
	(0.001)
Cost of modern compressing technology (Baht/rai)	0.005***
	(0.0001)
Transportation cost (Baht/rai/kilometer)	0.41***
	(0.01)
Observations	18,342
Log-likelihood	-7460

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.T statistics in parentheses.

In summary, evidence in Section 1.5.7 sheds light on farmers' valuation of technology and their willingness to invest in measures that reduce PM2.5 pollution. I find that PM2.5 pollution from crop burning impacts farmers' utility and that farmers are willing to pay approximately 140 Baht per rai (equivalent to USD 4 per rai) or 354 Baht per acre (equivalent to USD 10.13 per acre) in technology fees to avoid PM2.5 pollution.

1.6 Conclusion

This paper demonstrates that capital rental subsidy can significantly reduce crop residue burning. Using high-resolution satellite imagery, I find that the capital rental subsidy reduces crop residue burning by 32%. Treatment reduces crop residue burning through increasing crop residue production, access to the biogas market, and income from crop residues. Beyond direct effects, this study finds substantial spillover effects, where crop residue burning decreases not only among the treated group but also among neighbors and owners of large-scale rice plots.

These spillovers reduce burning among neighbors by 20% and among owners of large-scale rice fields by 3.6%.

Three key mechanisms drive these effects. Financial constraints are the primary barrier, with stronger effects among financially constrained farmers. The intervention also reduced transaction costs, generating substantial spillovers to untreated farmers within treated villages. However, learning effects are insufficient. Impacts disappear after subsidy removal, indicating that structural barriers prevent sustained adoption without continued support.

The cost-effectiveness results are striking. The intervention costs USD 1.42 per ton of CO_2 averted—54 times lower than European carbon market prices—and USD 2.77 per additional acre when spillovers are included. The damage from PM2.5 pollution (USD 4,673 per acre) exceeds the intervention costs by a factor of 166, indicating massive welfare gains from scaling such programs. These findings suggest that the capital rental subsidy is a relatively cost-effective mechanism for addressing environmental externalities.

From a policy perspective, the findings offer valuable insights for designing effective market-based interventions to address air quality issues in low- and middle-income countries. Rather than relying solely on regulations or payments for ecosystem services, governments could facilitate market connections that align private incentives with environmental goals. Future research should explore the long-term sustainability of these market linkages and their applicability across different agricultural contexts and regions. This study demonstrates that innovative market mechanisms can transform environmental challenges into economic opportunities, creating scalable solutions for sustainable agricultural development that benefit farmers, communities, and society at large.

Chapter 2

Market Incentives for Environmental Protection: Evidence from Biogas Plants in Thailand

Abstract

Agricultural burning is a significant contributor to air pollution and health costs in low- and middle-income countries. This paper examines whether creating markets for agricultural residues reduces farmers' burning behavior by exploiting the staggered timing of biogas plant openings across Thailand from 2001 to 2023. Biogas plants buy crop residues from farmers as feedstock for the production of renewable energy, providing an economic alternative to open burning. Using agricultural fires from MODIS satellite imagery, I compare agricultural fires near operational plants with those near plants not yet operational within a 5-km radius. I find that plant openings reduce agricultural fires by 8.5% with effects concentrated during the burning season. These reductions result in substantial air quality improvements that extend well beyond the immediate vicinity of biogas plants. PM2.5 concentrations decrease by 2.5% in local areas, but the effects are amplified in nearby urban centers, reaching 6.5% reductions. I find that plants offering high residue prices or those with high installed capacity reduce fires, suggesting that market mechanisms drive the estimated effects. Alternative explanations are ruled out, including enhanced fire enforcement, labor reallocation, and regulatory changes. These findings demonstrate that rural industrial policy that promotes renewable energy can mitigate urban air quality challenges in developing economies.

Keywords: Agricultural fires, environmental externality, biogas power plants, renewable energy

2.1 Introduction

In many low- and middle-income countries, existing agricultural practices generate a large amount of crop residue. In the absence of sustainable management practices, crop residue is burned after each crop cycle. Crop residue burning is a significant contributor to air pollution and poses serious threats to both the environment and human health in these countries (He et al. 2020, Vadrevu et al. 2021*b*, Rangel & Vogl 2019, Zivin et al. 2020).

Similar to other low- and middle-income countries, air pollution from crop residue burning is one of the critical environmental concerns in Thailand. The government imposes bans on crop residue burning; however, it faces high costs to effectively enforce such bans on large agricultural lands in rural areas. As part of its strategy to develop the renewable energy sector, the government has recognized the substantial potential to produce clean energy from abundant agricultural waste (e.g., rice straws, sugarcane waste) and introduced incentives for private firms to open and operate biogas power plants. These plants purchase agricultural wastes from farmers, thereby increasing renewable energy supply while creating the co-benefit of reducing crop residue burning through market-based incentives.[1]

This paper employs a staggered difference-in-differences (DiD) design, exploiting the variation in the timing of biogas plant openings in Thailand from 2001 to 2023 to examine whether the creation of markets for agricultural residues reduces farmers' burning behavior. The analysis leverages a natural experiment in which plants were established at different times and locations, generating plausibly exogenous variation in the timing of treatment. Using agricultural fires from the MODIS satellite imagery processed by the Ministry of Natural Resources and Environment (MNRE) for 2001-2023, I compare agricultural fires near operational plants (treated group) with those near plants that have not yet been operated (control group), within 5 km of the plants.

I find that the opening of a biogas power plant accounts for a 8.5% drop in the number of agricultural fires within a radius of 5 km. The estimated effects are concentrated during

[1]Open-field burning emits more CO_2 and CO than the biogas power plant. For 6.157 million tons of rice residues, the emission savings of the biomass-fired power plant compared to open-field burning are 0.61 million tons of CO_2 and 0.02 million tons of CO in Cambodia (Sokrethya et al. 2023).

the burning season, and no significant impact was observed outside this period. Importantly, event-study estimates indicate that the estimated effects are not driven by differential trends before plant openings. I further explore how the effects of biogas vary with distance and find that the reductions in agricultural fires are concentrated within 30km of a plant, with no statistically significant effects observed beyond that range. This spatial decay pattern reflects the increasing transaction costs with distance as the costs of collecting and selling residues increase, reducing the economic viability of residue sales for distant farmers.

The effects extend beyond agricultural fires, with the opening of a plant leading to a 2.5% drop in the levels of PM2.5 pollution in local areas. Event-study estimates indicate that this is not driven by differential pre-trends. Going beyond the existing literature, I examine spatial spillovers by focusing on nearby urban centers. I find that the opening of a plant reduces PM2.5 concentrations by 6.5%.[2] These amplified urban effects likely reflect the cumulative reduction in burning across multiple surrounding agricultural zones. From a public health perspective, the concentration of benefits in densely populated urban centers is particularly important, as air quality improvements translate into larger health gains.

Next, I explore whether the effects of the biogas plant vary by wind direction. Grid cells were defined as upwind if they fell within 45 degrees of the prevailing wind direction (fixed octants) calculated from a wind rose, while the opposite areas were defined as downwind. The findings indicate that biogas plant openings reduce PM2.5 concentrations by 2% in downwind locations, and the effects are stronger during the burning season. However, as expected, plant openings do not have a significant impact on PM2.5 concentrations in upwind areas.

As previous studies have been limited to aggregate fire counts, I leverage novel spatial data on land use from the Ministry of Agriculture and Cooperatives to examine plant effects by crop type. The estimates suggest that the opening of a plant reduces rice fires, sugarcane fires, and corn fires within a 5-km radius of the plant. Event-study estimates indicate parallel pre-treatment trends, with clear divergence occurring only after treatment begins. The consistent reductions across all three major crop types suggest that biogas plants create broad economic incentives for farmers to abandon burning practices.

To understand what drives the observed reductions in agricultural fire, I examine variation

[2]One possible explanation for why PM2.5 pollution decreases more in urban areas compared to local areas is that biogas generation may substitute for more polluting energy sources, such as coal-fired power plants, which are typically concentrated in or near urban centers. I will explore this mechanism further in subsequent analysis.

in plant characteristics. I find that only biogas plants offering high residue prices or operating at high production capacity reduce agricultural fires. Plants offering above-median prices reduce agricultural fires by 9%, and high-capacity plants-which require more feedstock and thus create stronger local demand for residues-reduce fires by 13%. These findings suggest that market forces, specifically residue prices and feedstock demand, drive farmers' decisions to abandon burning practices.

Next, this article presents evidence against alternative mechanisms. One possibility is that enhanced local fire enforcement, aimed at protecting plant infrastructure, could have reduced fires more broadly. If this were the case, we would also expect declines in forest fires. However, plant openings have no effect on forest fires, suggesting that improved fire management does not drive the observed reductions in agricultural burning. Another potential channel is labor market shifts. New industrial facilities might attract workers away from agriculture, mechanically reducing fire activity through land abandonment. However, I find that plant openings have a negative but statistically insignificant effect on land abandonment, ruling out labor reallocation as the main explanation. Finally, the 2017 burning ban implemented in nine northern provinces could also explain changes in fire activity. However, I find that the burning ban does not have a statistically significant effect on agricultural fires, indicating that the observed reductions are not driven by the burning ban.

Finally, I show that the estimated effects are robust across multiple checks, including alternative satellite imagery (VIIRS), fire detection confidence thresholds, and specifications without controls. Using the higher-resolution VIIRS satellite data, which offers improved sensitivity to small fires relative to MODIS satellite data, I continue to find statistically significant reductions in agricultural fires, with effect sizes even larger than in the main results. The estimates remain robust when restricting the sample to higher-confidence fire detections (30% and 50% thresholds), indicating that the results are not driven by false positives. The estimated effects are also robust when using Callaway & Sant'Anna (2021) estimator that addresses the potential bias of negative weighting in two ways fixed effects (TWFE) specifications and when excluding weather controls.

This paper contributes to several strands of literature. First, it adds to the literature on market-based environmental policies and markets for environmental goods. A large body of work examines how creating property rights or markets can address environmental externalities (Holland & Yates 2015, Jayachandran et al. 2017, Hernandez-Cortes & Meng 2023, Ayres

et al. 2021). Within this framework, recent studies focus on interventions that directly target agricultural fires through financial incentives, such as upfront payments to reduce burning (Jack et al. 2022, Lopes et al. 2023). This paper extends this literature by showing how industrial policy can indirectly create environmental markets by promoting biogas, which increases the demand for agricultural residues and generates economic incentives that reduce burning without direct environmental regulation.

Second, this study relates to the literature on how industrial policy shapes supply chains, particularly by stimulating the development of the upstream market. Existing studies find that new downstream industries create demand for inputs, which can transform upstream supplier markets and generate positive economic spillovers, such as productivity gains for local firms (Javorcik 2004, Atkin et al. 2017). However, this literature has focused almost exclusively on economic outcomes, overlooking the environmental externalities of upstream production. This paper uniquely contributes to the literature by showing how industrial policy can generate environmental benefits through upstream market creation. Specifically, I show how biogas plants—a downstream renewable energy policy—create a market for agricultural waste, thereby mitigating the negative externality of open burning and creating a positive environmental spillover.

Third, this study is closely related to the literature that examines the effect of biogas power plants on agricultural fires. Nian (2023) compares agricultural fires within 10 km of the plants (inner ring) with agricultural fires between 10 km and 15 km of the plants (outer ring). This "inner vs. outer ring" strategy requires assumptions beyond quasi-random variation in treatment locations (Pollmann 2023). While Cao & Ma (2023) compares fires near operational plants with fires near hypothetical locations where treatment could have been implemented but was never treated at the end of the sample period, this paper compares fires near operational plants (treated) with fires near not-yet-operational plants (not-yet-treated), avoiding potential selection issues from using hypothetical locations. More importantly, existing studies have been limited to analyzing aggregate fire counts, making it difficult to distinguish which specific crops are most responsive to market-based environmental interventions. Understanding crop-specific effects is crucial for policy design, as different crops have varying residue management practices, burning intensities, and economic returns to biomass sales. This paper leverages novel spatial administrative data to provide the first crop-specific evidence of biogas plant effects on rice, sugarcane, and corn fires separately.

Finally, this study contributes to the literature on the economics of air pollution and its mitigation policies. A substantial body of work documents the significant economic costs of air pollution.[3] Given the substantial costs of air pollution, researchers have examined various mitigation strategies, including environmental regulations (Greenstone & Hanna 2014) and information provision (Barwick et al. 2024). Agricultural fires contribute to air pollution (He et al. 2020). Recent studies have found that interventions, such as biogas plants, can reduce local PM2.5 concentrations (Nian 2023, Cao & Ma 2023). However, the literature has largely examined local impacts on rural residents, while spatial spillovers to urban populations remain unexplored, despite their importance in understanding whether rural interventions can mitigate urban air quality challenges in developing economies. This paper extends the literature by providing the first evidence that rural biogas promotion reduces PM2.5 pollution in nearby urban and downwind locations.

The remainder of the article is organized as follows. The next section provides an overview of Thailand's crop residue burning and biogas power plants. Section 3 discusses data and methodology. Section 4 presents the results, while Section 5 presents robustness checks. Section 6 summarizes the findings.

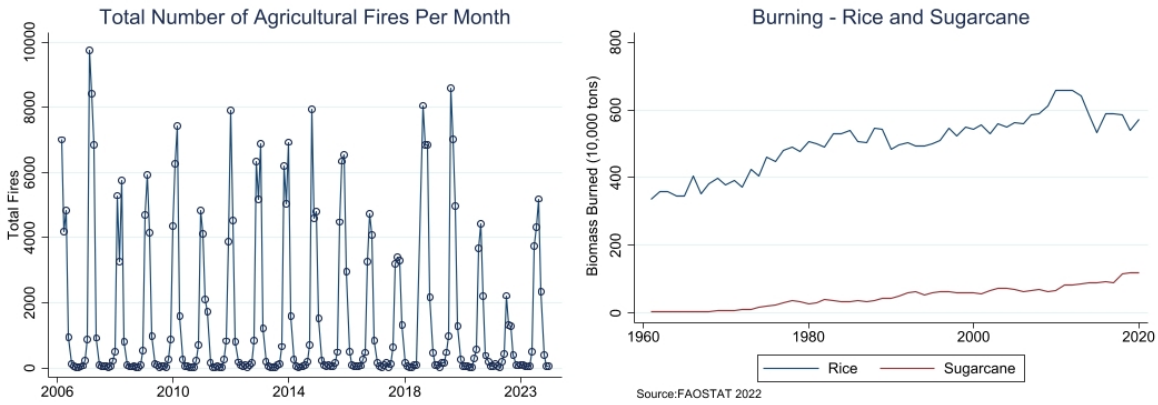
2.2 Background

2.2.1 Crop Residue Burning

Crop residue burning is a common practice in Thailand. As the world's seventh largest rice producer and the fifth largest sugarcane producer in 2020, Thailand's economy is heavily dependent on agriculture (FAOStat 2022*a*). The country is ranked 19th in the world for agricultural emissions, with a total emission of 1.1 million tonnes CO_2 equivalent in 2020 (FAOStat 2022*b*). Additionally, Thailand holds the 26th position globally for total biomass burned, with an alarming total of 27 million tonnes of biomass burned (FAOStat 2022*b*).[4]

[3] Air pollution reduces worker productivity in call centers (Chang et al. 2019), manufacturing (Hansen-Lewis 2025), and industrial settings (He et al. 2019, Zivin & Neidell 2012), while also increasing mortality and medical costs (Deryugina et al. 2019). Cross-border spillovers of pollution impose additional costs, as demonstrated by Indonesian forest fires that affect Singapore's health (Sheldon & Sankaran 2017).

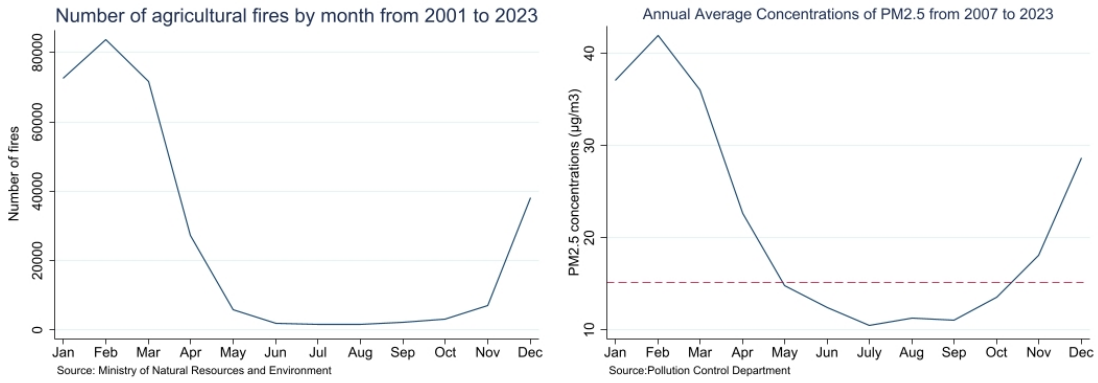
[4] Jusakulvijit et al. (2021) estimate that agriculture residues generated from major crops such as sugarcane, cassava, rice, and palm are around 174.1 million tons per year. The Food and Agriculture Organization (FAO) estimates that only 27 million tons are burned every year. This may be because FAO collects its data from national governments through responses to annual FAO questionnaires. Official data on burned biomass may focus on surveys or self-reported figures which may underreport burning activities due to administrative



(a) Total number of agricultural fires per month (b) Biomass burned from rice and sugarcane

Figure 21: Total number of agricultural fires per month and total biomass burned from rice and sugarcane in Thailand

Figure 21a shows that agricultural fires peak during the crop-burning season from November to February. Approximately 83% of the total burned residue in Thailand is attributed to residue burning in rice and sugarcane (Kumar et al. 2020). The total amount of rice residue burned is five times higher than the total amount of sugarcane burned, with 5.7 million tons and 1.1 million tons, respectively (Figure 21b). This is because the total harvested area for rice is more than 11 million hectares, while the total harvested area for sugarcane is only around 1.4 million hectares (FAOStat 2022*a*).



(a) Number of agricultural fires by month (b) Monthly average PM2.5

Figure 22: Number of agricultural fires by month and monthly average PM2.5

Crop residue burning is a significant contributor to air pollution in Thailand. Figure 22 shows that the level of PM2.5 pollution increases during the burning season from November

challenges.

to February. As a result, approximately 32,211 premature deaths in Thailand were attributed to PM2.5 pollution in 2019 (World Bank Group 2023).

2.2.2 Government Policies on Crop Residue Burning

The Government of Thailand has implemented various measures to address crop residue burning in Thailand. However, these efforts have not yielded results. In 2012, the national government introduced the 2012-2016 Pollution Management Plan. This plan provides guidelines for managing crop residue burning and promoting alternatives to crop residue burning (Junpen et al. 2018). The government also launched subsidy programs for soil equipment and farming technologies to curb emissions from crop residue burning (Junpen et al. 2018). In addition, the government introduced the Alternative Energy Development Plan (AEDP) 2015-2036, which aims to increase renewable energy supply by encouraging the conversion of crop residues into energy. As part of this plan, the government provides subsidies, loans, and tax incentives to promote biogas technology to facilitate the use of crop residues (Chaiprasert 2011).

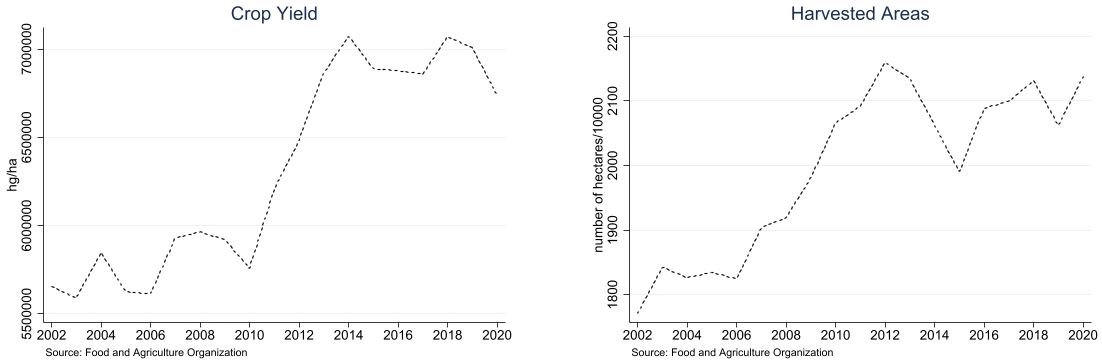
At the local level, provincial governments have implemented some initiatives to reduce air pollution from crop residue burning. For example, the provincial governments imposed 60-day burning bans during the burning season and introduced high fines of up to 14,000 Baht (USD 411) and/or a maximum of seven years imprisonment. On the other hand, those who report burning events are rewarded with 5,000 Baht (USD 147)(Bangkok Post 2019, Thaitrakulpanich 2019). Despite these incentives and penalties, policies have been largely ineffective due to high administrative costs.

2.2.3 Biogas Power Plants

Thailand is an agricultural country, and after harvesting, there is a large amount of crop residues left that could be used as biogas energy. Figure 23 shows that crop yield increased from 5,655,731 hg/ha in 2012 to 7,072,840 hg/ha in 2020, while the harvested area also increased from 17,703,692 hg/ha in 2012 to 21,369,861 hg/ha in 2020. It is estimated that the agriculture residues generated from major crops such as sugarcane, cassava, rice, and palm are around 174.1 million tons per year (Jusakulvijit et al. 2021).

With the goals to meet energy demands and reduce the country's dependence on fossil

fuels, the Government of Thailand aims to increase the share of renewables in energy consumption to 30% by 2036 under the Alternative Energy Development Plan 2018 – 2037. In response to this policy, Thailand's Board of Investment also grants tax incentives to developers of renewable energy projects (including agricultural waste). The renewable energy company can receive an exemption from corporate income tax for eight years with no maximum limit and an exemption from import duties on the machinery (Thailand Board of Investment 2019).



(a) Crop yield

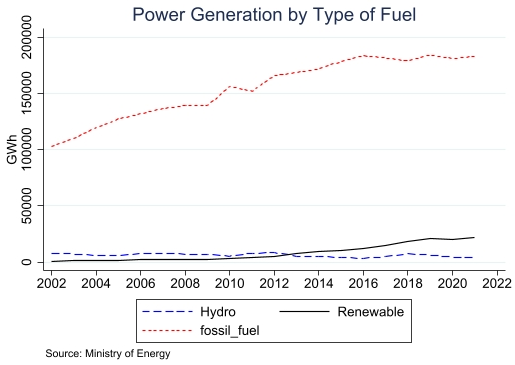
(b) Harvested areas

Figure 23: Crop yield and harvested areas

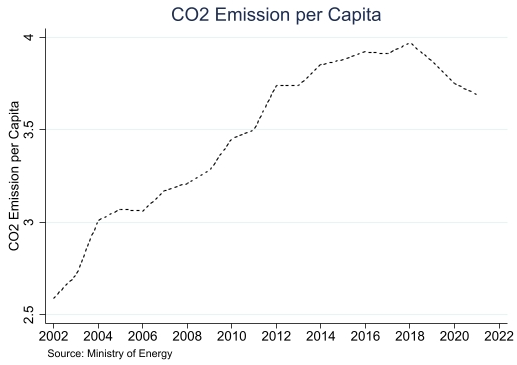
Thailand's energy consumption has also increased from 100,091 GWh in 2002 to 190,468 GWh in 2021 and the industrial sector accounts for 46% of energy (Ministry of Energy 2024). Figure 24a shows that the share of fossil fuels in electricity generation is very high (i.e., above 88%), resulting in a steady increase in greenhouse gas emissions (Ministry of Energy 2024). For instance, the total CO_2 emission from energy consumption increased from 165 million tons in 2002 to 250 million tons in 2021 (Ministry of Energy 2024). Figure 24b shows CO_2 emission per capita increased from 2.45 in 2001 to 3.69 in 2021.

In response to the Thai government's policy to promote the use of renewable energy in place of fossil fuels and an increase in electricity prices due to fuel costs since 2016, biogas power plants have started buying agricultural wastes (e.g. rice husk, rice straw, corn husks, and wood chips) and convert them into alternative energy/electricity. Given the enormous availability of agricultural waste, Thailand can generate approximately 64,594 GWh of electricity from 174.1 million tons of waste per year (Jusakulvijit et al. 2021, Thailand Board of Investment 2019). However, the total renewable energy is only around 21,000 GWh in 2021 (Figure 24a).[5]

[5]Renewable energy includes solar, wind, hydropower, and biomass.



(a) Power generation by type of fuel



(b) CO_2 emission per capita

Figure 24: Power generation by type of fuel and CO_2 emission per capita

Biogas power plants in Thailand are developed by private energy companies, agroindustrial companies (such as sugar mills and cassava starch factories) and specialized renewable energy developers such as Asia Biogas. The total number of biogas power plants in Thailand is 140 (Royal Forest Department 2016). Appendix Figure B5 shows that the plants are located across the country (Royal Forest Department 2016). Most biomass power plants are small to medium-sized, with capacity ranges of less than 1 MW, 1-3 MW, 3-5 MW and 5-6 MW being the most common. Only a few exceed 20 MW, mainly in the Central and Northeastern regions. The plants either use electricity for on-site manufacturing processes or sell power to the national grid under long-term power purchase agreements with the Electricity Generating Authority of Thailand (EGAT). Plants offer different prices for crop residues based on energy content and local market conditions. For instance, the price offered for sugarcane leaves varies across firms: Absolute Clean Energy (ACE) firm offers 800 Baht per ton (USD 23.52), while Mitr Phol firm offers 1,000 Baht per ton (USD 29.41) (Absolute Clean Energy 2020, Mitr Phol Group 2020).[6] These differences partly reflect variations in plant size that affect processing capacity.

[6]ACE firm purchases a wide range of agricultural residues, including sugarcane leaves, corn stalks and cobs, rice straw and husks, cassava roots and stalks, sawdust, wood chips, acacia and rubberwood logs, tree roots, coconut shells and husks, tapioca roots, oil palm fronds, napier grass, used mushroom substrate bags, and mango seed husks.

2.3 Data and Methodology

2.3.1 Data

I combine geolocalized fire data from the Ministry of Natural Resources and Environment from 2001 to 2023 at a 5-square-km grid level (each grid measuring 2.25 km by 2.25 km). Within the sample area, I can observe 2,399 grids each year from 2001 to 2023, for a total of 52,785 observations.

Fires data. Fire data comes from MODIS satellite imagery, processed and classified by the Ministry of Natural Resources and Environment (MNRE) to distinguish between forest fires, agricultural fires, and fires in conservation areas. I obtained information on types of fires, geolocation of fires, and the specific time in which fires occur (i.e., year and month) from 2001 to 2023. Appendix Figure B1 shows the distribution of agricultural and forest fires during the sample period.

In addition to MODIS satellite imagery, I use an alternative dataset from the Visible Infrared Imaging Radiometer Suite (VIIRS) to validate my main findings. VIIRS offers higher spatial resolution (375m) compared to MODIS and improved sensitivity for detecting small fires. The Ministry of Natural Resources and Environment (MNRE) similarly processes VIIRS data and classifies fires into three categories: agricultural fires, forest fires, and fires in conservation areas. However, VIIRS data are only available only from 2012 to 2023, providing a shorter time series than MODIS.

Biogas power plants data. Data on biomass power plants are obtained from the Royal Forest Department under the Ministry of Natural Resources and Environment (MNRE). The total number of biomass power plants is 140. The information includes plant name, address, installed capacity (megawatts) and export capacity/grid-connected capacity (megawatts). I geocoded the plants to get the latitudes and longitudes. I also called all the factories to verify the status of the operation, the year of opening, and the price for crop residues in 2023. The spatial distribution of the plants is shown in Appendix Figure B2, which shows that biogas plants are widely distributed across the country.

Crops data. The land use data for different crops from 2006 to 2023 comes from the Department of Land Development under the Ministry of Agriculture and Cooperatives. Land use data are collected every four years: 2006/2007; 2011/2012; 2017/2018; and 2020/2021.

The database has crop areas for all the major types of crops in Thailand, including rice, sugarcane, cassava, rubber, and others. I extracted land-use data for rice, sugarcane, and corn and merged it with the fire data to determine fires occurring in specific fields. I define a fire as a "rice fire" if its location is within a rice field. Appendix Figure B8 shows the fields of three major crops (i.e., rice, sugarcane, and corn) in 2021.

Pollution data. Data on PM2.5 pollution at the resolution of 0.01° × 0.01° from 2006 to 2023 are from Washington University in the Atmospheric Composition Analysis Group of St.Louis. The annual PM2.5 pollution is estimated using Aerosol Optical Depth (AOD) retrievals from the NASA MODIS, MISR, and SeaWiFS instruments and the GEOS-Chem chemical transport model. I converted PM2.5 pollution data to 5 square km (2.25 x 2.25). Appendix Figure B10 shows the distribution of PM2.5 pollution during the burning season in 2021.

Data for control variables. Data on temperature, wind speed, and wind direction are obtained from the National Oceanic and Atmospheric Administration (NOAA).

Wind direction data. Data on wind direction data is obtained from the National Oceanic and Atmospheric Administration (NOAA). The daily wind direction information from the nearest weather station is assigned to a plant. I then determine whether each grid cell is situated either downwind or upwind of the plant. Following the literature of Rangel & Vogl (2019); Zivin et al. (2020); He et al. (2020), upwind areas are defined as regions within 45 degrees of the daily prevailing wind direction (fixed octants) calculated from a wind rose, while the opposite direction is defined as downwind areas. Appendix Figure B3 illustrates wind direction with downwind and upwind areas.[7]

2.3.2 Summary Statistics for the Main Variables

Table 1 presents summary statistics for the main variables. The average monthly agricultural fires and forest fires are 0.23 and 0.02, respectively. Regarding crop-related fires, the highest average is observed for sugarcane fires (0.22), followed by corn fires (0.20) and rice fires (0.15). On average, the price for residues is 1055 Baht (31 USD). The average installed capacity of biogas power plants is 10.58 megawatts. Pollution is relatively high in Thailand, with an average PM2.5 level of 26.03 µg/m3.

[7]This is based on a fixed, daily prevailing wind direction, which is calculated from a wind rose and does not change throughout the study period.

Table 21: Summary statistics for the main variables

	mean	p50	sd	min	max	observation
Agricultural fires	0.23	0.00	0.67	0	28	52,785
Forest fires	0.02	0.00	0.17	0	9	52,785
Rice fires	0.22	0.00	0.66	0	28	52,785
Sugarcane fires	0.15	0.00	0.57	0	22	52,785
Corn fires	0.20	0.00	0.63	0	28	52,785
Temperature (Celsius)	21.34	21.03	2.96	15.62	51.05	52,785
Wind speed (mph)	5.05	4.55	3.26	0	18.56	52,785
Dew Point	15.96	15.65	3.07	8.81	32.15	52,785
PM2.5 Pollution	26.03	26.40	5.20	14.2	44.4	52,785
Installed capacity (MW)	10.58	9.50	7.73	0.3	39.40	52,785
Price of residues (Baht)	1055	1055	807	700	4200	52,785

†1 USD *is equal to* 34 *Thailand Baht*

2.3.3 Identification Strategy

I estimate the effect of biogas plants on agricultural fires using a staggered difference-in-differences design that exploits variation in the timing of plant openings between 2001 and 2023. The baseline specification employs a two-way fixed effects (TWFE) estimator:

$$Y_{ijt} = \theta_j + \delta_i + \upsilon_t + \alpha X_{ijt} + \beta \text{Biogas}_{ijt} + \varepsilon_{ijt} \tag{2.1}$$

where the unit of observation is 2.25 km $\times$ 2.25 km grid cells. Y_{ijt} represents the outcome variable (agricultural fires) in grid cell i within a 5 km radius of biogas plant j at time t. I include plant fixed effects (θ_j), grid cell fixed effects (δ_i), and year fixed effects (υ_t) to control for unobserved time-invariant characteristics at the plant and grid cell levels, as well as time-varying factors common across all observations. αX_{ijt} is a set of weather control variables, including temperature, dew temperature, wind speed, and wind direction. β captures the average treatment effect on the treated (ATT).

Treatment is defined as having an operational biogas plant within 5 km of a grid cell. The 5 km radius captures the expected operational scope where farmers closest to plants face the lowest costs of selling their residues. As the actual operational scope of the plant is not observable, I also estimate effects across different distance rings: 0-10 km, 10-20 km, 20-30 km, and 30-40 km from biogas plants.

Recent literature highlights that the two-way fixed effects (TWFE) estimator in staggered adoption settings can suffer from negative weighting problems where already-treated units serve as implicit controls for newly-treated units, potentially biasing estimates when treatment effects are heterogeneous across cohorts or time (Goodman-Bacon 2021, Sun & Abraham 2021). I address this concern by re-estimating the main specification using Callaway & Sant'Anna (2021) estimator. Callaway & Sant'Anna (2021) approach computes separate average treatment effects for each cohort (defined by treatment timing) in each post-treatment period, using only not-yet-treated units as controls. These group-time average treatment effects are then aggregated into an overall treatment effect estimate using appropriate weights. This "clean control" strategy eliminates contamination from already-treated units and explicitly allows for treatment effect heterogeneity across cohorts and time.

The key assumption of the difference-in-differences relies on "parallel trends". This means that with the absence of the plant, agricultural fires in treatment and control group should follow a parallel trend. Following Borusyak et al. (2024), I use a staggered event-study design to test whether there exist any diverging pre-trends:

$$\text{Fire}_{ijt}^{5km} = \sum_{h=-k}^{h=-1} T_h \, \mathbb{I}\left[K_{ijt} = h\right] + \theta_{jt} + \delta_i + \upsilon_t + \alpha X_{ijt} + \varepsilon_{ijt} \tag{2.2}$$

where Fire_{ijt}^{5km} is the number of agricultural fires in grid cell i within a 5km raduis of a plant j in year t. T_h captures the treatment effects h years before the plant opening (leads, where h < 0). $\mathbb{I}\left[K_{ijt} = h\right]$ represents the event indicator, which takes the value of 1 for observations occurring h years before the onset of treatment. The year prior to a plant opening (k=-1) is omitted as the reference year. The parallel trend holds if pre-treatment coefficients are centered around 0 and not statistically significant.

2.4 Main Results

Average Treatment Effects. Table 22 presents the difference-in-differences estimation of the effects of biogas power plants on the number of agricultural fires within a 5-kilometer treatment radius, following the specification outlined in Equation (2.1). All specifications include grid cell fixed effects to control for time-invariant geographic and infrastructure characteristics, year fixed effects to absorb common temporal shocks, and plant fixed effects

to account for facility-specific attributes, including capacity, technology type, ownership structure, and operational efficiency. All regressions incorporate weather controls, including temperature, wind speed, wind direction, and dew temperature, which directly affect burning conditions and fire detection probability.

Table 22: Effects of Biogas Power Plants on Agricultural Fires

	Number of agricultural fires		
	All months	Burn season	Outside burn season
Treatment	-0.022**	-0.021**	-0.001
	(0.010)	(0.010)	(0.002)
Fixed Effects	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes
Control mean	0.26	0.25	0.009
Observations	52785	52785	52785

Note: The unit of observation is at the grid-year level, with each grid cell representing a 2.25 km x 2.25 km area (approximately 5 kilometer square). The outcome variables in columns (1) - (3) represent the total number of agricultural fires within a 5km radius of the plants for all months, the burning season from October to March, and outside burning season from April to September, respectively. All regressions include plant fixed effects, grid cell fixed effects, and year fixed effects. Weather controls include temperature, dews temperature, wind speed, and wind direction. Standard errors, clustered at the grid level, are in parenthesis. *, **, and *** indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

In column (1) of Table 22, the coefficient for the treatment indicator is -0.022 and statistically significant at the 5% level. Compared to the sample mean (0.26), this estimate suggests that the opening of biogas power plants accounts for a 8.5% drop in the number of agricultural fires in the treated areas.

Agricultural fires follow a seasonal cycle with sharp increases following harvest periods. Column (2) of Table 22 restricts the sample to the crop burning season (October - March) to examine whether the impact of biogas plants varies by season. During this high-fire period, the coefficient estimate is –0.021, significant at the 5% level, indicating that plant openings reduce agricultural fires by 8.4% relative to the sample mean of 0.25. However, I find no statistically significant effects during the off-season months (April to September), when agricultural burning is minimal, regardless of the presence of biogas plants.

Next, I explore how the effects of biogas plants vary with distance by estimating the treatment effect in four rings: 0-10 km, 10-20 km, 20-30 km, and 30-40 km from plant locations. As shown in Figure 25, the reductions in agricultural fires are concentrated within 30 km of a plant, with no statistically significant effects observed beyond that range. This spatial decay pattern reflects how transport costs shape economic behavior. As collection costs increase with distance, the economic viability of residue sales diminishes, eventually falling below the price biogas plants offer for raw materials. This finding thus highlights the geographic boundaries within which market-based environmental interventions are most effective, emphasizing that proximity to facilities is a key factor in the success of such policies.

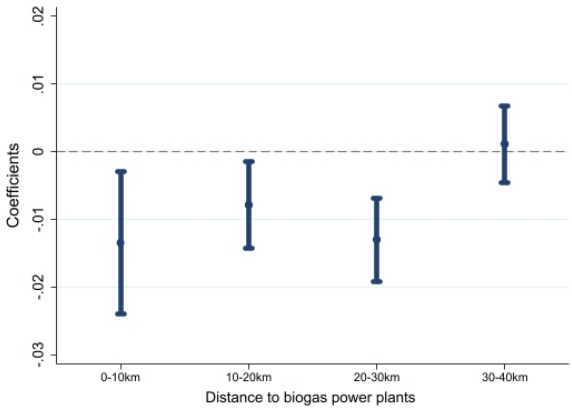


Figure 25: Effects of Biogas Power Plants by Distance

The spatial constraint has important implications when compared to similar interventions in different economic contexts. Cao & Ma (2023) document biogas plant effects extending up to 90 kilometers in China, which is three times the radius observed in this study. This contrast highlights how price signals shape the effectiveness of policy. Crop residues sell for roughly $90 per ton in China, compared with $30 per ton in Thailand, which fundamentally changes the economics of collection over distance. This threefold price difference directly expands the range over which collection is profitable, providing evidence that economic incentives, specifically residue prices and transport costs, determine the geographic reach of environmental policy impacts.

Event Study. Figure 26 presents the visualization for the estimates of the "event-study" regression described by Equation (2.2). The pre-treatment coefficients before the opening of a plant are centered around zero and are not statistically significant. However, the coefficients after the opening of a plant decline. This pattern confirms that the treated and control groups

share similar trends in the number of agricultural fires before the opening of a plant, but these trends began to diverge after the opening of a plant.

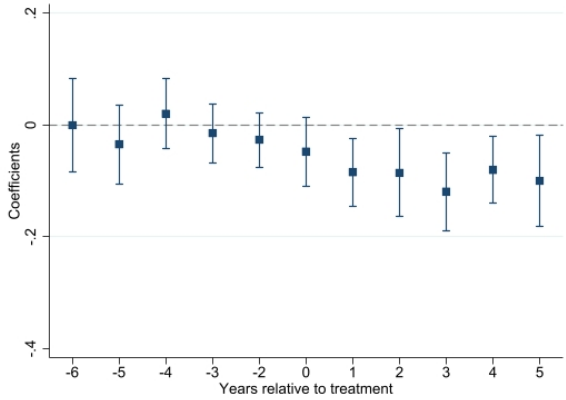


Figure 26: Biogas Power Plants & Agricultural Fires: Event-Study Estimates. The graph plots the coefficients of event-study regressions described by Equation 2

In summary, evidence in Section 2.4 shows that the opening of a plant accounts for a 8.5% reduction in agricultural fires, primarily during the crop-burning season and within 30 km of plants. The spatial decay reflects transaction costs with distance and shows that the effectiveness of market-based interventions depends on local economic incentives. While these policies can reduce agricultural fires, their geographic reach is limited by commodity prices and the costs of market participation. More importantly, these effects are not driven by pre-existing differential trends.

2.5 Further Results

2.5.1 Effects on Air Pollution

Average effects on PM2.5 pollution. Existing studies show that agricultural burning contributes significantly to air pollution (He et al. 2020). This subsection explores whether the opening of the plant affects PM2.5 pollution. Table 23 presents estimates of the effects of biogas plants on PM2.5 concentrations in different spatial and temporal dimensions, showing that biogas plants generate substantial improvements in local air quality through reduced agricultural burning.

Column (1) shows that the opening of a biogas plant reduces annual PM2.5 concentrations by 0.666 μg/m^3, corresponding to a 2.5% decrease relative to the control mean of 26.98

$\mu g/m^3$. This effect persists during the crop burning season (October to March), with a nearly identical coefficient of -0.659 $\mu g/m^3$, indicating that air quality gains align with the peak agricultural burning period when biogas plants compete more directly for crop residues. These findings align with evidence that market opportunities can help inspire innovation in cleaner technologies, as biogas plants create economic incentives for farmers to adopt alternative residue management practices.

Table 23: Effects of Biogas Power Plants on Air Pollution

	PM2.5 Pollution						
	All months	Burn season	Nearby urban centers	Nearby urban centers during burn season	Downwind areas	Downwind areas during burn season	Upwind areas
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment	-0.666***	-0.659***	-1.322***	-1.365***	-0.540***	-0.562***	0.347
	(0.0793)	(0.0796)	(0.308)	(0.335)	(0.0895)	(0.0910)	(0.267)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Control mean	26.98	27	20.42	19.65	26.90	26.93	26.12
Observations	45333	44373	20332	20332	34330	33712	1176

Note: The unit of observation is at the grid-year level, with each grid cell representing a 2.25 km x 2.25 km area (approximately 5 kilometer square). The outcome variable measures PM2.5 pollution within 5km of biogas plants across different subsamples: (1) full sample; (2) burning season only (October-March); (3-4) urban centers during all periods and burning season; (5-6) downwind areas during all periods and burning season; (7) upwind areas. Upwind areas are defined as regions within 45 degrees of the daily prevailing wind direction (fixed octants) calculated from a wind rose, while the opposite direction is defined as downwind areas. All regressions include plant fixed effects, grid cell fixed effects, and year fixed effects. Weather controls include temperature, dews temperature, wind speed, and wind direction. Standard errors, clustered at the grid level, are in parenthesis. *, **, and *** indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

While existing studies examine the local effects of biogas power plants on air pollution (Nian 2023), I extend this literature to investigate spatial spillovers by examining impacts on nearby urban centers. Column (3) shows a coefficient of -1.322, significant at the 1% level. This finding suggests that the opening of a plant reduces PM2.5 pollution by 6.5% in nearby urban centers compared to the control mean of 20.42 $\mu g/m^3$. The effect is slightly stronger during the burning season. Column (4) shows a reduction of 1.365 $\mu g/m^3$, corresponding to a decrease of 6.9% relative to the seasonal mean of 19.65 $\mu g/m^3$. This amplified urban effect probably reflects the cumulative impact of the reduction of burning in multiple surrounding agricultural zones.[8] These concentrated urban benefits are particularly important from a

[8]It is also possible that biogas generation may substitute for more polluting energy sources, such as coal-fired

public health perspective, as they deliver air quality improvements in densely populated areas where exposure and health impacts are typically highest.

I further investigate the spatial pattern of spillover effects by examining whether impacts vary by wind direction. Following the literature of Rangel & Vogl (2019); Zivin et al. (2020); He et al. (2020), upwind areas are defined as regions within 45 degrees of the daily prevailing wind direction (fixed octants) calculated from a wind rose, while the opposite direction is defined as downwind areas. Column (5) presents results for the downwind areas. The coefficient of -0.540 is statistically significant at the 1% level, indicating that biogas plant openings reduce PM2.5 concentrations by 2% in downwind locations relative to the sample mean. The effect is stronger during the burning season, with a coefficient of -0.562 that is significant at the 1% level (column 6). As expected, plant openings have no significant impact on PM2.5 concentrations in upwind areas, consistent with the transport of pollutants by prevailing winds (column 7).

Event Study. Figure 29 presents the results for the parallel trends assumption described by Equation (2.2). In this equation, I create interactions between the treatment indicators and a set of indicators indicating whether a specific year is before or after the opening of a plant. The coefficients in the figure represent the differences in PM2.5 pollution between treated and non-treated grids before and after the opening of a plant. The difference in PM2.5 pollution between treated and non-treated grids is relatively constant prior to the opening of a plant. However, the estimates decline remarkably after the opening of a plant.

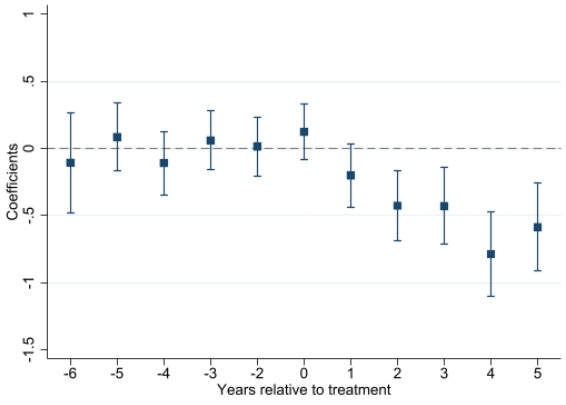


Figure 27: Biogas Power Plants & PM2.5 Pollution: Event-Study Estimates. The graph plots the coefficients of event-study regressions described by Equation 2

power plants, which are concentrated in or near urban centers. I will explore this further in subsequent analysis.

In summary, evidence in Section 2.5.1 shows that biogas plants generate substantial spatial spillovers in air quality improvements that extend well beyond their immediate vicinity. Although local effects reduce PM2.5 concentrations by 2.5%, nearby urban centers experience amplified benefits of 6.5-6.9%, suggesting that previous research focused solely on local impacts significantly underestimates the welfare gains from biogas policies. More importantly, these effects are not driven by pre-existing differential trends.

2.5.2 Effects on Different Types of Fires

Average effects by fire type. I utilize the unique administrative data on land use for various crops to explore the effect of biogas power plants on different types of fires, including rice fires, sugarcane fires and corn fires. Rice fires are defined as agricultural fires that occur within rice cultivation areas. Sugarcane fires and corn fires are defined identically for their respective cultivation areas. This approach allows me to identify which crop residues are most responsive to the economic incentives created by biogas plants. Table 24 shows the estimation results for different types of fires.

Table 24: Effects of Biogas Power Plants on Different Types of Fires

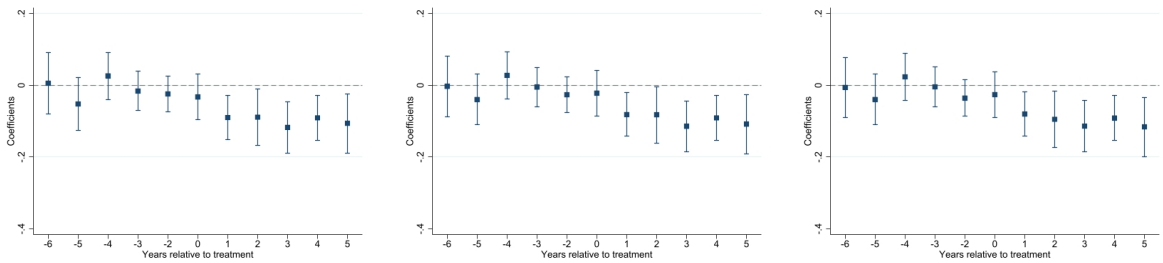
	(1)	(2)	(3)
	Rice fires	Sugarcane fires	Corn fires
Treatment	-0.027***	-0.034***	-0.029***
	(0.010)	(0.009)	(0.010)
Fixed Effects	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes
Control mean	0.25	0.18	0.23
Observations	52785	52785	52785

Note: The unit of observation is at the grid-year level, with each grid cell representing a 2.25 km x 2.25 km area (approximately 5 kilometer square). Columns (1) - (3) represent the effects of biogas plant openings on the incidence of rice, sugarcane, and rice fires, respectively, within a 5-kilometer radius of the plants. I construct a measure of rice fires as the number of agricultural fires occurring within grids that contain rice cultivation areas. Sugarcane fires are measured as the number of agricultural fires in grids with sugarcane cultivation. Corn fires are defined in the same way, based on the number of agricultural fires within grids containing corn cultivation. All regressions include plant fixed effects, grid cell fixed effects, and year fixed effects. Weather controls include temperature, dews temperature, wind speed, and wind direction. Standard errors, clustered at the grid level, are in parenthesis. *, **, and *** indicate statistical significant at the 1%, 5%, and 10% levels, respectively

This crop-specific analysis represents a significant advance over existing studies in the agricultural burning literature. Previous research examining the effects of environmental policies on agricultural burning (Nian 2023, Cao & Ma 2023, He et al. 2020) has been limited to analyzing aggregate fire counts, making it impossible to distinguish which specific crops or farming practices drive the observed changes. The lack of detailed crop-level data in prior studies has prevented researchers from understanding the heterogeneous responses across different agricultural systems. This study leverages comprehensive geospatial land-use data linked to fire locations to provide the first systematic examination of crop-specific responses to biogas incentives and provide insight for designing targeted agricultural environmental policies.

Column (1) explores the number of rice fires. The coefficient for the treatment indicator is -0.027 and significant at the 1% level. Compared to its respective mean (0.25), this result indicates a reduction in rice fires by 10.8%. Similarly, column (2) examines sugarcane fires and shows a coefficient of -0.034, also significant at the 1% level. Compared to the control mean of 0.18, this corresponds to a reduction 18.8% in sugarcane fires after plant openings. Column (3) presents results for corn fires, with a coefficient of -0.029 that is statistically significant at the 1% level. This represents a 12.6% decrease relative to the control mean of 0.28. The consistent pattern of reductions across all three major crop types suggests that biogas plants create broad economic incentives for farmers to abandon burning practices within a 5-km distance from the plants.

Event Study. The event study analysis confirms the estimated effects are not driven by pre-existing differential trends. Figure 28 shows that treated and control areas follow parallel trajectories prior to plant openings, with clear divergence occurring only after treatment begins.



(a) Rice fires (b) Sugarcane fires (c) Corn fires

Figure 28: Event study: Effects of biogas power plants on rice, sugarcane, and corn fires

In summary, evidence in Section 2.5.2 shows that biogas plants reduce agricultural burning in all major crop types within 5 km of plant locations. The parallel pre-trends and consistent treatment effects across different crops provide evidence that biogas plants create economic incentives for farmers to adopt alternative residue management practices rather than burning their fields.

2.5.3 Mechanisms

To understand the potential mechanisms by which a biogas power plant leads to a decrease in agricultural fires, I explore the role of economic incentives and the demand for biogas feedstock. Table 25 presents the results.

Economic incentive. Biogas plants create markets for agricultural residues that would otherwise be burned. However, farmer participation depends on the prices offered. To test this mechanism, I construct a dummy variable that equals 1 if the total price of residues is equal to or above the mean.

The results strongly support the economic incentive channel. Column (1) shows that plants offering low prices for residues have no significant effect on agricultural burning within a 5-km radius of the plants. The coefficient is negative, but statistically insignificant, indicating that farmers do not change their practices when economic returns are minimal. However, plants offering high prices for residues reduce agricultural fires by 14% relative to the control mean of 0.27 (coefficient = -0.038, $p < 0.006$, column 2). This discontinuous response across the price distribution reveals farmers' participation thresholds. Residue sales occur only when prices exceed the opportunity cost of burning. These findings suggest that market mechanisms drive the observed behavioral changes.

Biogas feedstock demand. I next explore whether plants with higher feedstock demand generate larger fire reductions. Using a plant's installed capacity as a proxy for feedstock demand, I construct a dummy variable equal to 1 if a plant's installed capacity is equal to or greater than the sample mean. Plants with high installed capacity may require proportionally more crop residues as inputs.

The results provide strong support for the biogas feedstock demand channel. Plants with low installed capacity generate no statistically significant reduction in agricultural burning (column 3), while plants with high installed capacity reduce agricultural fires by 13.8%

relative to the control mean of 0.26 (column 4). This differential response suggests that the intensity of feedstock demand drives the effects of treatment. Plants with greater processing capacity purchase larger quantities of residues from local farmers, directly reducing the volume of crop waste available for burning.

Table 25: Mechanism

	Number of agricultural fires			
	Economic incentive		Biogas feedstock demand	
	Low price of residues	High price of residues	Low installed capacity	High installed capacity
Treatment	-0.0004	-0.038***	-0.00724	-0.0360***
	(0.019)	(0.013)	(0.0206)	(0.0138)
Fixed Effects	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes
Control mean	0.24	0.27	0.27	0.26
Observations	23713	29072	20447	32338

Note: The unit of observation is at the grid-year level, with each grid cell representing a 2.25 km x 2.25 km area (approximately 5 kilometer square). The outcome variables in columns(1)-(4) represent the total number of agricultural fires within a 5km radius of the plants. High price of residues is a binary indicator equal to 1 if the total residue price is at or above the median. High installed capacity is a binary indicator equal to 1 if the plant's capacity is at or above the median. All regressions include plant fixed effects, grid cell fixed effects, and year fixed effects. Weather controls include temperature, dews temperature, wind speed, and wind direction. Standard errors, clustered at the grid level, are in parenthesis. *, **, and *** indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

In summary, evidence in Section 25 suggests that biogas plants reduce agricultural fires through two complementary market mechanisms. First, farmers respond to price incentives, participating in residue markets only when prices exceed the opportunity cost of burning. Second, plants with higher processing capacity generate larger effects by purchasing more residues from local farmers. Together, these findings indicate that market forces drive the observed fire reductions.

2.6 Alternative Accounts

In this section, I examine two plausible alternative explanations for the observed reduction in fires after the opening of biogas power plants: (1) improvements in local fire management near the plants and (2) abandonment of land or reallocation of labor after plant openings. I provide empirical evidence inconsistent with these alternatives that supports the conclusion that biogas plant openings are the main driver of reducing agricultural fires.

Improvements in local fire management near the plants. One potential reason for a reduction in agricultural fires following the plant's opening could be attributed to local enforcement efforts aimed at safeguarding the plant's infrastructure against fire incidents. If the observed effect is a result of local enforcement initiatives, I anticipate a reduction in other types of fires, such as forest fires. Using Equation (2.1), I replace the dependent variable with the number of forest fires. Columns (1) - (2) of Table 26 present the effect of biogas power plants on forest fires. The coefficients are statistically insignificant, rejecting the enforcement hypothesis.

Table 26: Alternative Accounts

	Local enforcement		Factor reallocation		Burning ban policy	
	# forest fires	# forest fires	Abandoned land	Abandoned land	# agri fires	# agri fires
Treatment	-0.003	-0.003	-0.158	-0.151	-0.0140	-0.0139
	(0.002)	(0.002)	(0.315)	(0.315)	(0.028)	(0.028)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	No	Yes	No	Yes	No	Yes
Control mean	0.24	0.27	4.74	4.74	0.23	0.23
Observations	52785	52785	52785	52785	52785	52785

Note: The unit of observation is at the grid-year level, with each grid cell representing a 2.25 km x 2.25 km area (approximately 5 kilometer square). The outcome variables in columns (1)-(2) represent the total number of forest fires, while the outcome variables in columns (3)-(4) represent abandoned land within a 5km radius of the plants. The outcome variables in columns (5)-(6) represent the total number of agricultural fires within a 5km radius of the plants. All regressions include plant fixed effects, grid cell fixed effects, and year fixed effects. Columns (2),(4), and(6) include weather controls such as temperature, dews temperature, wind speed, and wind direction. Standard errors, clustered at the grid level, are in parenthesis. *, **, and *** indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

Abandonment of land or reallocation of labor. Biogas plants may reduce agricultural fires through labor market channels that operate independently of residue pricing. New industrial facilities create employment opportunities that can draw workers away from farming, potentially leading to land abandonment or reduced agricultural intensity. When farmers transition to higher-paying industrial jobs, they may scale back farming operations or leave

plots uncultivated, mechanically reducing fire activity.

To test whether labor reallocation drives the reduction in agricultural fires, I examine data on abandoned land from the Ministry of Agriculture and Cooperatives. Columns (3) - (4) of Table 26 shows that biogas plant openings have a negative but statistically insignificant effect on land abandonment, suggesting that labor market dynamics do not explain the observed fire reductions. This finding suggests that a decrease in agricultural fires primarily results from farmers' incentives to sell crop residues to biogas facilities rather than reduced agricultural activity due to employment substitution.

Government burning ban. In 2017, Thailand implemented a strict one-month open-burning ban in nine northern provinces that were severely affected by seasonal haze from illegal forest and agricultural burning (Pollution Control Department 2017). The policy was enforced under a Single Command system, with provincial governors coordinating compliance and monitoring. To evaluate whether this policy intervention explains the observed reduction in agricultural fires, I use a difference-in-differences (DID) that compares treated and control provinces before and after the burning ban. Column (6) of Table 3.7, which presents my preferred specification with fixed effects and weather controls, shows that the burning ban had no statistically significant effect on agricultural fires, indicating that the observed reductions are not driven by the burning ban.

2.7 Cost Benefit Analysis

The cost of electricity generation from biogas varies significantly with plant capacity, ranging from 0.0676 USD/kWh for large 20 MWe plants to 0.0899 USD/kWh for smaller 5 MWe facilities (Delivand, Barz, Gheewala & Sajjakulnukit 2011). Given that Thailand can generate approximately 64,594 GWh of electricity from 174.1 million tons of waste per year (Jusakulvijit et al. 2021, Thailand Board of Investment 2019), the operational costs would be between 4.37 and 5.81 billion USD annually.

The potential annual revenue of generating 64,594 GWh of electricity from agricultural waste would range between 4.78 and 7.36 billion USD, given Thailand's Feed-in Tariff rates of 0.074 - 0.114 USD/kWh for biomass and biogas plants (Provincial Electricity Authority 2025). This represents a substantial revenue opportunity for the renewable energy sector.

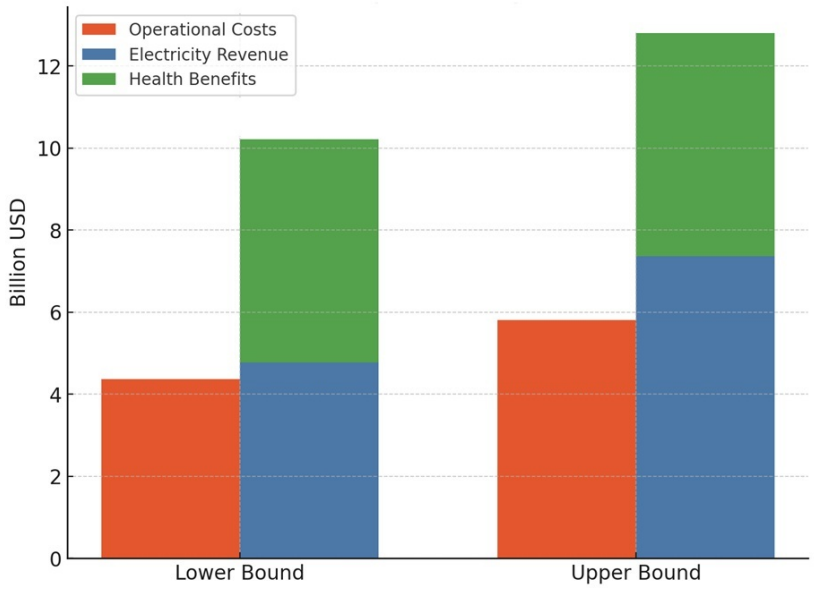


Figure 29: Cost Benefit Analysis

Next, I compare the program cost to the benefit of reducing pollution from agricultural burning. Mueller et al. (2021) estimates approximately 50,000 premature deaths per year from PM2.5 pollution. Using a mean value of statistical life (VSL) of $1.21 million, these deaths translate into an annual damage of approximately $60.55 billion (Witvorapong & Komonpaisarn 2020).[9] In rural areas, the treatment reduces PM 2.5 pollution by 2.5 percent, corresponding to health benefits of approximately 1.51 billion USD annually (0.025 × $60 billion USD). The health benefits are even higher for urban residents, as the treatment reduces PM2.5 pollution in nearby urban centers by 6.5 percent, generating approximately $3.9 billion USD in annual health benefits (0.065 × $60 billion USD). Combined, the total health benefits from pollution reduction is approximately $5.41 billion annually ($1.51 billion from rural areas and $3.9 billion from urban areas). These health benefits are equivalent to preventing approximately 4,470 premature deaths annually (3,220 in urban areas and 1,250 in rural areas).

In summary, the cost-benefit analysis shows that biogas power plants represent a cost-effective investment from both economic and social perspectives. While operational costs range from 4.37 to 5.81 billion USD annually, the program generates substantial returns

[9] Witvorapong & Komonpaisarn (2020) estimate the value of statistical life (VSL) in Thailand using nationally representative labor market data, including the 2012–2014 Labour Force Survey (N = 109,947) and Social Security office records, and applying the standard hedonic wage approach.

through electricity revenue (4.78 to 7.36 billion USD) and health benefits (5.44 billion USD). The health benefits alone, equivalent to preventing approximately 4,500 premature deaths annually, nearly offset operational costs. Combined with electricity revenue, total benefits significantly exceed program costs, making biogas power plants economically attractive while delivering critical public health improvements.

2.8 Robustness tests

I find that results are robust across multiple checks, including alternative specifications, data sources, and sample restrictions.

Callaway-Sant'Anna estimator. The main results are robust to using Callaway & Sant'Anna (2021) estimator, which addresses potential bias from negative weighting that can arise in two ways fixed effects (TWFE) specifications with staggered treatment timing. As shown in Appendix Tables B1 and B2, biogas plant openings continue to significantly reduce both agricultural fires and PM2.5 pollution, with all estimates statistically significant.

Alternative satellite dataset (VIIRS). To verify the robustness of the estimated effect and address potential concerns regarding measurement error or dataset selection, I re-estimate Equation 1 using an alternative satellite dataset: Visible Infrared Imaging Radiometer Suite (VIIRS) fire product. Relative to the MODIS dataset used in the main analysis (1km resolution), VIIRS offers higher spatial resolution (375m) and improved sensitivity to small fires. Agricultural fires are defined as VIIRS-detected fires that fall within agricultural land, as processed and classified by the Ministry of Natural Resources and Environment of Thailand. However, VIIRS data are only available from 2012 to 2023, so I restrict the sample to this period.

If the opening of biogas power plants truly reduces agricultural fires, its effect should persist using an alternative satellite dataset. Indeed, the estimates remain statistically significant and negative. Appendix Table B3 shows that the opening of a plant reduces agricultural fires, rice fires, sugarcane fires, and corn fires. In column (1) of Appendix Table B3, the coefficient is -0.140 and statistically significant at the 1% level. Compared to the relative sample mean (0.25), this represents a 56% reduction in agricultural fires. This percentage reduction in the number of agricultural fires using the VIIRS dataset (56%) is even larger than my main result in column (1) of Table 2.4, which is based on the MODIS satellite dataset. The results

remain unchanged without controls (Appendix Table B4).

Fire detection confidence thresholds. MODIS satellite assigns confidence scores (0-100%) to each fire detection based on the probability of representing actual fires rather than false positives from reflective surfaces or heated smoke. Users are generally advised to exclude low-confidence hotspots (confidence levels below 30%) to minimize potential false alarms.

In Appendix Table B5, I exclude fires below the 30% confidence threshold and find that biogas plant openings continue to significantly reduce agricultural fires across all major crop types. The results remain robust under a more stringent 50% threshold (Appendix Table B6). Omitting low-confidence fires causes the average number of fires within a 5-km radius to decrease from 0.23 to 0.20 per year. Although the estimated effects are slightly smaller under the stricter 50% threshold, the treatment effects remain statistically significant for agricultural, rice, sugarcane, and corn fires.

Consistent with the spatial patterns shown in Figure 25 and the results reported in Appendix Tables B5 and B6 for the 30% and 50% confidence thresholds, the reductions in agricultural fires are concentrated within 30 km of a biogas plant, with no statistically significant effects observed beyond that distance. The consistency of statistical significance across thresholds indicates that the observed reductions are not driven by measurement error from low-confidence detections but instead reflect changes in agricultural burning following biogas plant operations.

Alternative specification without controls. Appendix Table B7 shows that excluding weather controls does not materially affect the estimated treatment effects. The coefficients remain negative and statistically significant for all types of fires, suggesting that the results are not driven by systematic differences in weather patterns between the treated and control areas. Similarly, Appendix Table B8 shows that biogas plant openings continue to reduce PM2.5 concentrations locally, in nearby urban centers, and in downwind areas without controls.

2.9 Conclusion

This paper provides empirical evidence that the creation of markets for agricultural residues through biogas power plants effectively reduces agricultural burning and improves air quality in Thailand. By exploiting the staggered entry of plants from 2001 to 2023, the findings

show that the opening of a plant leads to an 8.5% reduction in agricultural fires within a 5-km radius of a plant, which in turn generates significant public health benefits through lower PM2.5 pollution.

Three key findings stand out. First, the environmental benefits extend well beyond local areas. While local PM2.5 concentrations decrease by 2.5%, the effects are amplified in nearby urban centers, where pollution falls by 6.5%. This spatial spillover is critical, demonstrating that rural industrial policy can mitigate urban air quality challenges in developing economies. Second, the mechanism is unequivocally market-driven. Reductions in agricultural burning are concentrated near plants offering high residue prices and operating at high capacity, confirming that farmers respond to economic incentives rather than indirect factors like labor reallocation or enhanced enforcement. Third, the policy impact is broad-based. Using novel spatial data on land use, I find that biogas plants reduce burning for all major crop types-rice, sugarcane, and corn-indicating that the intervention creates widespread incentives for sustainable residue management.

The findings have important policy implications. They highlight that market-creating industrial policy to address environmental externalities without direct regulation. Instead of relying on costly and often ineffective burning bans, governments can promote renewable energy sectors that generate demand for agricultural waste. However, the effectiveness of such policies is constrained by economic geography. The findings indicate that the impact on agricultural fires decays beyond a 30-km radius due to transaction costs, a radius three times smaller than that observed in China where residue prices are higher (Cao & Ma 2023). This suggests that policy success depends not only on plant deployment but also on complementary measures, such as improving rural transportation infrastructure or providing targeted subsidies to offset collection and transaction costs in remote areas, to expand the market's reach.

In conclusion, this research demonstrates that well-designed industrial policy can increase renewable energy supply, raise farmer incomes, and mitigate the severe public health costs of agricultural pollution. By turning a harmful waste product into a valuable commodity, biogas development offers a sustainable path for agricultural regions in low- and middle-income countries to achieve both economic and environmental gains.

Chapter 3

Mining Policy Reform and Civil Conflict: Evidence from Myanmar

Abstract

This paper inverts the standard resource-conflict paradigm by examining how resource contraction, rather than expansion, affects civil violence. Exploiting a 2016 moratorium in Myanmar that halted new mining licenses, I implement a difference-in-differences strategy using a novel spatially disaggregated database linking mining activity with geo-coded conflict events from 2011–2020. The contraction led to a 69% reduction in conflict incidents—particularly violent and fatal events—in previously licensed townships. The effects were stronger in ethnic homelands, poorer areas, and remote regions. Strikingly, the analysis uncovers positive spatial spillovers: conflict also declined in neighboring non-mining areas, suggesting that reduced resource extraction diffuses peace rather than displacing violence. Evidence supports three mechanisms: (1) lower mineral rents constrained armed group financing; (2) labor reallocation to productive sectors increased the opportunity cost of violence; and (3) reduced elite rents mitigated local inequality, dampening grievance-based mobilization.

Keywords: Natural resources, minerals, mining, extractive policy reform, civil conflict, ethnicity

JEL Classification: D74, H56, O13, Q34

3.1 Introduction

Natural resource extraction constitutes a critical economic sector in many low- and middle-income countries, providing substantial investment inflows, employment opportunities, and fiscal revenues that support local development (Caselli & Michaels 2013, Black et al. 2005). However, this resource wealth is frequently accompanied by significant adverse outcomes, including governance challenges, environmental degradation, displacement of local communities, and heightened risks of violent conflict (Brollo et al. 2013, Chuhan-Pole et al. 2017). Striking a delicate balance between these competing effects remains a central challenge in development economics.

A significant amount of empirical evidence highlights how intensifying natural resource extraction often exacerbates conflict in low- and middle-income countries (Collier & Hoeffler 2004, Fearon 2003, Ross 2006). For instance, Berman et al. (2017) show that rising mineral prices have fueled conflict outbreaks in Africa. Similarly, Crost & Felter (2020) uncover that a reform program aimed at increasing investment in mining in the Philippines leads to a substantial increase in conflict. Conversely, what happens to conflict when the State attempts to reduce mining activity?

This paper examines how a policy restricting resource extraction—specifically, a ban on issuing new mining licenses—influences the dynamics of civil conflict in Myanmar. In April 2016, the government introduced a moratorium aimed at promoting responsible mining practices. Since most licenses were small-scale and short-term, the moratorium precipitated a sharp decline in active mining licenses following the reform. To explore the effects of this regulatory shift on civil conflict, I use a difference-in-differences (DID) strategy and compare townships with and without mining licenses before and after the mining policy reform. I construct a novel dataset by merging mining license records from Myanmar's Ministry of Natural Resources and Environmental Conservation (MONREC) with spatially disaggregated conflict event data from the Armed Conflict Location and Event Data Project (ACLED) for 2011–2020. This integrated dataset facilitates a detailed analysis of temporal and geographic variation in mining activity and conflict incidence across Myanmar at the township level.

I find that the 2016 mining moratorium led to a significant reduction in conflict events: mining townships experienced 3.935 fewer conflict incidents per year compared to non-mining

townships, representing a 69% decrease relative to the sample mean.[1] When exploring different types of conflict, the reduction is stronger among extreme conflict events such as deadly events, battles, violence events, and state-perpetrated violence, while non-extreme conflict events like protests show no significant effect. The estimated effects remain robust across multiple specifications, including synthetic difference-in-differences estimation, alternative conflict dataset (Uppsala Conflict Data Program), and restriction to minerals less susceptible to illegal extraction and smuggling. The effect strengthens steadily over the three years following the ban, consistent with a progressive intensification of treatment exposure as existing licenses expire and mining activity contracts. Importantly, event-study estimates confirm that mining townships and non-mining townships shared similar conflict patterns before the mining ban, with trends beginning to diverge only after the mining ban.

To assess whether the observed decline in conflict merely reflects a geographic displacement of violence, I examine spillover effects on non-mining townships that border mining townships. The analysis provides no evidence of spatial diffusion following the 2016 mining ban. Instead, conflict declines in adjacent non-mining townships. These positive spillovers are consistent across multiple outcomes, including deadly events, battles, violent events, and state-perpetrated violence. The results suggest that the reform does not shift violence to nearby areas but instead generates broader conflict-reducing effects. To the best of my knowledge, this is the first evidence of such positive spillovers from the mining ban.

The effects of resource wealth on conflict depend on local mechanisms. Dube & Vargas (2013) distinguish between a rapacity channel, where resource rents from oil fund violence, and an opportunity cost channel, where rising wages from labor-intensive commodities deter it. Myanmar's small-scale but high-value minerals resemble oil in that extraction generates local rents; thus, I expect the mining ban to reduce conflict by reducing funding for armed groups. But unlike oil, small-scale mining in Myanmar is labor intensive and short-term. As such, the ban may also shift workers toward other sectors, increasing the opportunity cost of joining conflict. Lastly, by reducing elite-captured rents, the mining ban may also ease grievances in a state where resource wealth has long been a source of inequality and resentment. While the Dube & Vargas (2013) framework examines market-driven price shocks in two-sided conflicts, I test this theory where the state plays a central role not just in

[1] Mining townships are defined as those with active mining licenses prior to 2016; non-mining townships had none.

policy reform but also in perpetrating violence.

I examine whether the mining ban's effects vary across township characteristics, including ethnic homeland status, poverty, remoteness (proxied by road density), and coethnic political representation. I find stronger effects of the "license ban" in ethnic homelands, poorer townships, and more remote regions - areas where resource extraction has historically been closely linked to armed conflict and local grievances. These patterns hold across multiple measures of conflict, including deadly events, battles, violent events, and state-perpetrated violence. More strikingly, the differential effects between high and low co-ethnic representation townships are statistically insignificant. This suggests that ethnic representation does not moderate the conflict-reducing effects of the mining ban. While prior work emphasizes the potential of shared ethnic identity between constituents and legislators to mitigate group-based grievances (Mansbridge 1999, Reynal-Querol 2002), my results suggest that such descriptive representation alone is insufficient to reduce violence without substantive political power or influence.

The study explores the channels through which the mining ban impacts conflict, grounding the analysis in the rapacity and opportunity cost effects identified by the Dube-Vargas framework, while introducing grievances as a third complementary mechanism. First, the rapacity effect operates through a substantial contraction in high-value commodity production, thereby constraining the financial resources available to mineral-dependent armed groups and limiting their operational capacity. Second, the opportunity cost effect is evidenced by suggestive labor shifts toward agriculture and manufacturing sectors two years post-ban, potentially increasing the cost of joining armed groups. Third, recognizing the salience of entrenched ethnic grievances in Myanmar's conflict dynamics, the analysis incorporates a grievances mechanism, whereby the mining ban's attenuation of elite rents contributes to a statistically significant decrease in income inequality. This reduction in income concentration likely alleviates grievance-based incentives for mobilization, thereby complementing the other two mechanisms in explaining the overall decline in conflict.

In addition, this article presents evidence against alternative mechanisms. Given that the National League for Democracy (NLD) came to power in 2015, one concern is that the observed effects may be driven by the change in government rather than the mining ban itself. However, even after controlling for NLD vote shares, the mining ban consistently reduces all conflict measures, suggesting that the reduction of conflicts is not driven by the government

transition. I also examine whether the effects are driven by development initiatives, such as Community-Driven Development (CDD) programs implemented around the same time. When controlling for CDD programs, I find that this initiative has minimal impact on all conflict outcomes, indicating that development program does not account for the observed reduction in conflict events.

This paper contributes to several strands of literature. First, it contributes to the growing literature that exploits exogenous variation in resource extraction to identify causal effects on conflict. Previous studies have leveraged both market-driven and policy-driven shocks to examine this relationship. Market-based studies using commodity price fluctuations consistently find that resource booms increase local conflict through rent-seeking and competition mechanisms. For example, Dube & Vargas (2013) find that conflict in Colombia increases when coffee prices decline (labor-intensive sector) and when oil prices increase (capital-intensive sector), while studies of mineral price increases demonstrate that rising prices fuel local conflict in Africa (Berman et al. 2017, Denly et al. 2022). Similarly, policy-based studies have examined the government intervention. For example, Crost & Felter (2020) find that investment-promoting mining reforms increased local conflict in the Philippines. However, it is not entirely clear what happens to conflict when the State attempts to reduce mining. This paper directly addresses this gap by investigating the causal impact of a state-induced reduction in mining activity—through moratoriums and suspensions—influence conflict dynamics.

Second, this paper directly engages a core but underexplored question in the resource–conflict literature: is the relationship between resource extraction and violence symmetric—do reductions in mining activity mitigate conflict as systematically as expansions exacerbate it?[2] While existing studies show that commodity booms and mining expansions fuel conflict through rent-seeking and rebel financing (Dube & Vargas 2013, Berman et al. 2017, Crost & Felter 2020, Denly et al. 2022), it remains unclear whether the inverse holds. This paper finds that a mining ban reduces conflict by 69%—a decline comparable in magnitude, but opposite in direction, to the 60% increase associated with mining expansions in Crost & Felter (2020).

Third, this paper offers a novel application of the Dube–Vargas framework by examining how resource-conflict mechanisms operate in response to a policy-driven contraction in re-

[2]For foundational studies on the "resource curse" and conflict, see Collier & Hoeffler (2004), Fearon (2003), Collier (2019), Caselli & Michaels (2013), Ross (2006), Lujala et al. (2005), Morelli & Rohner (2015).

source rents, rather than an exogenous commodity boom.[3] I focus on Myanmar's mineral-rich regions, where the state plays a central role not just in policy reform but also in perpetrating violence. The original framework theorizes that commodity booms generate conflict through two opposing forces: the rapacity effect, where rising rents increase contestation, and the opportunity cost effect, where higher wages reduce incentives to fight. Most studies apply this model to two-sided conflicts and exogenous price shocks. In contrast, I treat a state-imposed mining ban as a negative resource shock, asking whether it reduces the incentives for violence, particularly state-perpetrated violence, by lowering the value of contestable rents. The central idea is that a reforming state, unlike insurgents, has fewer reasons to deploy violence when it voluntarily constrains access to rents. This asymmetric logic allows me to test whether state-led reform leads to a decline in state-led violence. In doing so, the paper expands the empirical scope of resource-conflict theories to better account for the role of the state, not only as a coercive actor but also as a potential source of restraint.

The final strand of literature relevant to my study examines the spatial diffusion of conflict, or how violence in one area can spill over into neighboring regions. A prominent example is Berman et al. (2017), who show that rising mineral prices can escalate conflict not just locally but across space, as armed groups gain the resources to expand their operations beyond their home territories. While Berman et al. (2017) highlight the conflict-amplifying effects of resource booms, my study provides the first evidence of a countervailing dynamic: that a mining ban can produce conflict-reducing spillovers. Specifically, I find that non-mining townships located adjacent to mining townships experience a decline in conflict following the imposition of the ban. In contrast to the existing literature, which largely focuses on how resource wealth fuels violence, my findings suggest that policy interventions targeting resource extraction can have pacifying effects that extend beyond their immediate jurisdiction.

The remainder of the article is organized as follows. Section 2 discusses mining and conflict in Myanmar. Section 3 describes the data and the identification strategy. Section 4 presents the main results and robustness checks. Section 5 provides additional results, while Section 6 explores the transmission mechanisms. Section 7 considers alternative

[3]The literature has documented a number of resource-conflict mechanisms: Natural resources have been linked to conflict through several channels: low opportunity costs of joining rebel groups (Collier & Hoeffler 2004), rent-seeking behaviors that undermine institutional and state counterinsurgency capacity (Fearon 2003, Fearon & Laitin 2003), and mismatches between expected and actual payoffs from extraction (Collier 2019); see Ross (2006) for a comprehensive review.

explanations, and Section 8 concludes with a summary of the findings.

3.2 Institutional Background

3.2.1 Mining and Conflict in Myanmar

Myanmar has endured one of the world's longest-running civil conflicts, persisting for over seven decades. Since its independence in 1948, the Tatmadaw (Myanmar's military) has engaged in armed conflict with numerous ethnic armed organizations (EAOs). Myanmar's protracted civil war is rooted in deep ethnic divisions but sustained and shaped by competition over natural resource rents. The Tatmadaw has fought dozens of EAOs, whose demands for autonomy have increasingly centered on control over lucrative resource regions. These frontier areas—rich in jade, timber, and gold—offer both strategic and fiscal benefits. Control over extraction sites enables the generation of revenue streams that fund military operations, sustain patronage and recruitment, and underwrite governance structures—for both the Tatmadaw and EAOs.

Firms operating in conflict-affected zones often paid informal fees to Tatmadaw and EAOs (Oo 2014, Sahla 2018). For example, the Kachin Independence Army (KIA) has demanded payments ranging from 10 to 20 percent of transaction value—or up to one-third of profits—from jade mining operations, in addition to levies on labor, fuel, equipment use, and site access (Bissinger 2019, Global Witness 2015). Meanwhile, Tatmadaw-linked firms and military-affiliated conglomerates extracted substantial rents in parallel. These overlapping revenue streams have made control over extraction sites a crucial source of conflict financing and intensified intergroup competition.

Disputes over the distribution and governance of resource revenues have further exacerbated tensions. The 2008 Constitution—drafted by the military—centralized virtually all taxation and royalties from natural resource extraction under the central government. Subnational entities are constitutionally entitled to only a marginal share. This centralization has been a persistent point of contention, with ethnic armed groups demanding greater authority over resource governance and revenue allocation in their territories (Woods 2019, Bauer & Sahla 2018). These unresolved disputes have contributed to the collapse of ceasefires, notably the KIA's return to active conflict in 2011—a resumption linked closely to disagreements

over jade mining and timber extraction.

The costs of resource-driven conflict fall disproportionately on local populations. Economic benefits accrue primarily to military and ethnic elites, while civilians in resource-rich areas face land dispossession, environmental degradation, and the militarization of daily life. Infrastructure and public services—such as schools and clinics—remain scarce. These conditions fuel enduring grievances tied to both economic exclusion and social marginalization (Smith et al. 1994, Myanmar Peace Monitor 2013).

The geography of violence often mirrors the geology of extraction. As of 2020, nearly a third of Myanmar's townships were affected by conflict—and almost half of these overlapped with active or recent mining operations (The Asia Foundation 2017). That correlation raises a critical question: To what extent is violence in Myanmar driven by resource extraction itself?

3.2.2 Mining in Myanmar

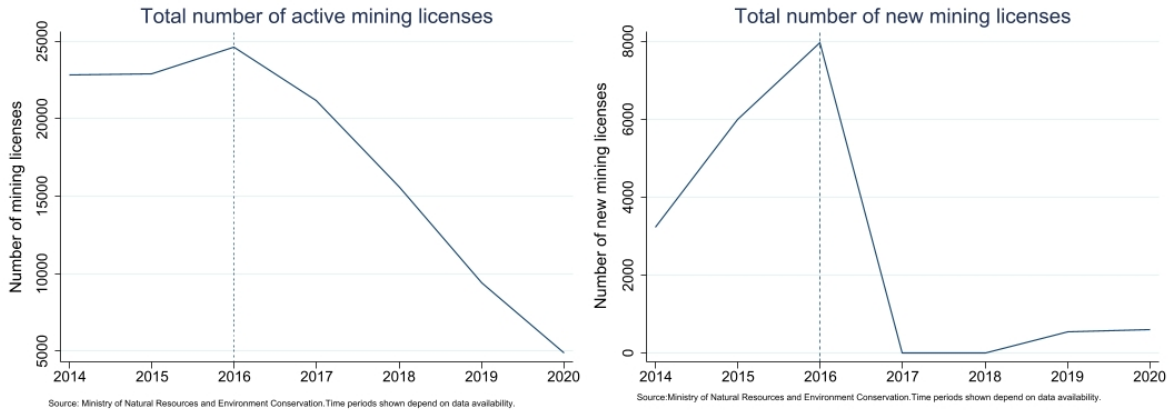
The extractive sector constitutes a central pillar of economic activity in many low- and middle-income countries, including Myanmar. It is endowed with a diverse array of 28 minerals, such as copper, gold, jade, and ruby,[4] distributed across its territory. Myanmar holds a significant position in the global mining industry, supplying approximately 10% of the world's tin, 90% of rubies, and 79% of jade (Myanmar EITI 2018). In the fiscal year 2013–2014, extractive industries accounted for 23.6% of government revenues and contributed 6% of GDP, while mineral exports comprised 38.5% of total national exports (Myanmar EITI 2018). These figures highlight the considerable economic importance of mining to Myanmar's national economy.

The weak regulatory frameworks governing mining practices resulted in substantial social and environmental harms in mining regions, including land confiscation, water pollution, deforestation, and landslides (Asia Development Bank 2015). These issues came to a head in 2015, when a landslide at a jade mine caused at least 116 deaths (Guardian 2015). In response, the National League for Democracy (NLD) government, which came to power following the 2015 general election, imposed a two-year suspension on the issuance of mining licenses

[4]These minerals include copper, zinc, limestone, coal, antimony, gypsum, tungsten, barite, chromium, feldspar, glass sand, clay, granite, manganese dioxide, rare earth, shieldite, dolomite, nickel, gem, tin, gold, iron, quartz, bauxite, lead, marble, jade, and oil/gas.

beginning in April 2016. This moratorium aimed to provide a window for comprehensive sectoral reform to address longstanding challenges in Myanmar's extractive industries. The policy intervention represents a critical natural experiment, offering an opportunity to analyze the impact of regulatory changes on mining activity and their broader social implications.

Following the NLD government's temporary mining ban in 2016, the total number of mining licenses and new license issuances declined sharply, with the majority of lost licenses concentrated among small-scale mining operations approved for one- or two-year terms (Figure **??**). This led to a pronounced contraction in active small-scale mining licenses in 2016, while large-scale licenses experienced a more moderate decline (Figure 32a). Correspondingly, total mineral production, including the gems and jade subsector, declined significantly in 2016. Although total mineral output partially recovered after 2018, production of gems and jade stabilized at reduced levels following 2017 (Figure 32b). These trends underscore the substantive impact of regulatory reforms on mining activity and output, establishing an important empirical context for the mechanisms explored in this study.

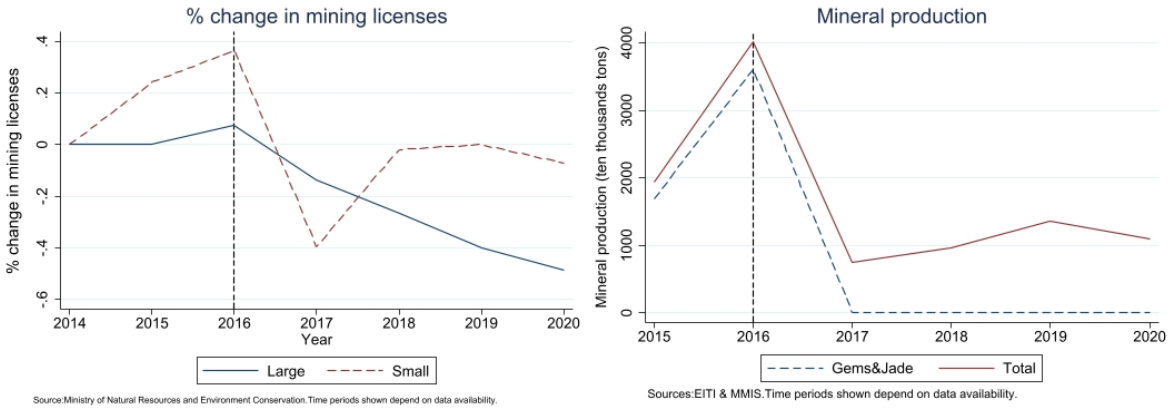


(a) Total number of mining licenses (b) Total number of new mining licenses

Figure 31: Total number of mining licenses and new mining licenses

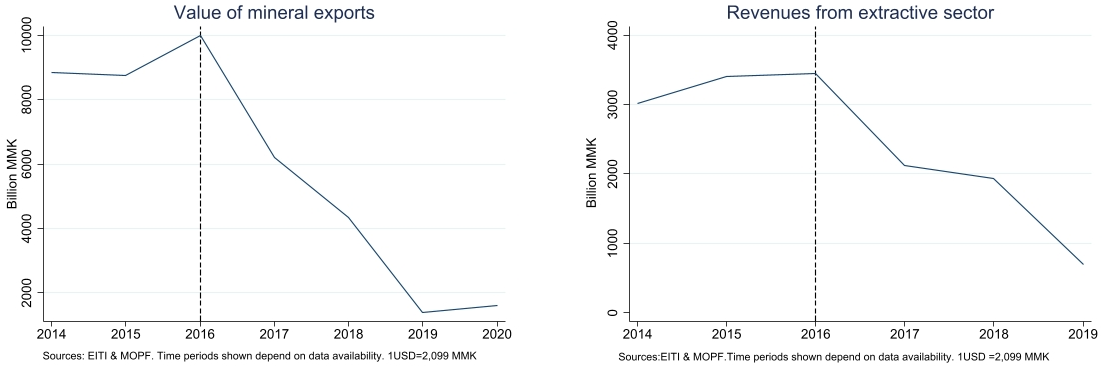
In tandem with the decline in active mining licenses, the extractive sector's contributions to both exports and revenue diminished significantly. Following the launch of mining sector reforms in 2016, both the value of mineral exports and revenue from the industry exhibited a clear downward trend (Figure 33). For example, the value of mineral exports fell sharply from 8,800 billion MMK in 2016 to 6,200 billion MMK in 2017 (Figure 33a). Likewise, revenues from the mining sector dropped from 3,450 billion MMK to 2,100 billion MMK over the same period (Figure 33b). These declines reflect the broader contraction of the

industry in response to regulatory tightening.



(a) Percentage change in mining licenses (b) Mineral production

Figure 32: Percentage change in mining licenses and mineral production



(a) Value of mineral export (b) Revenues from extractive sector

Figure 33: Value of mineral exports and revenues from the extractive sector

These observable shifts in mining licenses, production, and revenues following the 2016 mining ban raise key empirical questions about the policy's broader consequences, particularly regarding local conflict dynamics. Did the moratorium on mining licenses reduce or exacerbate conflict in affected communities? How did the decline in mining activity, especially among small-scale operators, interact with political and social tensions at the township level? Understanding these effects is crucial because mining areas in Myanmar have historically been sites of contestation over resources, land, and livelihoods.

3.3 Data and Empirical Strategies

3.3.1 Data

In this paper, the data have been aggregated by township and year, and the unit of analysis is the township-year level. Township is the third level of administrative division in Myanmar, below states/regions and districts, and above village tracts. Myanmar has 330 townships. The main outcomes of interest are the number of conflict events, deadly events, battles, violent events, state-perpetrated violence, and protests and riots.

Conflict Data Data on conflict (2011 to 2020) comes from the Armed Conflict Location and Event Dataset (ACLED) (Raleigh et al. 2010). The ACLDE dataset covers six major types of incidents: battles, explosions/remote violence, protests, riots, strategic developments, and violence against civilians (such as extrajudicial killings of unarmed prisoners of war, as well as acts such as beating, shooting, torture). These incidents are obtained from local and regional news and humanitarian agencies. A detailed description of the data collection procedure can be found in Raleigh et al. (2010).

From the ACLED dataset, I extract precise dates, geocoded locations, and incident initiators to construct outcome variables such as conflict events, deadly events, battles, violent events, state-perpetrated violence, and protests and riots. Conflict events include all types of events such as battles, explosions, strategic developments, violence against civilians (e.g., extrajudicial killings of unarmed prisoners of war and shooting), protests, and riots. Deadly events include battles, explosions, strategic developments, and violence against civilians. Battles include clashes between Myanmar's military forces (the Tatmadaw) and ethnic militias, as well as clashes between different ethnic militias. Violence events are defined as the number of incidents that result in at least one fatality. State-perpetrated violence is incidents initiated by the Tatmadaw and police forces.

In addition to the ACLED conflict dataset (Raleigh et al. 2010), I also use an alternative conflict dataset named the Uppsala Conflict Data Program Georeferenced Events Dataset (UCDP) to validate my main findings (Sundberg & Melander 2013). UCDP is widely used by researchers in conflict studies and focuses on fatal episodes with at least one direct death, excluding riots and protests. However, it is essential to acknowledge that this data set covers fewer conflicts, with an average of 0.38 events per township year (2011-2020)

compared to ACLED's average of 5.67 events. Although UCDP limits its conflict scope to fatal episodes with at least one direct fatality and excludes riots and protests, it brings about an advantage: UCDP incorporates conflict events reported in public sources (newspaper articles, for example), leaving reporting duties to non-conflict parties and reducing the risk of biased reporting by the conflict parties.

Mines Data Regarding mines data, gathered from MONREC (Ministry of Natural Resources and Environmental Conservation), four types of licenses were documented, including large-scale, medium-scale, small-scale, and exploration licenses. For this paper, I focus on large-scale, medium-scale, and small-scale licenses, excluding exploration licenses. I got data on the license start and end dates, mineral deposit areas, and mine geolocations. The distribution of mineral deposits, mining licenses, and commodities shows minimal spatial clustering and is geographically well-dispersed across states and regions of the country (Appendix Figure C2). Details on the construction of other data are available in Section C.2.

3.3.2 Descriptive Statistics

Table 31 presents the descriptive statistics for the final sample, which includes 3,300 observations over the ten-year period from 2011 to 2020. In terms of conflict events, the average number of conflict events per township-year for the ACLED conflict dataset is 5.67, while the average number of conflict events for the UCDP dataset is 0.38. This is because UCDP restricts conflict events to those resulting in at least one direct death and excludes riots and protests. Looking at different types of conflict events, the ACLED data set shows that, on average, there are 4.71 deadly events, 2.75 battles, 4.50 violent events, 2.06 state-perpetrated violence and 0.96 protests and riots.

Conflict events are more prevalent in ethnic homelands, poor townships, remote townships, and areas with low coethnic representation compared to their respective counterparts. For instance, the average conflict events in ethnic homelands, poor townships, remote townships, and areas with low coethnic representation are 12.48, 12.22, 8.97, and 7.66 respectively, while their counterparts average 1.46, 3.36, 2.38, and 3.62 (Appendix Table C1). This pattern holds for all extreme conflict incidents such as deadly events, battles, violent events, and state-perpetrated violence (Appendix Table C1).

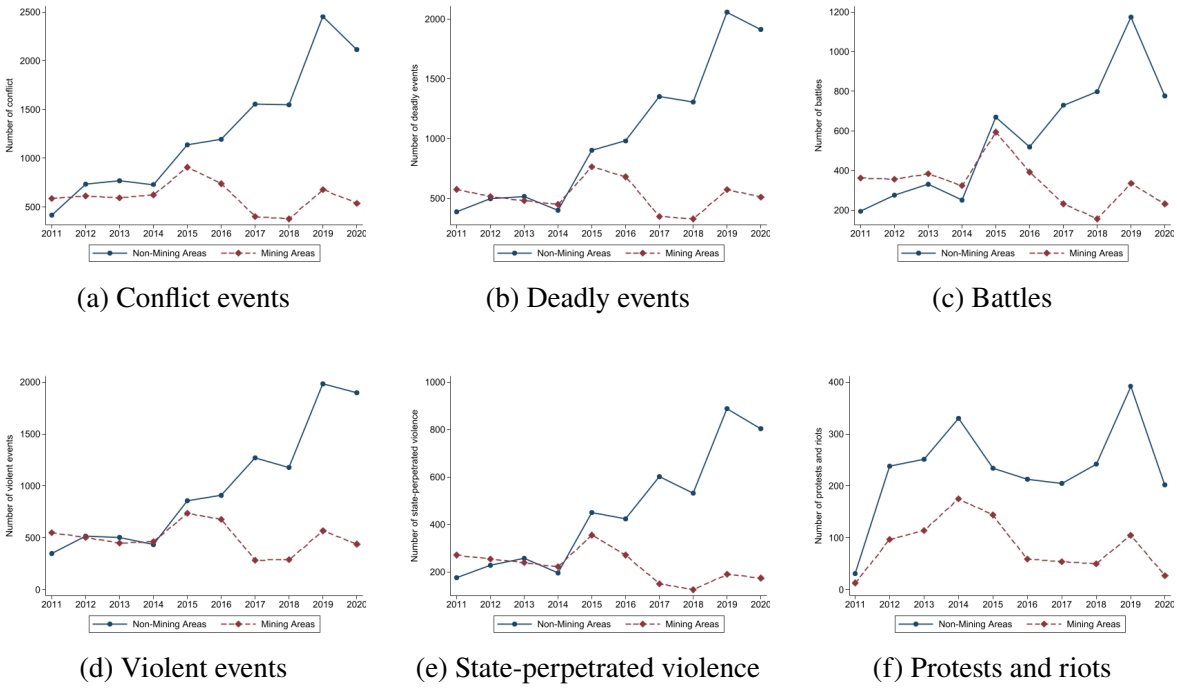
Table 31: Summary statistics for the main variables

	Mean	P50.	Std.Dev.	Min.	Max.	Obs.
Conflict Events						
Conflict events (ACLED dataset)	5.67	0	22.16	0	299	3300
Deadly events (ACLED dataset)	4.71	0	21.89	0	299	3300
Battles (ACLED dataset)	2.75	0	13.37	0	172	3300
Violent events (ACLED dataset)	4.50	0	22.15	0	299	3300
State-perpetrated violence (ACLED dataset)	2.06	0	9.84	0	139	3300
Protests and riots (ACLED dataset)	0.96	0	2.91	0	48	3300
Conflict events (UCDP dataset)	0.38	0	2.86	0	109	3300
Mining Licenses						
Mining licenses	0.31	0	0.46	0	1	3300
Mining licenses in ethnic homelands	0.36	0	0.48	0	1	1260
Mining licenses in non-ethnic homelands	0.28	0	0.45	0	1	2040
Mining licenses in poor townships	0.43	0	0.50	0	1	860
Mining licenses in non-poor townships	0.27	0	0.44	0	1	2440
Mining licenses in remote townships	0.42	0	0.49	0	1	1649
Mining licenses in non-remote townships	0.20	0	0.40	0	1	1651
Mining licenses in townships with high coethnic represent	0.22	0	0.41	0	1	1625
Mining licenses in townships with low coethnic represent	0.40	0	0.49	0	1	1675
Ethnic homelands	0.38	0	0.49	0	1	3300
Poor townships	0.26	0	0.44	0	1	3300
High road density townships	0.50	1	0.50	0	1	3300

Approximately 31% of townships have mining licenses.[5] Mineral deposits, mining licenses, and commodities are geographically dispersed throughout the country (Appendix Figure C2). Approximately 38% of townships are home to ethnic groups, whose homelands are geographically dispersed across the country (Appendix Figure C3). Twenty-six percent of townships are classified as poor, which is defined as a GDP below the 25th percentile of the distribution. Half of all townships (50%) are located in remote areas, as defined by the density of the roads. Additional variables for control, heterogeneity, and mechanisms are available in (Appendix Table C1).

[5]This paper focuses on large-scale, medium-scale, and small-scale licenses, excluding exploration licenses.

Figure 34: Trends in different types of conflict events between mining and non-mining townships



(a) Conflict events (b) Deadly events (c) Battles

(d) Violent events (e) State-perpetrated violence (f) Protests and riots

To visually examine the relationship between mining and conflict incidents, Figure 34 shows the number of conflict incidents in mining and non-mining areas from 2011 to 2020. Figure 34a shows that the conflict trends between mining and non-mining townships were similar during the pre-ban period (2011-2015), before diverging after the introduction of the mining ban in 2016. This pattern is also visible for other extreme conflict outcomes, such as deadly events (Figure 34b), battles (Figure 34c), violent events (Figure 34d), and state-perpetrated violence (Figure 34e). These figures seem to suggest a potential negative relationship between the mining ban and extreme conflict outcomes. However, they only show the raw incident count and do not correspond directly to my estimation strategy. In the identification strategy below, I will build on this suggestive visual representation to discuss how I estimate the effects of the mining ban on both extreme and non-extreme conflict outcomes.

3.3.3 Identification Strategy

I use a difference-in-differences approach that compares conflict outcomes in townships with and without mining licenses, before and after the start of the mining ban in 2016. My

estimation strategy is based on the following equation:

$$Y_{it} = \beta M_i \; + \; \gamma POST16_t \; + \; \varphi POST16_t \times M_i \; + \; \delta X_{it} \; + \; U_i \; + \; V_t \; + \; \varepsilon_{it} \tag{3.1}$$

In this equation, Y_{it} denotes the number of conflict events in township i in year t. I explore both extreme and non-extreme conflict events, including number of conflict events, deadly events, battles, violent events, state-perpetrated violence, and protests and riots. M_i is an indicator for whether township i has active mining licenses for any of the minerals produced in Myanmar before 2016.[6] The $POST16_t$ is an indicator for the post-treatment period (2016-2020). X_{it} includes interactions between year fixed effects and baseline characteristics like GDP per capita and population density. This allows me to account for time-varying shocks that affect townships differentially with different observed baseline characteristics. I include township fixed effects (U_i) and year fixed effects (V_t). The coefficient of interest is φ, which represents the average treatment effect of the mining ban. Standard errors are clustered at the township level to account for potential correlation in the error terms within townships over time.

The key assumption of difference-in-differences relies on "parallel trends". This means that conflict outcomes in all areas would have followed a parallel trend without the mining ban. I therefore conduct a test for the "parallel trends" assumption. I delve into the details of this test in Section 3.4, and I estimate an "event study" type regression based on the following regression:

$$Y_{it} = \sum_{2011}^{2020} \beta_j (year = j) \times M_i + \delta X_{it}, + U_i \; + \; V_t \; + \varepsilon_{it} \tag{3.2}$$

where $j \in (2011, 2020)$. The coefficients from 2011 to 2020 reflect the difference in conflict outcomes between townships with and without mining licenses, relative to the baseline year 2015. This regression allows us to test whether conflict outcomes in townships with and without mining licenses followed a parallel time trend before the mining ban.

To validate my main findings, I also estimate the treatment effect using the Synthetic

[6]These minerals include tin, gold, copper, zinc, iron, limestone, coal, lead, antimony, gypsum, marble, quartz, tungsten, barite, bauxite, chromium, feldspar, glass sand, clay, granite, manganese dioxide, rare earth, shieldite, dolomite, nickel, jade, and gem.

Difference-in-Differences (SDID) following Arkhangelsky et al. (2021). While my primary specification relies on the difference-in-differences (DID), SDID makes it a valuable complementary approach to estimate the effect of the mining ban on conflict outcomes. Specifically, SDID relaxes the parallel trends assumption by allowing for flexible time trends through unit-specific weighting. This addresses potential concerns that mining and non-mining townships followed systematically different pre-treatment trajectories due to geological, economic, and historical differences that could bias traditional DID estimates. By constructing a more appropriate counterfactual through weighted combinations of control units, SDID provides a valuable robustness check that is less sensitive to violations of the parallel trends assumption. I estimate the following regression:

$$Y_{it} = \beta M_{it} + \delta X_{it} + \varepsilon_{it} \tag{3.3}$$

where β is the treatment effect using Synthetic Difference-in-Differences (SDID).

To evaluate heterogenous effects of the mining ban, I estimate Equation 3.1 on different subsamples based on four township characteristics: ethnic homeland status, poverty levels, remoteness (measured by road density), and coethnic parliamentary representation.

3.4 Results

3.4.1 Mining Ban Reduces Conflict

Table 32 reports difference-in-differences estimates of the impact of the 2016 mining ban on conflict incidence at the township level. The results indicate that the ban led to a statistically significant reduction in the number of conflict events. The decline is concentrated in severe forms of violence, including deadly events, battles, violent events, and state-perpetrated violence. In contrast, there is no evidence of a statistically significant effect on lower-intensity events such as protests. All specifications include township and year fixed effects, as well as interactions between year fixed effects and pre-treatment township characteristics (GDP per capita and population density).

In column (1), the coefficient on Mining licenses $\times$ Year $\geq$ 2016 is –3.935, statistically significant at the 5% level. Compared to the sample mean (5.67), this estimate suggests that the mining ban accounts for a 69% drop in conflict events in mining townships. This

estimated reduction is comparable in magnitude—though opposite in direction—to the increase in conflict associated with investment-enhancing extractive resource policies. For example, Crost & Felter (2020) find that such expansionary policies raise conflict events by approximately 60 percent, whereas the mining ban in this study reduces conflict by 69 percent. Taken together, these findings suggest that mining-related policy changes exert roughly symmetric effects on conflict: expansions increase violence, while contractions reduce it by a comparable magnitude.

Table 32: Mining reform and conflict events

	Overall conflict events	Extreme conflict events				Non-extreme conflict events
	No. of conflicts	No. of deadly events	No. of battles	No. of violent events	No. of state-violence	No. of protests
	(1)	(2)	(3)	(4)	(5)	(6)
Mining licenses × Year ≥ 2016	-3.935**	-3.860**	-2.513***	-3.765**	-1.941***	-0.0746
	(1.574)	(1.556)	(0.851)	(1.585)	(0.638)	(0.165)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Mean of Dependent Variable	5.67	4.70	2.75	4.50	2.06	0.96
Observation	3300	3300	3300	3300	3300	3300

Note: The unit of observation is at the township level, and the study period covers 2011 to 2020. This table shows that the mining ban reduces conflict events. Conflict events include all types of events, including battles, explosions, strategic developments, violence against civilians (e.g., extrajudicial killings of unarmed prisoners of war and shooting), protests,and riots. Deadly conflict events include all types of events except protests and riots. Battles include clashes between Myanmar's military forces (the Tatmadaw) and ethnic militias, as well as clashes between different ethnic militias. Violence events are defined as the number of conflict events that result in at least one fatality. State-perpetrated violence are incidents initiated by the Tatmadaw and police forces. All regressions control for township fixed effects, year fixed effects and the interaction between year fixed effects and the following baseline characteristics: GDP per capita and population density. Standard errors, clustered at the township level, are in parenthesis. *, **, and *** indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

Columns (2)-(4) show that the mining ban has substantial and statistically significant effects on extreme conflict events, with all measures significantly dropping in mining townships after the mining ban. Specifically, mining townships experience 3.86 fewer deadly events annually (sample mean of 4.70), 2.513 fewer battles (sample mean of 2.75), 3.765 fewer violent events (sample mean of 4.50), and 1.941 fewer state-perpetrated violence (sample mean of 2.06). However, the mining ban has no significant effect on non-extreme events such as protests (column 6). This pattern may reflect the geographic concentration of protests and

riots, with nearly half occurring in Yangon and Mandalay—urban manufacturing hubs characterized by labor unrest and political mobilization. Because these non-extreme events likely stem from social, political, and economic grievances distinct from the resource competition driving extreme violence in mining areas, the mining ban may have limited influence on their incidence.

The estimated effect is larger and remains persistent in the long term. As the reform is a "license ban", the treatment effect intensifies over time as more licenses expire. In column (1) of Appendix Table C2, the coefficients for "mining licenses × year ≥ 2017", "mining licenses × year ≥ 2018", and "mining licenses × year ≥ 2019" are -5.964, -6.282 and -7.391, respectively, and are statistically significant. This pattern also holds for specific forms of extreme conflict, including deadly events, armed battles, violent events, and state-perpetrated violence (columns 2 - 5).

3.4.2 Robustness Tests

In this section, I explore the robustness of my main findings. Together, these robustness checks strongly suggest that the observed reduction in conflict is driven by the mining ban itself, rather than by other concurrent shocks, illegal smuggling or unregulated mining activity, and sample selection concerns.

The estimated effects remain consistent when using the Synthetic Difference-in-Differences (Synthetic DID), which improves the standard DID approach by constructing a control group that more closely tracks the treated group's pre-treatment trends (Arkhangelsky et al. 2021). This helps address concerns about non-parallel trends prior to the intervention. As shown in Appendix Table C3, the mining ban continues to significantly reduce conflict across several dimensions: conflict events (-3.60), deadly events (-3.628), battles (-2.373), violent incidents (-3.448), and state-perpetrated violence (-1.874). All estimates are statistically significant.

The results are robust to various ways of dealing with outliers. Appendix Table C4 reports estimates using conflict outcomes winsorized at the 5% level. The mining ban continues to show a statistically significant effect on a range of conflict outcomes, including deadly events, battles, violent incidents, and state-perpetrated violence. This suggests that the main results are not driven by a small number of extreme cases with very high levels of conflict events but instead reflect a broader pattern of conflict reduction following the mining ban.

The relationship between the mining reform and conflict reduction proves highly robust across a range of specification checks. When I remove all control variables, the results remain largely unchanged, suggesting that the findings are not driven by the included covariates (Appendix Table C5). To address potential spatial correlation in conflict dynamics, I aggregate data at the district-year level and re-estimate Equation 3.1, clustering standard errors at the district level. As shown in Appendix Table C6, the estimated effects are even larger at the district level, indicating a 97% reduction in conflict events. A similar pattern is observed across all extreme conflict outcomes, including deadly events, battles, violent incidents, and state-perpetrated violence. This suggests that the observed reduction in conflict is not driven by highly localized shocks and holds at broader spatial scales.

The results consistently show a reduction in conflict events when excluding townships affected by the Rohingya crisis. Given the significant increase in military operations and armed group activity in the Rakhine townships linked to the Rohingya crisis after 2017, I restrict the analysis to areas not affected by this crisis.[7] Even within this restricted sample, the negative association between mining reform and conflict remains significant (Appendix Table C7) and is robust to the exclusion of controls (Appendix Table C8).

Another potential concern is that illegal mining could continue despite the government's moratorium—particularly for minerals that are easily extracted and smuggled. To address this, I restrict the analysis to minerals less susceptible to illegal extraction and smuggling. Even when excluding high-value, easily smuggled minerals such as jade, gold, gems, and copper, the mining ban still leads to a statistically significant reduction in conflict events (Appendix Table C10). Crucially, this effect persists across a range of severe conflict outcomes, including deadly events, battles, violent incidents, and state-perpetrated violence. Together with the geographic restrictions, these results indicate that the conflict-reducing effect of the mining ban is not driven by external shocks or illegal extraction of high-value minerals.

To verify the robustness of the estimated effect and address potential concerns regarding measurement error or dataset selection, I re-estimate Equation 3.1 using an alternative conflict dataset: the Uppsala Conflict Data Program (UCDP) (Sundberg & Melander 2013). The UCDP dataset is widely recognized in conflict research and differs from the ACLED dataset by including only conflict events that result in fatalities (i.e., at least one direct death),

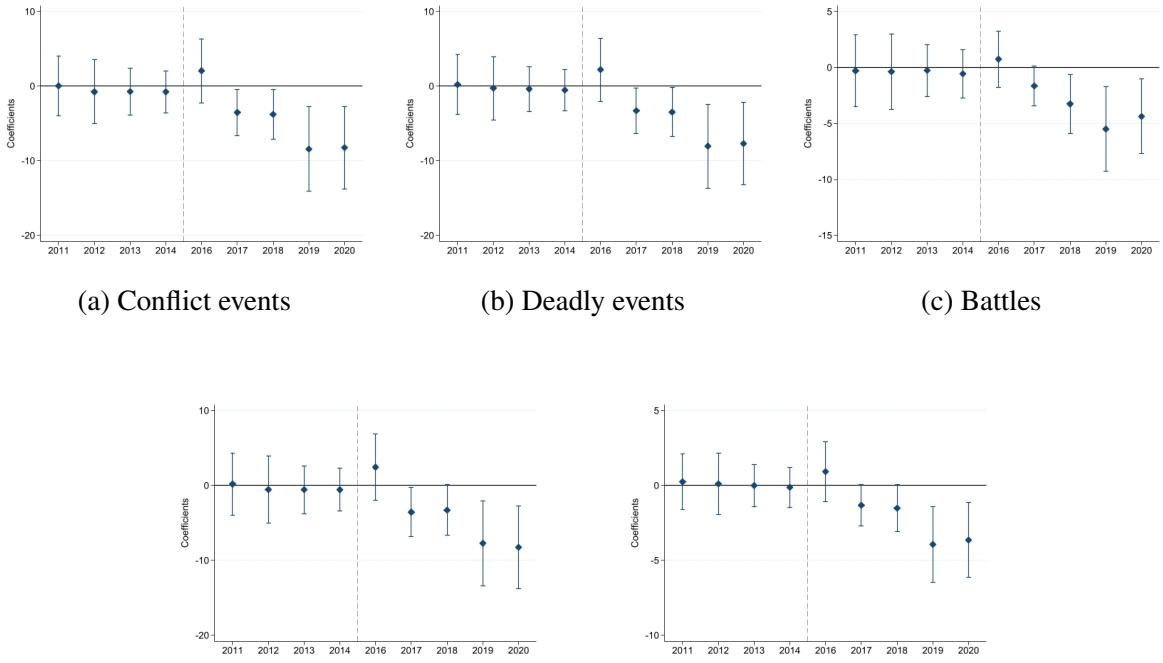
[7]The sample excludes three townships with highest Rohingya populations: Buthidaung, Maungtaw, and Yathedaung.

while excluding riots and protests. If the mining ban truly reduces conflict, its effect should persist under this stricter definition. Indeed, the estimates remain statistically significant and negative. The preferred specification (column 2, Appendix Table C11), which controls for covariates and includes fixed effects, yields a coefficient of –0.497, significant at the 5% level. Compared to the relative sample mean (0.38), this represents a 131% differential decrease in the number of conflict events. This percentage reduction in the number of conflict events using the UCDP dataset (131%) is even larger than my main result in column 1 of Table 32, which is based on the ACLED conflict dataset.

3.4.3 Event Study

Figure 35 presents the visualization for the estimates of the "event-study" regressions described by Equation 3.2, where I interact the treatment indicator with a set of indicators denoting years before and after the mining ban. In Figure 35a, the coefficients show the evolution of differences in the number of conflict events between townships with and without active mining licenses, relative to the omitted year 2015. The estimates are consistent with the timing of the mining ban. From 2011 to 2014, the coefficients are close to zero and statistically insignificant, supporting the assumption of parallel trends. Beginning in 2016—the year the moratorium on license renewals was introduced—the estimates decline steadily, indicating a growing post-treatment divergence between treated and control townships. This dynamic pattern supports the interpretation that the mining ban contributed to a substantial and significant decrease in conflict events. Similar patterns emerge for extreme conflict outcomes, including deadly events (Figure 35b), battles (Figure 35c), violent events (Figure 35d), and state-perpetrated violence (Figure 35e).

Appendix Figure C4 additionally shows the robustness of these event-study estimates using a Synthetic Difference-in-Differences specification (Arkhangelsky et al. 2021). For all conflict outcomes, including extreme conflict events, the coefficients are close to zero and statistically insignificant before the mining ban in 2016. However, the estimates dropped substantially and statistically significant after the mining ban.



(a) Conflict events (b) Deadly events (c) Battles

(d) Violent events (e) State-perpetrated violence

Figure 35: Mining Reform and Conflict: Event-Study Estimates. The graph plots the coefficients of event-study regressions described by Equation 3.2.

In summary, the results presented in Section 3.4 indicate that the mining ban leads to substantial declines in conflict events, including severe conflict outcomes such as deadly events, battles, violent events, and state-perpetrated violence. More importantly, these effects are not driven by pre-existing differential trends. The results are robust across multiple checks, including the use of Synthetic Difference-in-Differences(SDID), the removal of outliers, specifications without controls, district-level analysis, exclusion of Rohingya-affected townships, restricting analysis to minerals less susceptible to illegal extraction and smuggling, and using alternative conflict dataset (UCDP).

3.5 Further Results

Spillovers Building on the estimated average treatment effects, I investigate whether conflict dynamics in mining townships generate spillover effects in neighboring areas. Prior research, notably Berman et al. (2017), find that mining-related shocks can escalate conflict in adjacent regions, potentially driven by the movement of armed actors. To assess whether the observed reductions in conflict within mining townships are offset by increases in neighbor-

ing non-mining townships, I construct a binary indicator for townships adjacent to mining townships but lacking mining licenses. This specification facilitates a rigorous test for spatial displacement or spillover effects in conflict incidence.

Table 33 provides compelling evidence rejecting the spatial diffusion hypothesis following the 2016 mining license ban. The coefficient of the interaction between mining license status and the post-ban period (Year ≥ 2016) in column (1) is estimated at -5.442 and statistically significant at the 1% level, demonstrating a sizable decline in conflict incidents within mining townships. This negative effect persists uniformly across multiple measures of severe conflict—including deadly events, battles, violent events and state-perpetrated violence (columns 2–5)—indicating that the decline in conflict in treated townships is not attributable to spatial reallocation of violence to adjacent mining areas.

Table 33: Testing for spillovers in neighboring mining townships

	No. of conflicts	No. of deadly events	No. of battles	No. of violence	No. of state-violence
	(1)	(2)	(3)	(4)	(5)
Mining licenses × Year ≥ 2016	-5.442***	-5.417***	-3.292***	-5.291***	-2.586***
	(2.003)	(1.986)	(1.090)	(2.007)	(0.831)
Townships without mining next to	-5.813***	-5.952***	-2.843***	-5.804***	-2.414***
another mining townships × Year ≥ 2016	(1.838)	(1.827)	(1.009)	(1.825)	(0.794)
Fixed Effects	Yes	Yes	Yes	Yes	Yes
Controls × Year FE	Yes	Yes	Yes	Yes	Yes
Mean of Dependent Variable	5.67	4.70	2.75	4.50	2.06
Observation	3300	3300	3300	3300	3300

Note: The unit of observation is at the township level, and the study period covers 2011 to 2020. This table shows that the mining ban reduces conflict events in neighboring mining townships that do not have mining licenses. Townships that neighbor with mining townships but do not have mining licenses is a dummy taking the value 1. Conflict events include all types of events, including battles, explosions, strategic developments, violence against civilians (e.g., extrajudicial killings of unarmed prisoners of war and shooting), protests, and riots. Deadly conflict events include all types of events except protests and riots. Battles include clashes between Myanmar's military forces (the Tatmadaw) and ethnic militias, as well as clashes between different ethnic militias. Violent events are defined as conflict events that result in at least one fatality. State-perpetrated violence are conflict events initiated by the Tatmadaw and police forces. All regressions control for township fixed effects, year fixed effects and the interaction between year fixed effects and the following baseline characteristics: GDP per capita and population density. Standard errors, clustered at the township level, are in parenthesis. *, **, and *** indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

This investigation contributes a novel empirical perspective to existing theoretical and

empirical models that emphasize spatial displacement of conflict in response to shocks to resource extraction (e.g., Berman et al. 2017). Contrary to prior empirical findings, I find that the 2016 mining ban in Myanmar induced a significant spatial contraction of conflict. Specifically, townships adjacent to mining areas, but lacking mining licenses themselves, experienced statistically robust and substantively meaningful reductions in conflict events. The estimated coefficient on the interaction between adjacency to mining townships and the post-ban period (Year $\geq$ 2016) is -5.813 (column 1), significant at the 1% level, and comparable in magnitude to the direct treatment effect observed within mining townships. This pattern holds consistently across multiple categories of conflict—including deadly events, battles, violent events, and state-perpetrated violence (columns 2–5)—and remains robust to alternative model specifications that exclude control variables (Appendix Table C12).

These findings suggest a departure from standard spatial diffusion models of conflict, which predict that suppressed violence in one area tends to shift to neighboring regions through strategic adaptation by armed actors. Instead, reductions in conflict within mining townships are nearly mirrored by similar declines in adjacent untreated areas. For comparison, Berman et al. (2017) find that positive resource shocks produce conflict spillovers into neighboring regions amounting to roughly 40% of the direct effect. In contrast, I find that the negative shock from the mining ban led to conflict reductions in adjacent townships that are similar in magnitude to those observed in directly affected mining areas. This asymmetry implies that while positive shocks may incentivize armed expansion into nearby regions, negative shocks reduce the strategic value of surrounding areas, leading to a contraction in the spatial diffusion of violence.

A plausible interpretation of the effect of negative shocks centers on the economic incentives faced by armed actors. When resource extraction is active, neighboring territories may offer strategic value as additional extraction sites or logistical corridors. However, following the mining ban, non-mining areas—lacking rents or exploitable resources—provide limited economic incentives for continued conflict engagement. Consequently, rather than serving as targets for displacement, these areas become relatively unattractive for armed mobilization, contributing to a broader suppression of violence. This interpretation aligns with rationalist models of conflict in which the spatial distribution of rents fundamentally shapes the strategic calculus of armed groups.

Taken together, the evidence indicates that resource governance policies such as mining

bans can induce broad-based reductions in violence that extend well beyond the directly targeted areas. The spatial spillovers documented here are not only statistically significant but approach parity in magnitude with the direct effects observed in treated townships. These findings contribute novel insights into the general equilibrium consequences of policy interventions in fragile settings and underscore the critical importance of incorporating spatial externalities into the design and implementation of resource governance policies.

Heterogeneity effect I next examine whether the impact of the mining ban varies systematically with township characteristics. Table 34 presents estimates of treatment heterogeneity by ethnic homeland status, income-based poverty, remoteness (as proxied by road density), and coethnic representation in parliament.

Ethnic Homelands Columns (1) and (2) of Panel A examine how the effects of the mining ban differ between ethnic homelands and other regions. A township is classified as an ethnic homeland if more than 50% of its population identifies with ethnic groups other than the majority Burman group. I expect larger treatment effects in ethnic homelands with mining licenses, owing to two reinforcing mechanisms that heighten their vulnerability to resource-related conflict: first, mining revenues directly finance armed groups; second, extraction activities intensify grievances over the inequitable distribution of resource wealth.

First, mining activities in ethnic homelands directly finance armed conflict. Conflict events are substantially more prevalent in these areas (Appendix Table C1), driven by protracted disputes between ethnic armed groups and the Tatmadaw over resource control. Armed organizations systematically extract rents from mining operations, creating strong economic incentives for recruitment and sustained military capacity (Sahla 2018, Bissinger 2019, Global Witness 2015). These revenues underpin a self-reinforcing cycle in which resource wealth perpetuates violence (Woods 2019). By suspending legal mining concessions, the moratorium curtails revenue streams and disrupts formal supply chains—raising logistical costs, increasing operational risks, and constraining market access. Even in areas under de facto rebel control, where illicit extraction persists, these disruptions are likely to reduce overall output and profitability, thereby diminishing the rents available to sustain recruitment and operations.

Table 34: Heterogeneity effects across different conflict measures

	Ethnic Homeland		Poor Townships		Road Density		Co-ethnic Represent	
	Yes	No	Yes	No	High	Low	High	Low
Panel A: Conflict Events								
Mining Licenses × Year ≥ 2016	-10.82***	-0.301	-15.49***	-0.657	-1.041	-8.678***	-4.246**	-2.797
	(4.064)	(0.312)	(5.626)	(1.153)	(0.906)	(3.205)	(1.828)	(2.562)
p-value of difference	0.01		0.01		0.02		0.65	
Panel B: Deadly Events								
Mining Licenses × Year ≥ 2016	-10.84***	-0.110	-15.21***	-0.627	-1.083	-8.398***	-3.648**	-2.967
	(4.050)	(0.201)	(5.634)	(1.112)	(0.899)	(3.186)	(1.794)	(2.528)
p-value of difference	0.009		0.01		0.02		0.82	
Panel C: Battles								
Mining Licenses × Year ≥ 2016	-6.661***	-0.104	-8.038**	-0.859	-0.528	-5.221***	-1.875**	-2.500
	(2.236)	(0.136)	(3.143)	(0.589)	(0.485)	(1.791)	(0.895)	(1.559)
p-value of difference	0.004		0.02		0.01		0.72	
Panel D: Violent Events								
Mining Licenses × Year ≥ 2016	-10.54**	-0.116	-14.72**	-0.613	-0.981	-8.177**	-3.540**	-2.804
	(4.113)	(0.221)	(5.644)	(1.189)	(0.909)	(3.217)	(1.748)	(2.623)
p-value of difference	0.01		0.01		0.03		0.81	
Panel E: State-perpetrated Violence								
Mining Licenses × Year ≥ 2016	-5.177***	-0.113	-6.546***	-0.596	-0.476	-3.986***	-1.823**	-1.490
	(1.687)	(0.101)	(2.403)	(0.425)	(0.378)	(1.352)	(0.829)	(0.989)
p-value of difference	0.003		0.01		0.01		0.79	
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1260	2040	860	2440	1650	1649	1625	1675

Note: The unit of observation is at the township level, and the study period covers 2011 to 2020. Ethnic homelands equals to 1 if less than 50% of the population are reported to belong to the other ethnic groups, rather than the dominant Burma ethnic identity. Poor townships equal to 1 if townships' GDP falls below the 25th percentile of the distribution. High road density is equal to 1 if a township's road density is greater than or equal to the median value. Co-ethnic representation is equal to 1 if a township's co-ethnic representation in parliament is greater than or equal to the median. Conflict events include all types of events, including battles, explosions, strategic developments, violence against civilians (e.g., extrajudicial killings of unarmed prisoners of war and shooting), protests,and riots. Deadly conflict events include all types of events except protests and riots. Battles include clashes between Myanmar's military forces (the Tatmadaw) and ethnic militias, as well as clashes between different ethnic militias. Violence events are defined as conflict events that result in at least one fatality. State-perpetrated violence are conflict events initiated by the Tatmadaw and police forces. All regressions control for township fixed effects, year fixed effects, and the interactions between year fixed effects and the following baseline characteristics: GDP per capita and population density. Standard errors, clustered at the township level, are in parentheses. *, **, and *** indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

Second, existing studies find that mining activities generate grievances related to resource distribution (Collier & Hoeffler 1998, Humphreys 2005). This grievance dynamic is particularly acute in Myanmar's ethnic homelands—where the number of mining licenses is 16% above the national average and conflict incidence in ethnic homelands is over seven times

higher than in non-ethnic areas (Table 31; Appendix Table C1). These grievances are amplified by Myanmar's 2008 constitution, which channels nearly all natural resource revenues to the central government, leaving ethnic regions with minimal local reinvestment despite bearing the brunt of extraction (Bauer & Sahla 2018). The few benefits that remain locally are typically captured by small groups of connected elites, further exacerbating perceptions of economic injustice and ethnic marginalization. In this context, the unequal distribution of resource wealth not only deepens local resentment, but also provides compelling recruitment narratives for ethnic armed groups (Collier & Hoeffler 1998, Humphreys 2005). With less active mining operations generating wealth that flows to the central government and local elites, the perceived economic injustice that fuels ethnic armed movements could potentially be reduced. Therefore, I expect the mining ban to have particularly strong conflict-reducing effects in ethnic homelands, where both the financing and grievance mechanisms are most pronounced.

As expected, the mining ban's effects are stronger in ethnic homelands with active mining licenses. In Panel A, Column 1, the coefficient on "Mining Licenses × Year ≥ 2016" is –10.82 ($p < 0.01$), indicating an average annual reduction of 10.82 conflict events. The corresponding estimate for non-ethnic homelands (column 2 of Panel A) is smaller in magnitude and statistically insignificant. The difference in coefficients between the two is itself significant ($p = 0.01$), suggesting a substantially larger treatment effect in ethnic areas. Similar patterns are observed for more severe forms of violence: deadly events fall by 10.84 (Panel B), with the difference relative to non-ethnic areas significant at the 1% level; battles decline by 6.661 (Panel C); violent events by 10.54 (Panel D); and state-perpetrated violence by 5.177 (Panel E).

Poor Townships Columns (3) and (4) of Panel A explore the heterogeneity of treatment effects by focusing on poor townships ("poor" being defined as those with GDP per capita below the 25th percentile of the distribution) and non-poor townships. In line with theoretical expectations, I find that the conflict-reducing effect of the mining ban is significantly stronger in poor townships with mining licenses.

This finding aligns with a well-established literature linking natural resource extraction to conflict, particularly under conditions of economic inequalities or distributive grievance. Prior work has documented that conflict is more likely to arise when resource-rich communities remain economically marginalized or when revenues from extraction are captured by

elites and fail to translate into broad-based development (Caselli & Michaels 2013, Cust & Poelhekke 2015). Myanmar offers an illustrative example of this dynamic: poorer townships host 59 percent more mining licenses than wealthier ones, yet continue to exhibit persistent underdevelopment (Table 31). These poor townships experience 3.6 times more conflict events on average than non-poor townships (Appendix Table C1). The coexistence of visible extraction and absent development renders distributive grievances especially potent (Morelli & Rohner 2015).

These conditions not only erode trust in state institutions but may also increase the opportunity and motivation for insurgent recruitment. Theories of rebellion emphasize both material incentives ("greed") and perceived injustice ("grievance") as pathways to mobilization (Collier & Hoeffler 2004). Empirical evidence further suggests that resource-endowed yet economically excluded populations are more likely to engage in violent contestation over control or redistribution of resource rents (Berman et al. 2017). The 2016 mining ban disrupts this equilibrium. By suspending extractive activity, the policy removes a salient and tangible symbol of inequality: the outward flow of mineral wealth from marginalized communities without local benefit. In doing so, the ban may reduce the salience of distributive grievance and weaken the strategic appeal of rebellion.

The empirical results are consistent with this interpretation. In Panel A, Column (3) of Table 34, the coefficient on the interaction between mining licenses and the post-ban period (Year $\geq$ 2016) is -15.49 and statistically significant at the 1 percent level. This effect—equivalent to a reduction of over 15 conflict events per township-year—is economically large and sharply distinct from the effect in non-poor townships (column 4), where the estimated coefficient is close to zero (-0.657, not statistically significant). The p-value for the difference between these two coefficients is 0.01, indicating that the post-ban conflict reduction is significantly more pronounced in poorer areas.

This heterogeneity persists across all extreme conflict outcomes. In Panels B through E, poor townships experience significantly larger post-ban declines in deadly events (-15.21), battles (-8.038), violent events (-14.72), and state-perpetrated violence (-6.546), with all coefficients statistically significant. In each case, the estimated effects for non-poor townships are small in magnitude and statistically insignificant. The differences between poor and non-poor townships are statistically significant across all violence measures ($p \leq 0.02$ in each case). These consistent patterns strengthen the conclusion that the conflict-reducing impact

of the ban is stronger in poor, resource-rich localities.

Together, these results offer two key contributions. First, they provide empirical support for grievance-based theories of conflict, demonstrating that distributive asymmetries around resource extraction can generate violence. Second, they suggest that even temporary policy interventions—if they alter the material or symbolic distribution of resource rents—may meaningfully reduce risk of conflict. In this setting, the mining ban served not only to regulate extraction activities, but also to attenuate grievances arising from the perceived inequity of resource distribution.

Remote Townships In columns (5) and (6) of Panel A, I explore heterogeneity by township remoteness, measured by road density. Following Fearon & Laitin (2003), Chow & Han (2024), who emphasize the strategic advantages remote, mountainous terrain offers to insurgent groups, I classify townships as remote if their road density falls below the median and non-remote otherwise. As shown in the summary statistics, remote areas in Myanmar not only exhibit significantly higher baseline levels of conflict but also host a disproportionate share of mining licenses (Appendix Table C1, Table 31). These zones, often characterized by poor infrastructure and limited state presence, are key arenas where ethnic armed groups and the Tatmadaw compete for control over high-value mineral rents and trade routes (Global Witness 2015).

Given these dynamics, I expect the mining ban to have larger conflict-reducing effects in remote areas, where extractive rents are a central driver of armed group activity. The results support this expectation. The interaction coefficient between mining licenses and the post-ban period (Year $\geq$ 2016) is –8.678 and statistically significant at the 1 percent level in remote townships (column 6). This represents a substantial drop in conflict events and suggests that the mining ban disrupted revenue flows crucial to sustaining violent competition in these hard-to-govern areas. The p-value for the difference in treatment effects between remote and non-remote townships is 0.02, indicating that the heterogeneity is both economically and statistically significant.

This pattern extends across multiple dimensions of conflict. In Panels B through E, remote townships see significantly greater declines in deadly incidents, battles, violent events, and state-perpetrated violence. The magnitudes are sizable, reinforcing the notion that remoteness magnifies the ban's pacifying effect by targeting a core economic incentive for insurgency.

Townships with High Co-Ethnic Representation Columns (7) and (8) of Panel A examine

whether the mining ban's conflict-reducing effects vary by the degree of co-ethnic political representation in parliament. I define high co-ethnic representation as townships in which the share of ethnic minority MPs exceeds the median level. The underlying hypothesis, drawn from a broad literature on political inclusion and conflict, is that co-ethnic representation may enhance perceived legitimacy of state actions and reduce grievances (Mansbridge 1999, Reynal-Querol 2002, Saideman et al. 2002).

The results show limited evidence for such a mechanism. Across all conflict measures—including conflict events, deadly incidents, battles, violent events, and state-perpetrated violence—the differential effects between high and low co-ethnic representation townships are statistically insignificant. This suggests that the presence of co-ethnic MPs does not meaningfully contributes to the ban's overall impact on conflict events.

The findings imply that descriptive representation—i.e., having MPs who share the same ethnic background as their constituents—may not suffice to mitigate violence unless it is accompanied by substantive influence over policy. In the Myanmar context, many ethnic minority MPs were elected under the banner of the National League for Democracy (NLD), a party often criticized for its centralized, Bamar-dominated leadership and limited responsiveness to ethnic minority demands (Egreteau & Mangan 2018). This mismatch between nominal representation and actual political empowerment underscores a key tension in post-conflict institutional design.

These findings contribute to the growing literature distinguishing between descriptive and substantive representation in divided societies (Wängnerud 2009, Lowande et al. 2019). While prior studies highlight the promise of co-ethnic representation in reducing group-based grievances, my results indicate that the conflict-reducing benefits hinge critically on the quality of representation. Simply electing ethnic minority MPs may not defuse conflict if those representatives lack real influence over distributive policy or fail to deliver perceived gains to their constituencies.

In general, the results show that the estimated effects are concentrated in ethnic homelands, poor townships, and townships with low road density (remote townships). These results extend to extreme conflict events, including deadly events, battles, violent events, and state-perpetrated violence. However, differential effects by coethnic representation are generally small and insignificant. This suggests that descriptive representation, i.e. having lawmakers who share the same ethnic background, may not suffice to mitigate violence

without substantive policy influence. My results remain robust without controls (Appendix Table C13) .

Mineral prices A potential concern for the identification strategy is that changes in conflict may partly reflect exogenous income shocks driven by fluctuations in world mineral prices. Prior work, such as Dube & Vargas (2013), has shown that commodity price booms can fuel conflict by increasing the value of contestable resources. Over the study period, the global prices of copper, coal, and antimony rose notably (Appendix Figure C5). To account for this, I include interactions between global prices and indicators for local deposits of each mineral.

Table 35: Mineral prices

	No. of conflicts	No. of deadly events	No. of battles	No. of violence	No. violent by the State
	(1)	(2)	(3)	(4)	(5)
Mining Licenses × Year ≥ 2016	-3.978**	-3.888**	-2.541***	-3.790**	-0.205*
	(1.589)	(1.571)	(0.861)	(1.600)	(0.113)
CopperPrice × Copper Deposit	0.00008	0.0002	-0.00009	0.0001	-0.000003
	(0.0004)	(0.0003)	(0.0001)	(0.0003)	(0.00002)
AntimonyPrice × Antimony Deposit	0.0002	0.0002	0.0001	0.0003	-0.00001
	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.00002)
CoalPrice × Coal Deposit	-0.003	-0.003	-0.002	-0.003	0.0001
	(0.004)	(0.004)	(0.002)	(0.004)	(0.0001)
Fixed Effects	Yes	Yes	Yes	Yes	Yes
Controls × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Mean of Dependent Variable	5.67	4.70	2.75	4.50	2.06
Observation	3300	3300	3300	3300	3300

Notes: The unit of observation is at the township level, and the study period covers 2011 to 2020. This table shows that the mining ban reduces conflict events from 2011 to 2020, when controlling for the potential effects of mineral prices. Conflict events include all types of events, including battles, explosions, strategic developments, violence against civilians (e.g., extrajudicial killings of unarmed prisoners of war and shooting), protests,and riots. Deadly conflict events include all types of events except protests and riots. Battles include clashes between Myanmar's military forces (the Tatmadaw) and ethnic militias, as well as clashes between different ethnic militias. Violent events are defined as incidents that result in at least one fatality. State-perpetrated violence are incidents initiated by the Tatmadaw and police forces. All regressions control for township fixed effects, year fixed effects and the interaction between year fixed effects and the following baseline characteristics: GDP per capita and population density. Standard errors, clustered at the township level, are in parenthesis. *, **, and *** indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

Table 35 presents the results. Column (1) shows number of conflict events, while columns (2) through (5) break this down into different forms of extreme violence. Across all specifications, the coefficient on the interaction between mining licenses and the post-2016 period

(Year ≥ 2016) remains negative and statistically significant. This suggests that the mining reform is associated with reductions in conflict even when accounting for contemporaneous mineral price trends.

In contrast, the interaction terms between mineral prices and corresponding deposits are statistically insignificant and close to zero across all conflict outcomes, suggesting that short-term fluctuations in mineral prices were not the primary drivers of local conflict intensity during this period.

While prior work has shown that global commodity price shocks can exacerbate conflict by increasing the value of contestable resources (Dube & Vargas 2013), these findings suggest that significant reforms in resource governance—such as the mining license ban—can exert an independent and potentially stronger effect on local violence. By reducing contestation over access to resource rents, such policy shocks may help mitigate some of the destabilizing effects commonly associated with natural resource wealth.

3.6 Mechanisms

I now study the potential mechanisms that might explain the relationship between the mining ban and conflicts (Appendix Table C15). I rely on the framework of Dube & Vargas (2013), which distinguishes between rapacity and opportunity cost channels, complemented here by a grievance channel relevant to Myanmar's context.

Rapacity Effects Dube & Vargas (2013) identifies the rapacity channel as a key mechanism through which resource wealth exacerbates conflict. Specifically, rising commodity prices, including those for oil, generate substantial rents that armed groups can appropriate to finance operations and sustain combatants. This theory aligns with broader findings that higher rents from valuable commodities intensify conflict by lowering the financial constraints on insurgency (Collier & Hoeffler 2004, Humphreys 2005, Berman et al. 2017, Crost & Felter 2020). In the case of Myanmar, high-value minerals such as jade and gold generate significant revenues that armed groups rely on to fund their activities and maintain territorial control (Woods 2019, Bauer & Sahla 2018). By restricting the production and trade of these commodities, a mining ban can substantially reduce the mineral rents available to local armed actors, thereby weakening their financial capacity and potentially mitigating conflict.

Column (4) of Appendix Table C15 shows that the mining ban is associated with a statisti-

cally significant decrease in the production of high-value commodities. These commodities, such as jade and gold, reflect the potential rents extractable in a given period, and serves as a proxy for the financial resources accessible to armed groups. The observed decline following the ban provides supportive evidence for the rapacity mechanism: by curbing the value of extractable resources, the policy plausibly restricts the ability of armed groups to finance and sustain violent operations. Consistent with this transmission channel, Table 32 documents a concurrent reduction in extreme conflict events, including the number of armed battles. These effects emerge immediately after the ban and persist for three years, indicating a sustained contraction in the economic base for armed groups financing.

I extend the rapacity channel framework to a context where the state plays a central role not only in policy reform but also in perpetrating violence. Although most studies focus on two-sided conflicts and exogenous price shocks, I analyze a state-imposed mining ban as a negative resource shock to examine whether it reduces incentives for violence, particularly state-perpetrated violence, by lowering contestable rents. The key idea is that when the mining ban reduces the accessibility to mineral rents, it simultaneously reduces the value of contested territories, creating fewer incentives for state violence. Consistent with this extended rapacity mechanism, I find that the mining ban reduces state-perpetrated violence, suggesting that contractions of resource extraction could constrain state coercion just as resource abundance fuels it.

Opportunity cost effect Dube & Vargas (2013) show that a fall in coffee prices lowered wages and increased violence by raising incentives to join armed groups through the opportunity cost channel. Similarly, I expect the mining ban, which primarily affected short-term small-scale licenses, to operate through the same channel by shifting labor toward alternative sectors. This reallocation to productive sectors could increase the economic cost of joining armed groups and reduce individuals' incentives to participate in violence. To evaluate whether this mechanism contributed to the observed decline in conflict following the mining ban, I analyze district-level employment shares from the 2014 and 2018 Censuses across agriculture, services, and manufacturing sectors. Given the data limitations—only two time points and aggregation at a relatively coarse spatial level—these findings should be regarded as suggestive.

Columns (1)–(3) of Appendix Table C15 show that following the mining ban, employment shares increased in agriculture and manufacturing but declined in services. This pattern

parallels national economic trends in 2018, when agricultural and industrial output grew modestly while the service sector experienced a slight decline.[8] One plausible explanation is labor reallocation: displaced mining workers may shift to sectors with lower entry costs and fewer regulatory barriers, which demand less capital investment and offer more accessible employment opportunities.

The nature of mining operations affected by the ban is crucial for understanding the employment reallocation patterns. Minerals such as jade, gems, and gold were predominantly extracted under short-term licenses lasting one to two years. This mining is extremely labor intensive, involving manual extraction techniques that employ a large number of workers with minimal skill requirements and low entry barriers. When these licenses expired and were not renewed due to the ban, it displaced workers from small-scale operations who possessed transferable skills suitable for other labor-intensive sectors such as agriculture and small-scale informal manufacturing.

Employment patterns also differ markedly across regions. Services are concentrated in urban centers like Yangon and Mandalay, while rural areas—where mining activity was concentrated—are dominated by agriculture and informal manufacturing. This spatial variation is critical to understanding how displaced mining workers were absorbed into the local labor market.

In these rural settings, agriculture and small-scale manufacturing likely served as primary absorbers of displaced labor. These sectors' low fixed costs, limited regulatory friction, and accessible inputs such as land and family labor make them well-suited to provide employment opportunities. Moreover, the reduction in mining-related conflict may have improved local perceptions of safety and stability, encouraging investment and labor demand in sectors with relatively low barriers to entry. Such labor reallocation could have softened the short-term economic shock and increased the opportunity cost of the rebellion, offering a channel linking the mining ban to the observed reduction in conflict. Even though Crost & Felter (2020) do not observe employment effects after mining expansions, I find suggestive evidence for this mechanism two years after the mining ban. This difference may reflect the nature of the shocks: large-scale mining expansions are capital-intensive and create few jobs, whereas the mining ban in Myanmar primarily affected labor-intensive small-scale mining, creating

[8] Myanmar's agriculture sector grew from 0.1% to 1.6%, industry from 8.3% to 9.4%, and services contracted from 8.7% to 8.3% (Basu 2021).

stronger incentives for labor reallocation. However, the disaggregated employment data (measured in 2014 and 2018) does not allow me to assess the precise time of the labor allocation.

Grievances In settings characterized by weak institutions and limited accountability, extraction of natural resources often generates concentrated rents that exacerbate local inequality and increase the risk of conflict (Caselli & Michaels 2013, Monteiro & Ferraz 2010, Bazillier & Girard 2020). In Myanmar, extractive industries have historically operated under opaque governance, with revenues flowing primarily to military-linked conglomerates and political elites. Local communities, especially in regions of ethnic minorities, rarely benefit from these rents (Smith et al. 1994). Qualitative evidence indicates that residents in mining areas often perceive themselves as economically marginalized and excluded from resource wealth (Myanmar Peace Monitor 2013), which can increase the likelihood of armed group recruitment.

To assess this grievance channel, I examine the impact of the mining ban on local income inequality, proxied by the Gini coefficient. Column (5) of Appendix Table C15 shows a negative and statistically significant effect of the ban on the Gini coefficient (–0.013, significant at the 5 percent level). This effect is observed two years after the mining ban in 2018, suggesting a gradual erosion of elite mining rents that reduced income concentration at the top and compressed inequality, but it is no longer statistically significant in 2019, indicating a temporary post-ban adjustment.

Reduced inequality may dampen mobilization incentives by narrowing the material and perceived gap between elites and local communities. Prior research links high inequality, especially when combined with resource extraction and weak redistribution, to heightened conflict risk (Caselli & Michaels 2013, Cust & Poelhekke 2015). In this context, the observed decline in inequality likely mitigated grievances and constrained armed group recruitment. More broadly, this disruption may have weakened armed groups' and local elites' ability to extract rents, redistribute patronage, and sustain informal governance structures. In many conflict-affected areas, armed actors maintain authority not only through violence but also by controlling resource flows and delivering public goods, a phenomenon described as "rebelocracy" (Arjona 2016). Similarly, access to fiscal rents underpins quasi-state capacity in fragile settings, enabling governance and coercion (Besley & Persson 2011). By cutting off key revenue streams, the mining ban may have undermined both the motivations and

organizational capacity for mobilization and territorial control. These dynamics complement grievance-based accounts by linking distributive shocks to both the incentives and the means for armed conflict.

In sum, I examine three mechanisms through which the mining ban may reduce conflict. First, the rapacity effect cuts off financing for armed groups: the ban reduced high-value commodity production, limiting the capacity of armed groups to fund operations in a context where Myanmar's armed groups are heavily dependent on mineral rents. Second, the opportunity cost effect shows suggestive evidence of labor reallocation, as displaced mining workers shifted toward agriculture and manufacturing with lower entry barriers, potentially increasing the economic cost of rebellion. Third, given long-standing ethnic grievances in Myanmar, I explore the grievance mechanism. I find that the ban led to a reduction in inequality by 0.004 percentage points two years after its implementation, likely through the gradual erosion of elite mining rents. This reduction in income concentration may have dampened mobilization incentives.

3.7 Alternative Accounts

In this section, I evaluate two plausible alternative explanations for the observed reduction in conflict following the mining ban: (1) the change in national political leadership after the 2015 general election, and (2) the implementation of Community Driven Development (CDD) programs. I present empirical evidence that is inconsistent with these alternative accounts, thereby supporting the claim that the mining ban itself is the primary driver of the conflict reduction.

First, I examine whether the observed decline in conflict following the mining ban may instead reflect the broader political realignment brought about by the 2015 general election, when the National League for Democracy (NLD) secured a sweeping victory and assumed national power for the first time. To address this, Panel A of Table 36 disaggregates the results by township-level NLD vote share. The specification includes an interaction between NLD vote share and the post-ban period (Year $\geq$ 2016), allowing for differential trends across townships. The results in columns (1) through (5) show that the mining ban significantly reduces all conflict measures even after controlling for the NLD vote share. The coefficients of "Mining Licenses $\times$ Year $\geq$ 2016" remain large, negative, and statistically significant,

indicating that the mining ban consistently reduces all conflict measures even when accounting for political changes.

Table 36: Alternative Accounts

	No. of conflicts	No. of deadly events	No. of battles	No. of violence	No. of state-violence
	(1)	(2)	(3)	(4)	(5)
Panel A: Support for National League for Democracy (NLD)					
Mining Licenses × Year ≥ 2016	-4.053***	-3.976**	-2.563***	-3.875**	-1.983***
	(1.556)	(1.541)	(0.855)	(1.572)	(0.641)
Vote share for NLD × Year ≥ 2016	-9.596***	-9.368***	-4.130***	-8.895***	-3.433***
	(2.630)	(2.625)	(1.446)	(2.639)	(1.119)
Panel B: Townships with Community Driven Development Projects					
Mining Licenses × Year ≥ 2016	-3.909**	-3.835**	-2.501***	-3.734**	-1.931***
	(1.572)	(1.553)	(0.849)	(1.582)	(0.637)
CDD Townships × Year ≥ 2016	-0.817	-1.357	-0.913	-2.045	-0.727
	(2.625)	(2.598)	(1.612)	(2.667)	(1.212)
Fixed Effects	Yes	Yes	Yes	Yes	Yes
Controls × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Mean of Dependent Variable	5.67	4.70	2.75	4.50	2.06
Observations	3300	3300	3300	3300	3300

Note: The unit of observation is at the township level, and the study period covers 2011 to 2020. Panel A explores NLD government's vote share and Panel B looks at Townships with Community Driven Development (CDD) program. Conflict events include all types of events, including battles, explosions, strategic developments, violence against civilians (e.g., extrajudicial killings of unarmed prisoners of war and shooting), protests,and riots. Deadly conflict events include all types of events except protests and riots. Battles include clashes between Myanmar's military forces (the Tatmadaw) and ethnic militias, as well as clashes between different ethnic militias. Violent events are defined as incidents that result in at least one fatality. State-perpetrated violence are incidents initiated by the Tatmadaw and police forces. All regressions control for township fixed effects, year fixed effects and the interaction between year fixed effects and the following baseline characteristics: GDP per capita and population density. Standard errors, clustered at the township level, are in parenthesis. *, **, and *** indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

Second, I investigate whether the observed reductions in conflict may instead be attributable to concurrent development initiatives, specifically Community Driven Development (CDD) programs, which aimed to improve local infrastructure and community welfare

and were implemented in some townships during the same period. To disentangle the effect of the mining ban from these development efforts, I include controls for the interaction between CDD townships and the post-ban period (CDD Townships $\times$ Year $\geq$ 2016). As shown in columns (1) through (5) of Panel B, the coefficients of this interaction are consistently negative but statistically insignificant across all conflict measures, suggesting that CDD programs do not account for the observed conflict reduction. Crucially, the coefficients of "Mining Licenses $\times$ Year $\geq$ 2016" remain large, negative, and statistically significant even after controlling for CDD programs. These findings suggest that the mining ban itself is the primary driver of reduced violence.

In sum, the evidence indicates that the observed reduction in conflict following the mining ban cannot be explained by alternative factors, including the political transition after the 2015 election or the implementation of Community Driven Development programs. These results are robust to the exclusion of additional controls (Appendix Table C17), indicating that the mining ban itself is the principal driver of the decline in conflict.

3.8 Conclusion

While a rich literature links natural resource extraction to violent conflict in fragile states (Collier & Hoeffler 1998, Fearon 2003, Ross 2006, Berman et al. 2017), far less is known about the consequences of curtailing extraction. This paper addresses this gap by examining whether reducing access to natural resources alters local conflict dynamics. Exploiting Myanmar's 2016 nationwide ban on new mining licenses—a setting characterized by substantial mineral wealth and protracted armed violence, I provide novel evidence on the causal impact of restricting resource extraction on conflict, including state-perpetrated conflict. I find that the mining ban significantly reduced conflict events by roughly 69 percent after 2016. This effect holds across various types of violence, including deadly events, armed battles, violent events, and state-perpetrated attacks. Moreover, the reduction in conflict intensifies over time after the ban as more licenses expire.

The decline in conflict following the mining ban appears to operate through multiple mechanisms. First, by reducing high-value mineral production, the ban limits the financial resources available to armed groups, thereby constraining their capacity to sustain violence (the rapacity effect). Second, the ban induces labor shifts toward agriculture and manufactur-

ing sectors, increasing the opportunity cost of engaging in conflict. Third, the ban contributes to a modest reduction in income inequality, which may alleviate economic grievances that often underlie ethnic tensions. Together, these channels suggest that resource governance reforms can alter the economic and social dynamics that sustain violence.

The primary contribution of this paper is deepening our understanding of how resource governance reforms affect civil conflict. The findings have important policy implications, especially for governments that have been trying to address violent conflict in low- and middle-income countries. First, the evidence suggests that a shift toward a less extractive policy regime can significantly reduce violence, even when the state itself is a key perpetrator of conflict. This underscores the potential for resource governance reforms to serve as a direct tool for mitigating violence and improving welfare outcomes in resource-rich, highly fragile contexts.

Second, while resource extraction ban may reduce conflict locally, the spatial dynamics of positive spillovers to neighboring regions presents important policy complications. However, the evidence here suggests that conflict does not relocate but may even decline in adjacent non-mining areas, indicating that well-designed reforms can generate broader peace dividends. Policymakers must remain vigilant, though, to the risk of unintended consequences, ensuring that reform efforts are paired with coordinated regional strategies to sustain and amplify conflict reduction.

Third, the analysis shows that the conflict-reducing effects of the mining ban are most pronounced in ethnic homelands, where political exclusion has historically fueled grievances. Crucially, the results indicate that co-ethnic representation alone is not sufficient to reduce violence; rather, inclusive governance must translate into substantive policy influence and decision-making power for marginalized groups. Strengthening institutions to ensure equitable political participation is therefore essential to resolving ethnic tensions tied to resource control.

Finally, the mining ban appears to encourage economic diversification by promoting a shift toward more stable and inclusive sectors such as agriculture and manufacturing. Supporting such diversification can provide more widespread employment opportunities and help alleviate economic grievances linked to resource dependence, contributing to more durable peace and development in resource-rich regions.

This study delivers a nuanced and hopeful message for policymakers addressing con-

flict in resource-rich, fragile settings. It shows that curtailing extractive activities can yield substantial peace dividends. However, sustaining these gains depends critically on complementary, often challenging reforms, including strengthening inclusive political institutions and fostering economic diversification. More broadly, the results question the conventional deterministic view that links resource wealth inexorably to conflict, demonstrating that strategic resource governance can serve as an effective instrument for conflict mitigation. These findings open avenues for future theoretical and empirical research on the nexus between resource governance, institutional reforms, and conflict dynamics.

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Appendix A

Appendix for Chapter 1

A.1 Additional Tables and Figures

Table A1: Costs and benefits of not burning and selling crop residues

Description	**USD (per acre)**	**USD (2.11 acres/average farm size in the study)**
Private benefit(selling price for residues at biogas market)	9.79	20.65
Private cost (capital rental fee/compressing fee)	36.12	76.21
Private cost (transport fee to biogas market)	2.19	4.62
Social benefits of avoiding PM2.5 pollution	159	335
Private benefit - Private cost	**-28.52**	**-60.18**

Note: This table presents costs and benefits of selling rice residues at biogas market. Private benefits are based on residue production in the study area for 2023. The benefits could be higher under normal weather conditions, since farmers in 2023 were affected by extreme heat waves that affected rice and rice residue production in Thailand. Additionally, transport costs are probably lower because farmers pool their residues for market sales. The social cost of PM2.5 from agricultural burning is estimated at USD 3.1 billion (Junpen et al. 2018, Thailand Environment Institute 2021). Given Thailand's 19.52 million acres of rice-growing areas, this translates into a marginal cost of about USD 159 per acre (Cheewaphongphan et al. 2018).

Table A2: Attrition

	(1)
	Attrition
Treatment	-0.00197
	(-0.47)
Sample Mean	0.005
Observations	1024

Note: This table shows that attrition does not differ significantly between treatment and control groups. Standard errors in parentheses are clustered at the village level. *, **, and *** indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

Table A3: Alternative specifications:Effects of capital rental subsidy on crop burning

	Crop Residue Burning								
	OLS			OLS + ANCOVA			OLS + Socio. Controls		
	PlanetScope	Sentinel2	Verification	PlanetScope	Sentinel2	Verification	PlanetScope	Sentinel2	Verification
Treatment	-0.139**	-0.143**	-0.172***	-0.100**	-0.101**	-0.123***	-0.138**	-0.138**	-0.173***
	(0.056)	(0.056)	(0.057)	(0.042)	(0.041)	(0.038)	(0.057)	(0.057)	(0.058)
Socio. Controls	No	No	No	No	No	No	Yes	Yes	Yes
Baseline Outcome	No	No	No	Yes	Yes	Yes	No	No	No
Control mean	0.30	0.33	0.36	0.30	0.33	0.36	0.30	0.33	0.36
Observations	1024	1024	1024	1024	1024	1024	1024	1024	1024

Note: This table presents the effects of the capital rental subsidy across different specifications. Columns (1) to (3) display the Ordinary Least Squares (OLS) estimates derived from Equation (1) without controlling for sociodemographic factors or baseline crop burning measure, using Analysis of Covariance (ANCOVA). Columns(4) to (6) include sociodemographic controls selected through a double-selection LASSO procedure (Belloni et al. 2014). Columns (7) to (9) control for baseline crop burning measure using Analysis of Covariance (ANCOVA). Standard errors in parentheses are clustered at the village level. *, **, and *** indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

Table A4: Consistency between three data sources

	Burn_PlanetScope	Burn_PlanetScope	Burn_Sentinel2
Burn_Sentinel2	0.937***		
	(0.014)		
Burn_Verification		0.817***	0.865***
		(0.042)	(0.041)
R-squared	0.89	0.73	0.81
Observation	1024	1024	1024

Note: This table shows the consistency between the three data sources: PlanetScope satellite, Sentinel-2 satellite, and ground-truth observation. All columns control for baseline characteristics such as income, gender, number of plots, land size, agricultural experience, agricultural workers, and tenure status. Standard errors in parentheses are clustered at the village level. *, **, and *** indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

Table A5: Other Indices: Effects of capital rental subsidy on crop burning

	Burn_PlanetScope	Burn_Sentinel2
Treatment	-0.076*	-0.076*
	(0.043)	(0.045)
Control Mean	0.30	0.29
Observations	1024	1024

Note: This table uses alternative indices to detect burned areas and reports the effects of the capital rental subsidy on crop residue burning. Column (1) uses Burn Area Index (BAI) from PlanetScope and column (2) uses Mid Infrared Bispectral Index (MIRBI) from Sentinel-2 imagery. Columns (1) and (2) display OLS estimates from Equation (1), controlling for baseline outcome using ANCOVA. Sociodemographic controls are included using double-selection LASSO (Belloni et al. 2014). Standard errors in parentheses are clustered at the village level. *, **, and *** indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

Table A6: Heterogeneous impacts using other data sources

	Crop residue burning							
	Sentinel-2 satellite				Field verification			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	-0.011	-0.094**	-0.086**	-0.058	-0.050	-0.110***	-0.114***	-0.089**
	(0.051)	(0.041)	(0.043)	(0.050)	(0.050)	(0.033)	(0.038)	(0.043)
High finance constraint	0.075**				0.077**			
	(0.032)				(0.037)			
Treatment × High finance constraint	-0.108**				-0.086*			
	(0.049)				(0.052)			
High distance constraint		0.012				0.035		
		(0.063)				(0.053)		
Treatment × High distance constraint		-0.012				-0.021		
		(0.072)				(0.062)		
High information constraint			0.038				0.021	
			(0.047)				(0.040)	
Treatment × High information constraint			-0.066				-0.036	
			(0.056)				(0.049)	
High age group				0.034				0.018
				(0.030)				(0.028)
Treatment × High age group				-0.084*				-0.063*
				(0.044)				(0.038)
Control Mean	0.32	0.32	0.32	0.32	0.37	0.37	0.37	0.37
Observation	1024	1024	1024	1024	1024	1024	1024	1024

Note: This table reports heterogeneous effects of the capital rental subsidy on crop burning based on two data sources: Sentinel-2 Satellite and ground field verification. Each column displays the Ordinary Least Squares (OLS) estimates derived from Equation (1), which incorporates treatment arm indicator and controls for baseline measures of the respective dependent variables using Analysis of Covariance (ANCOVA). Sociodemographic controls are based on a double-selection LASSO procedure (Belloni et al., 2014). High financial constraint equals 1 if a farmer's baseline savings are at or below the sample mean. High distance constraint equals 1 if the average baseline distance from the farm to the factory, road, and capital city is at or above the sample mean. High information constraint equals 1 for farmers with knowledge gaps at or above the sample mean regarding CRM practices and equipment rental locations. High age group equals 1 if the respondent's age is greater than or equal to the sample mean, and 0 otherwise. Standard errors in parentheses are clustered at the village level. *, **, and *** indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

Table A7: Spillover effect (Sentinel-2 satellite)

	Sentinel-2 imagery			
	Burn (main neighbors plots)	Burn (all neighbors' plots)	Burn (nonoverlap plots)	Burn (big plots)
Treatment	-0.117**	-0.087**	-0.074**	-0.033**
	(0.047)	(0.042)	(0.033)	(0.016)
Control Mean	0.31	0.35	0.31	0.89
Observation	1024	1024	973	1024

Note: This table presents the effect of the capital rental subsidy on crop burning of respondents' neighbors and owners of large-scale rice fields. Each column displays OLS estimates from Equation (1) with treatment arm indicator, baseline measures of the respective dependent variable (ANCOVA), and sociodemographic controls selected through a double-selection LASSO procedure (Belloni et al. 2014). Main neighbors' plots are those with whom respondents interacted most often, including on agricultural matters. Non-overlap plots refer to neighbors' plots that were not recipients of the intervention. Big plots or Large-scale rice plots are defined as those with a cultivation area greater than 2.4 hectares. Standard errors in parentheses are clustered at the village level. *, **, and *** indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

Table A8: Wild-bootstrapped t-statistics

	(1)	(2)	(3)
	Burn_PlanetScope	Burn_Sentinel2	Burn_Verification
Treatment	-0.100**	-0.101**	-0.123***
	(0.042)	(0.043)	(0.039)
Control Mean	0.31	0.32	0.37
Observation	1024	1024	1024

Note: This table presents the effect of the capital rental subsidy on crop burning from three data sources: PlanetScope satellite, Sentinel-2 satellite, and ground field verification. Each column displays the Ordinary Least Squares (OLS) estimates derived from Equation (1), which incorporates treatment arm indicator and controls for baseline measures of the respective dependent variables using Analysis of Covariance (ANCOVA). Sociodemographic controls are included based on a double-selection LASSO procedure (Belloni et al. 2014). Standard errors in parentheses are clustered at the village level. *, **, and *** indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

Table A9: Cost-effectiveness of the program in terms of averting CO_2 emissions

Amount of delayed CO_2 emissions for the study area				
No	**Description**	**Total**	**Unit**	**Remark**
1	Areas that are not burned (PlanetScope satellite)	1565	acre	
2	CO_2 emissions per acre	2.81	ton	Junpel et al (2018)

Program costs per ton of delayed CO_2 emissions for the study area				
1	Average payment per acre (account for spillover effects)	4	USD/ per acre	Exclude monitoring costs
2	Total program cost	6262	USD	4 USD * 1565 acre
3	Total CO_2 emissions	4400	ton	2.81 ton * 1565 acre
	Cost per ton of CO_2 averted	1.42	USD/ton	USD 6262/4400 ton

Social benefit per ton of delayed CO2 emissions				
1	EU carbon market price (2025)	77	USD /per ton	European Union Emissions Trading System (EU ETS)
2	Cost per ton of CO_2 averted	1.42	USD/per ton	
	Cost-effectivness	54.22		USD 77 / USD 1.42

Table A10: Attributes and levels

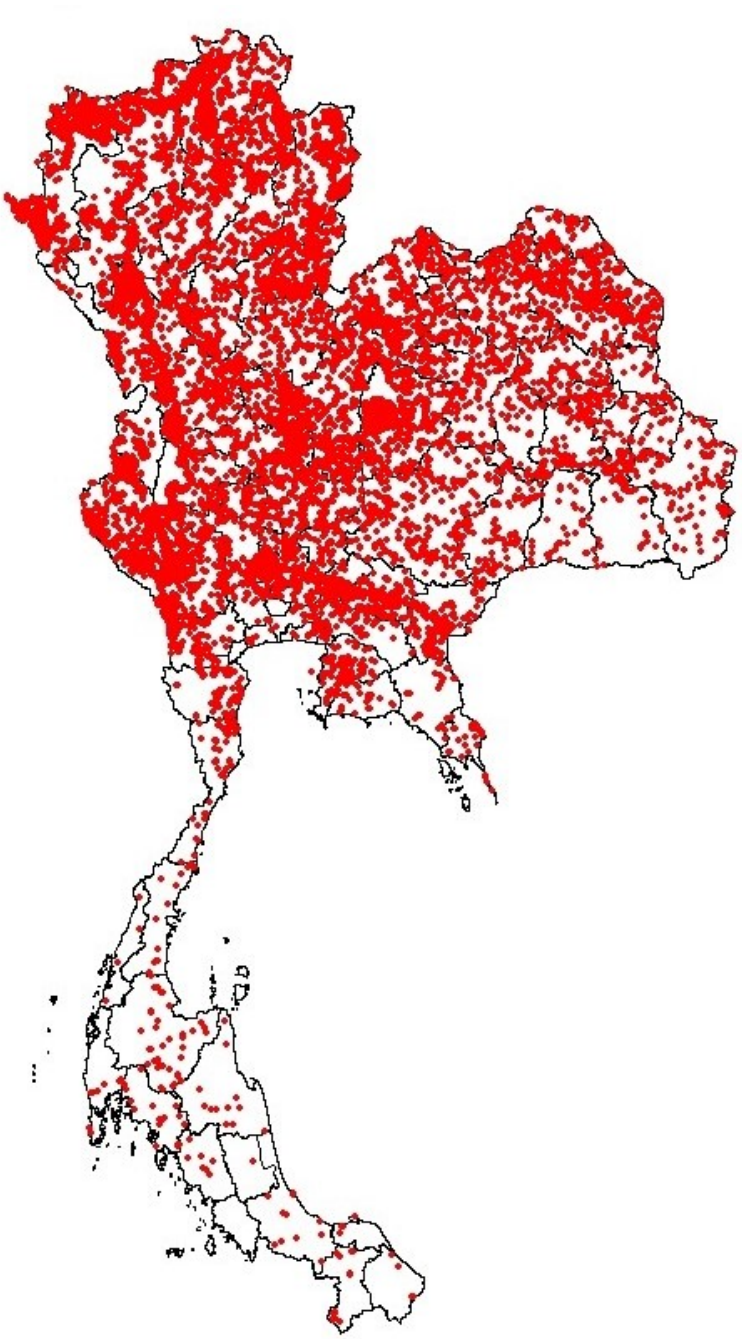
Attribute	Description	Levels
PM2.5	Variation in the number of days exposed to PM2.5 pollution	70 days, 80 days, 90 days
Technology cost	Variation in the costs of renting modern compressing technology	250 Baht, 350 Baht, 450 Baht
Transport cost	Variation in the transportation cost to sell rice residues at the market (per rai per kilometer)	2 Baht, 4 Baht, and 6 Baht

Figure A1: Rice growing areas in 2021



Source: Land Development Department

Figure A2: Hotspots in 2023



Source: Ministry of Natural Resources and Environment 2023

Figure A3: PM2.5 pollution during the burning season

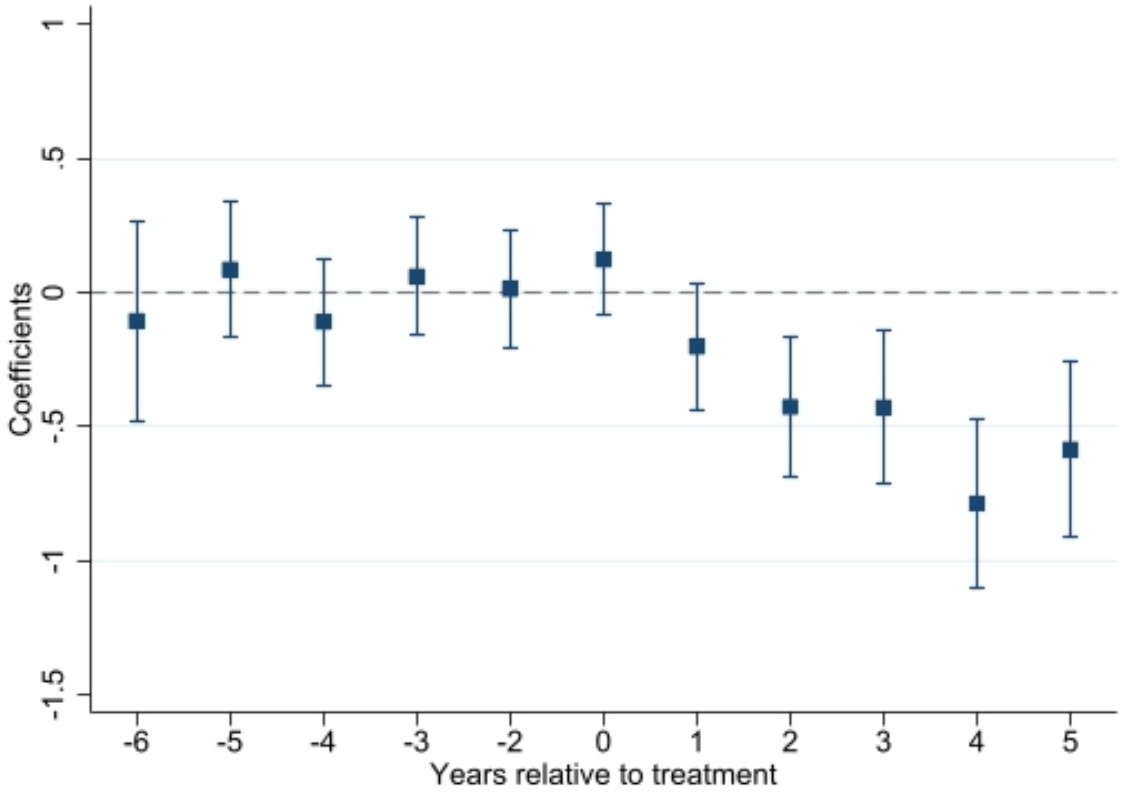


Figure A4: Farming calendar

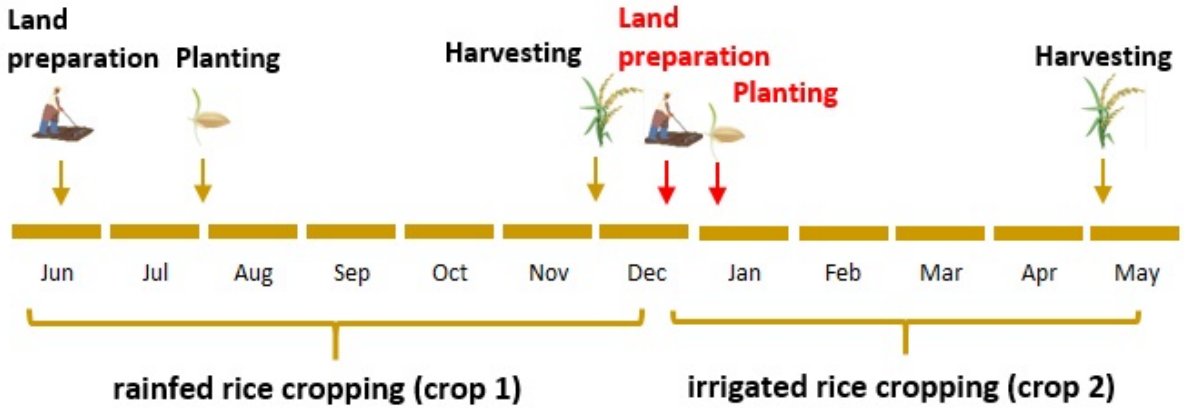
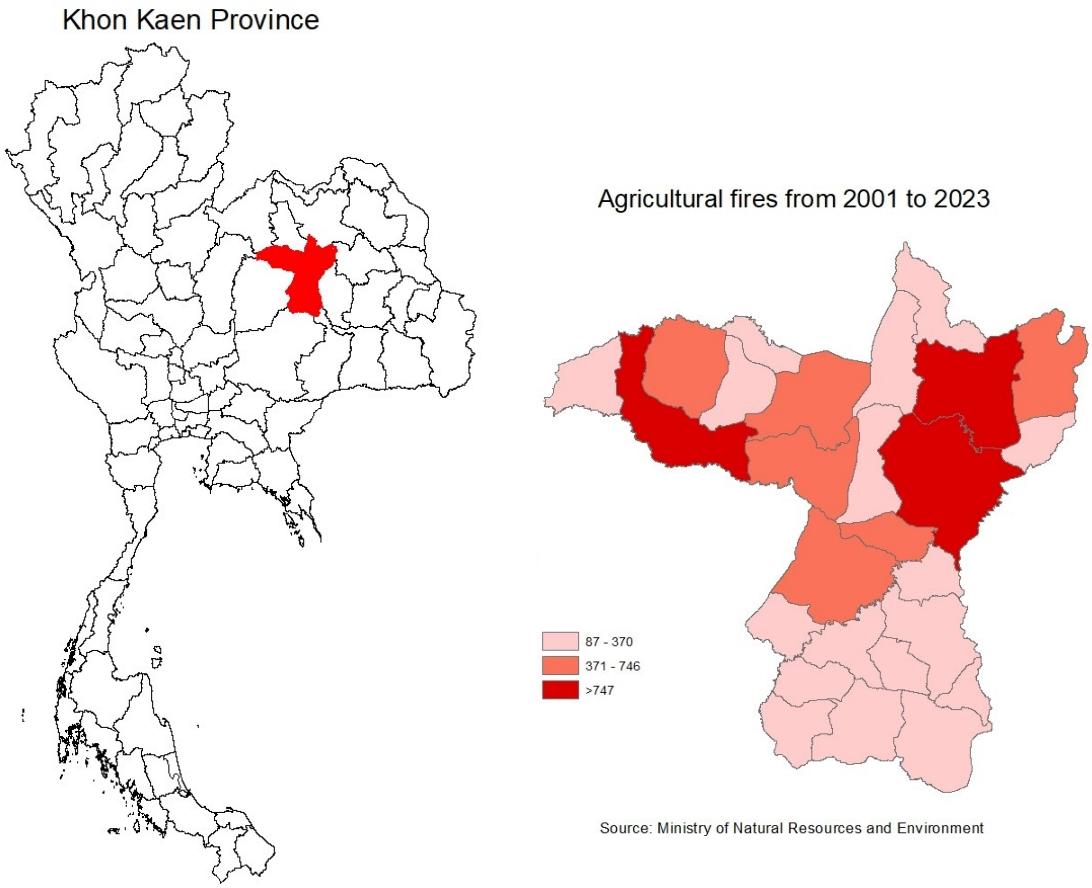


Figure A5: Agricultural fires in Khon Kaen province



(a) Khon Kaen province

(b) Agricultural fires in Khon Kaen province

Figure A6: Study area

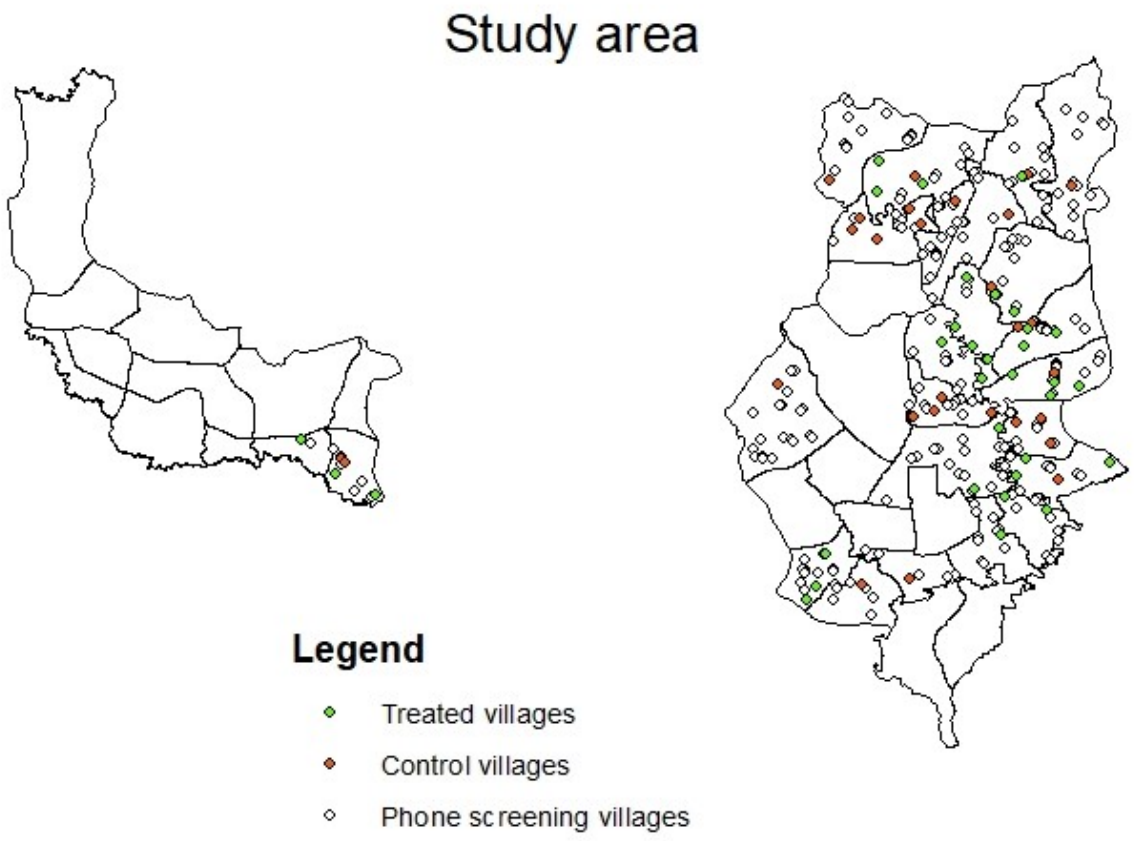


Figure A7: Mapping plots of farmland



Figure A8: Some treated plots, control plots, and neighbors' plots

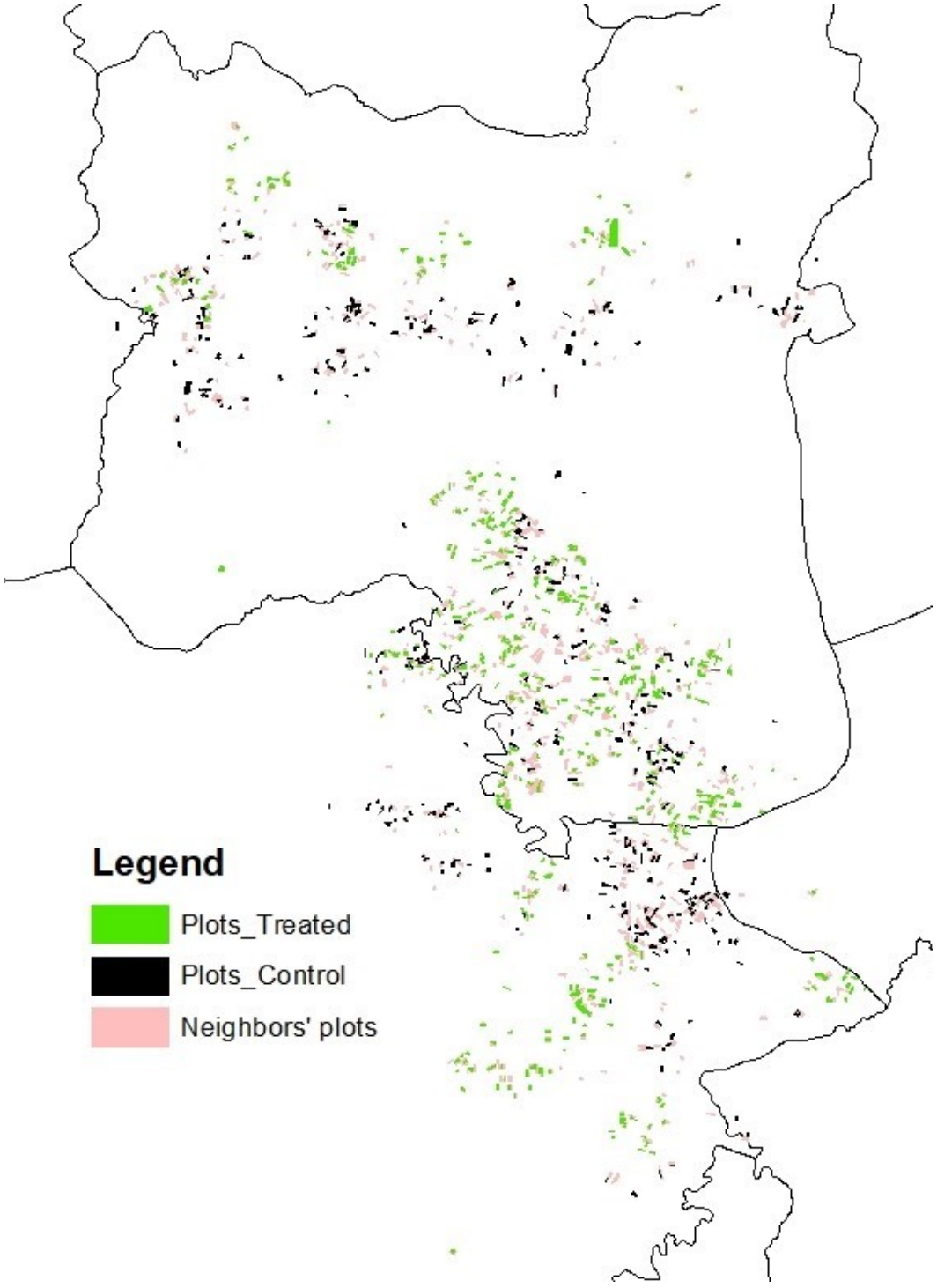


Figure A9: Experimental design

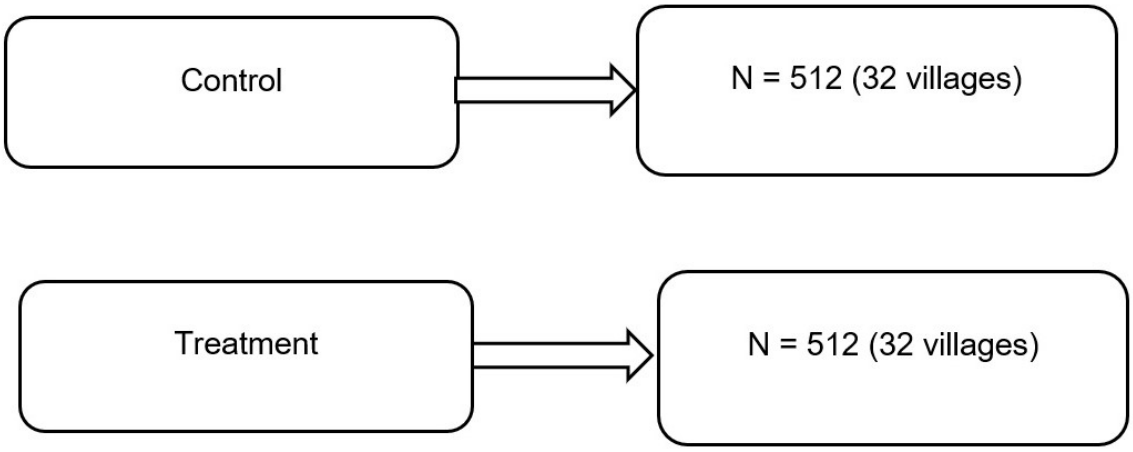


Figure A10: Voucher

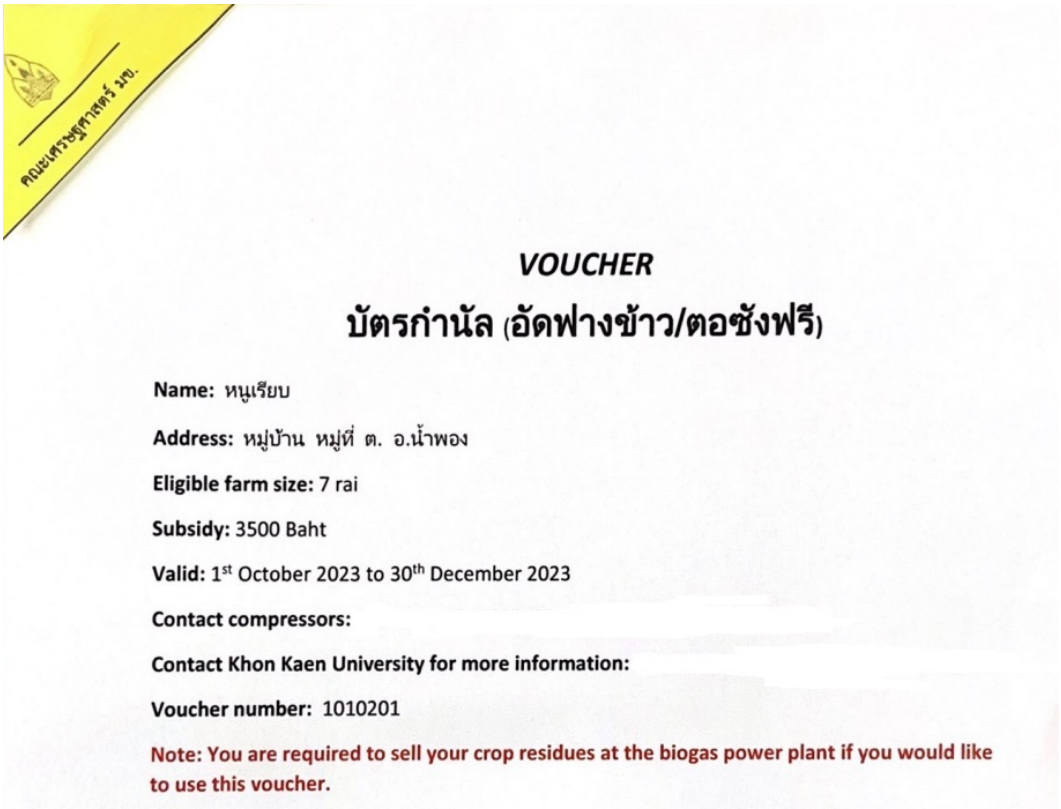


Figure A11: Study activities

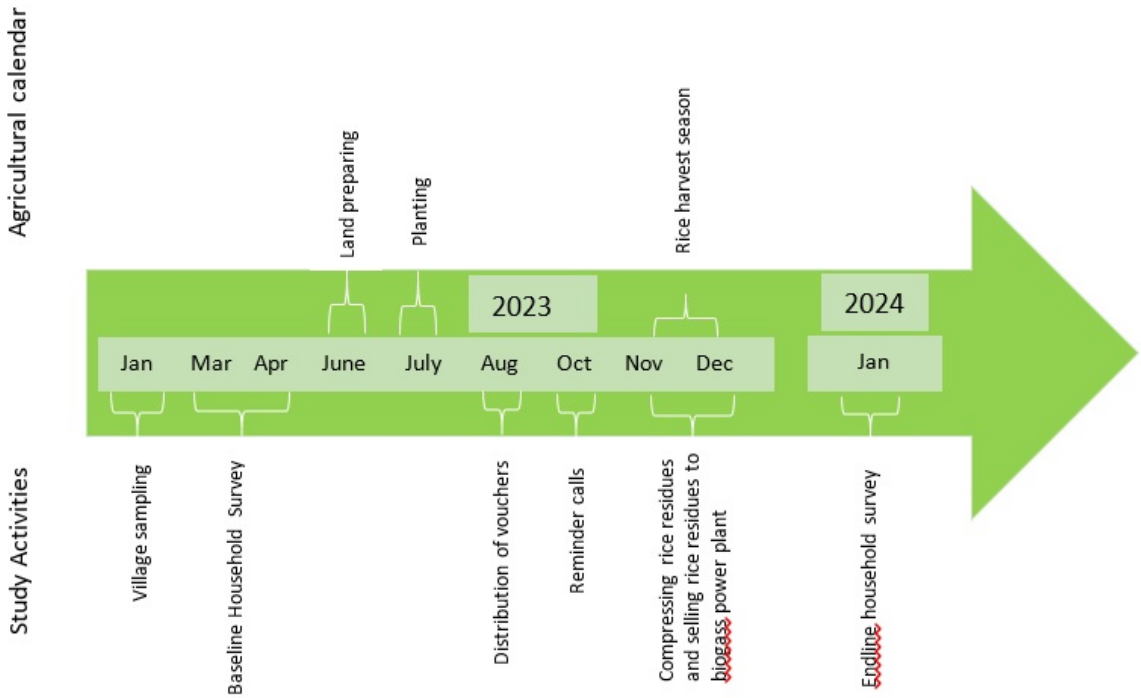


Figure A12: Partial burn rice field

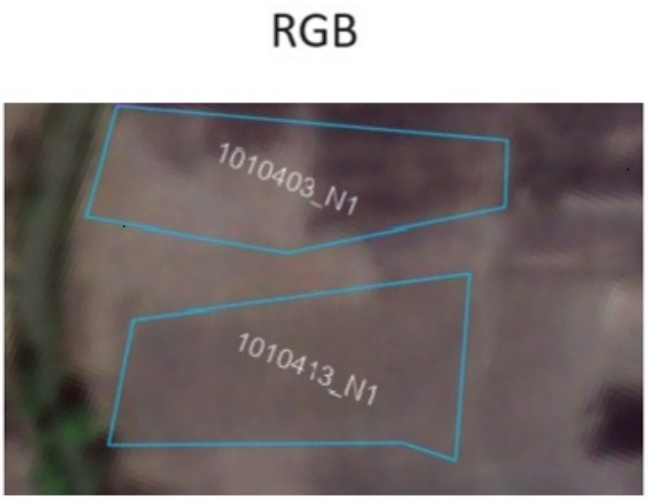


Figure A13: Treatment effect across percentiles (PlanetScope satellite)

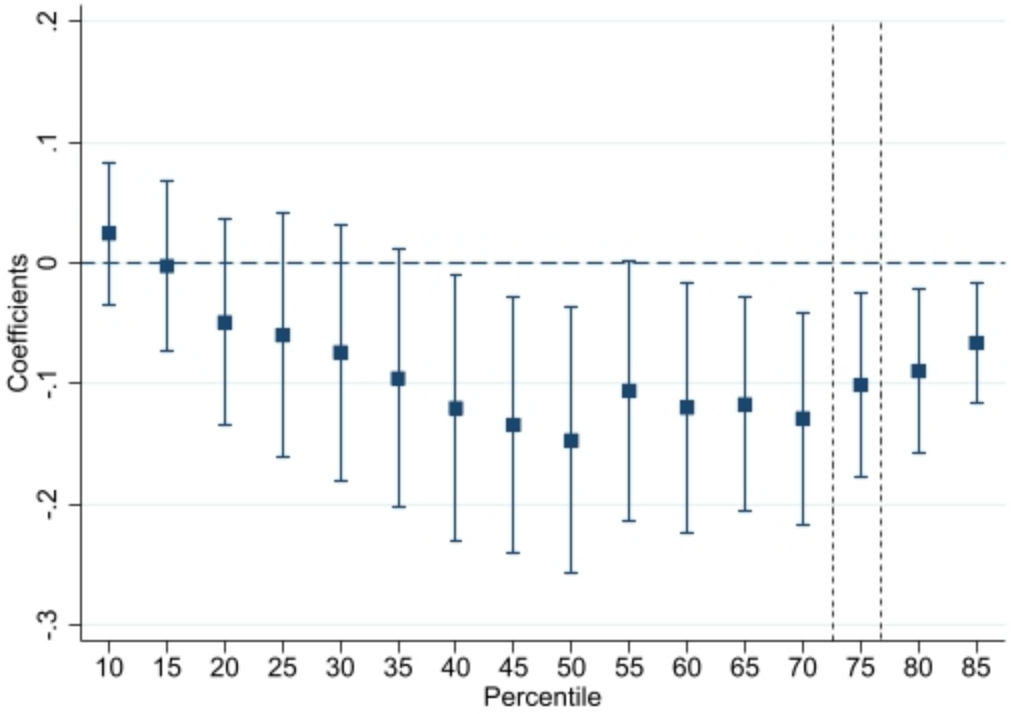


Figure A14: Treatment effect across percentiles (Sentinel-2 Satellite)

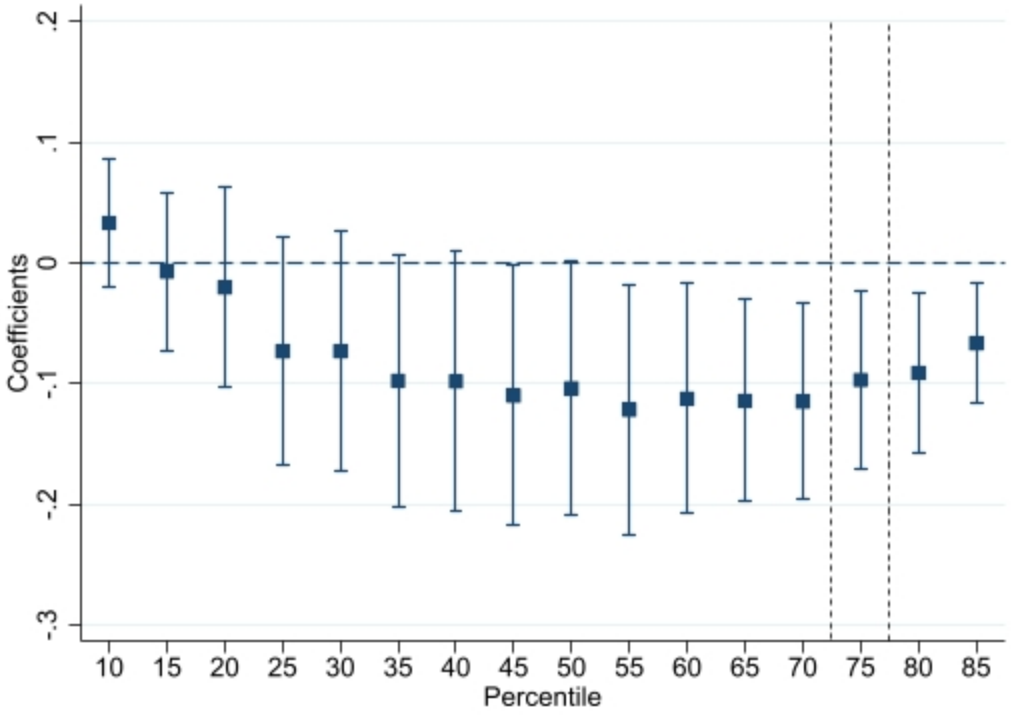


Figure A15: Example of a choice set (translated from Thai)

Choice 1: Please consider the option that you like the most

Attributes	A	B	C
PM 2.5	90 days	70 days	Not choose both A and B
Compressing fee (Baht/Rai)	350	450	
Transport fee (Baht/Kilometer)	2	4	
Choose	☐	☐	☐

Choice 2: Please consider the option that you like the most

Attributes	A	B	C
PM 2.5	90 days	70 days	Not choose both A and B
Compressing fee (Baht/Rai)	250	350	
Transport fee (Baht/kilometer)	4	6	
Choose	☐	☐	☐

Choice 3: Please consider the option that you like the most

Attributes	A	B	C
PM 2.5	80 days	90 days	Not choose both A and B
Compressing fee (Baht/Rai)	450	250	
Transport fee (Baht/kilometer)	2	4	
Choose	☐	☐	☐

Choice 4: Please consider the option that you like the most

Attributes	A	B	C
PM 2.5	80 days	90 days	Not choose both A and B
Compressing fee (Baht/Rai)	250	350	
Transport fee (Baht/Kilometer)	6	2	
Choose	☐	☐	☐

Choice 5: Please consider the option that you like the most

Attributes	A	B	C
PM 2.5	70 days	80 days	Not choose both A and B
Compressing fee (Baht/Rai)	350	450	
Transport fee (Baht/Kilometer)	6	2	
Choose	☐	☐	☐

Choice 6: Please consider the option that you like the most

Attributes	A	B	C
PM 2.5	70 days	80 days	Not choose both A and B
Compressing fee (Baht/Rai)	450	250	
Transport fee (Baht/Kilometer)	4	6	
Choose	☐	☐	☐

A.2 Burn Indices Used in Analysis

Indices derived from PlanetScope imagery:

1. **Bare Soil Index (BSoI)**:

$$\text{BSoI} = \frac{(NIR + Green) - (Red + Blue)}{NIR + Green + Red + Blue} \times 100 + 100$$

2. **Burn Area Index (BAI)**:

$$\text{BAI} = \frac{1}{(0.06 - \frac{NIR}{10000})^2 + \left(1 - \frac{Red}{10000}\right)^2}$$

Indices derived from Sentinel-2 imagery:

1. **Spectral Mixture Analysis (BASMA)**:

$$\text{BASMA} = \begin{cases} \text{band 1} & \text{Green vegetation} \\ \text{band 2} & \text{Soil and non-productive vegetation} \\ \text{band 3} & \text{Charred areas} \end{cases}$$

2. **Mid Infrared Bispectral Index (MIRBI)**:

$$\text{MIRBI} = 10 * SWIR2 - 9.8 * SWIR1 + 2$$

Band definitions:

- **NIR**: Near-infrared reflectance
- **Green**: Green band reflectance
- **Red**: Red band reflectance
- **Blue**: Blue band reflectance
- **SWIR2**: Short-wave infrared band 2 reflectance

A.3 Survey questions for heterogeneous effects

Distance constraint

1. What is the distance from your farm to the biomass market/biomass factory where rice residues are sold (kilometers)?
2. What is the distance from your farm to the main road (Kilometers)?
3. What is the distance from your farm to the nearest capital city (Kilometers)?

Information constraint index

1. Is using crop residue management technique better for long-term soil health or worse for soil health than burning rice residues?

Worse	1
Better	2
Same	3
Donot know	96

2. Where can you rent your crop residue management equipment?

Co-operative	1
Customer Hiring Center	2
Family/friend	3
No rent	0
Don’t know	96

Appendix B

Appendix for Chapter 2

B.1 Additional Tables and Figures

Table B1: Effects of Biogas Power Plants on Agricultural Fires: Callaway & Sant'Anna (2021) Estimator

	Number of agricultural fires		
	All months	Burn season	Outside burn season
Treatment	-0.089**	-0.080**	-0.008
	(0.034)	(0.029)	(0.010)
Fixed Effects	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes
Control mean	0.26	0.25	0.009
Observations	35,548	35,548	35,548

Note: The unit of observation is at the grid-year level, with each grid cell representing a 2.25 km x 2.25 km area (approximately 5 kilometer square). The outcome variables in columns (1) - (3) represent the total number of agricultural fires within a 5km radius of the plants for all months, the burning season from October to March, and outside burning season from April to September, respectively. All regressions include plant fixed effects, grid cell fixed effects, and year fixed effects. Weather controls include temperature, dews temperature, wind speed, and wind direction. Standard errors, clustered at the grid level, are in parenthesis. *, **, and *** indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

Table B2: Effects of Biogas Power Plants on Air Pollution:Callaway & Sant'Anna (2021) Estimator

	PM2.5 Pollution					
	All months	Burn season	Nearby urban centers	Nearby urban centers during burn season	Downwind areas	Downwind areas during burn season
	(1)	(2)	(3)	(4)	(5)	(6)
Treatment	-0.46***	-0.55***	-0.77**	-0.84**	-0.69***	-0.904***
	(0.11)	(0.12	(0.35)	(0.37)	(0.16)	(0.18)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes
Control mean	26.98	27	20.42	19.65	26.90	26.93
Observations	31,132	25,361	9,372	9,372	19,084	17,797

Note: The unit of observation is at the grid-year level, with each grid cell representing a 2.25 km x 2.25 km area (approximately 5 kilometer square). The outcome variable measures PM2.5 pollution within 5km of biogas plants across different subsamples: (1) full sample; (2) burning season only (October-March); (3-4) urban centers during all periods and burning season; and (5-6) downwind areas during all periods and burning season. Upwind areas are defined as regions within 45 degrees of the daily prevailing wind direction (fixed octants) calculated from a wind rose, while the opposite direction is defined as downwind areas. All regressions include plant fixed effects, grid cell fixed effects, and year fixed effects. Weather controls include temperature, dews temperature, wind speed, and wind direction. Standard errors, clustered at the grid level, are in parenthesis. *, **, and *** indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

Table B3: Effects of Biogas Power Plants on Agricultural Fires (Using Alternative Satellite Dataset of VIIRS with Controls)

	Number of agricultural fires			Number of different types of fires		
	All months	Burn season	Outside burn	Rice fires	Sugarcane fires	Corn fires
Treatment	-0.140***	-0.141***	0.0003	-0.140***	-0.139***	-0.140***
	(0.033)	(0.033)	(0.0002)	(0.033)	(0.033)	(0.033)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes
Control mean	0.25	0.25	0.0001	0.25	0.25	0.25
Observations	27540	27540	27540	27540	27540	27540

Note: The unit of observation is at the grid-year level, with each grid cell representing a 2.25 km x 2.25 km area (5.06 kilometer square). All the fires outcomes in columns (1) - (6) use alternative satellite data of VIIRS from 2012 to 2023 and exclude low-confidence incidence (confidence levels lower than 30 percent). The outcome variables in columns (1) - (3) represent the total number of agricultural fires within a 5km radius of the plants for all months, the burning season from November to March, and the non-burning season from April to October, respectively. Columns (4) - (6) explore rice fires, sugarcane fires, and corn fires. I construct a measure of rice fires as the number of agricultural fires occurring within grids that contain rice cultivation areas. Sugarcane fires are measured as the number of agricultural fires in grids with sugarcane cultivation. Corn fires are defined in the same way, based on the number of agricultural fires within grids containing corn cultivation. All regressions include plant fixed effects, grid cell fixed effects, and year fixed effects. Weather controls include temperature, dews temperature, wind speed, and wind direction.Standard errors, clustered at the grid level, are in parenthesis. *, **, and *** indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

Table B4: Effects of Biogas Power Plants on Agricultural Fires (Using Alternative Satellite Dataset of VIIRS without Controls)

	Number of agricultural fires			Number of different types of fires		
	All months	Burn season	Outside burn	Rice fires	Sugarcane fires	Corn fires
Treatment	-0.1408***	-0.1412***	0.000381	-0.1407***	-0.1405***	-0.1409***
	(0.0337)	(0.0337)	(0.000270)	(0.0337)	(0.0337)	(0.0337)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	No	No	No	No	No	No
Control mean	0.25	0.25	0.0005	0.25	0.25	0.25
Observations	27540	27540	27540	27540	27540	27540

Note: The unit of observation is at the grid-year level, with each grid cell representing a 2.25 km x 2.25 km area (5.06 kilometer square). All the fires outcomes in columns (1) - (6) use alternative satellite data of VIIRS from 2012 to 2023 and exclude low-confidence incidence (confidence levels lower than 30 percent). The outcome variables in columns (1) - (3) represent the total number of agricultural fires within a 5km radius of the plants for all months, the burning season from November to March, and the non-burning season from April to October, respectively. Columns (4) - (6) explore rice fires, sugarcane fires, and corn fires. I construct a measure of rice fires as the number of agricultural fires occurring within grids that contain rice cultivation areas. Sugarcane fires are measured as the number of agricultural fires in grids with sugarcane cultivation. Corn fires are defined in the same way, based on the number of agricultural fires within grids containing corn cultivation. All regressions include plant fixed effects, grid cell fixed effects, and year fixed effects. Standard errors, clustered at the grid level, are in parenthesis. *, **, and *** indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

Table B5: Effects of Biogas Power Plants on Agricultural Fires (Excluding Hotspots < 30% Confidence)

	Number of agricultural fires			Number of different types of fires		
	All months	Burn season	Outside burn	Rice fires	Sugarcane fires	Corn fires
Treatment	-0.018*	-0.018*	-0.0003	-0.023**	-0.025**	-0.026**
	(0.010)	(0.009)	(0.002)	(0.010)	(0.010)	(0.010)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes
Control mean	0.25	0.25	0.008	0.24	0.24	0.25
Observations	52785	52785	52785	52785	52785	52785

Note: The unit of observation is at the grid-year level, with each grid cell representing a 2.25 km x 2.25 km area (5.06 kilometer square). All the fires outcomes in columns (1) - (6) exclude low-confidence incidence (confidence levels lower than 30 percent). The outcome variables in columns (1) - (3) represent the total number of agricultural fires within a 5km radius of the plants for all months, the burning season from November to March, and the non-burning season from April to October, respectively. Columns (4) - (6) explore rice fires, sugarcane fires, and corn fires. I construct a measure of rice fires as the number of agricultural fires occurring within grids that contain rice cultivation areas. Sugarcane fires are measured as the number of agricultural fires in grids with sugarcane cultivation. Corn fires are defined in the same way, based on the number of agricultural fires within grids containing corn cultivation. All regressions include plant fixed effects, grid cell fixed effects, and year fixed effects. Weather controls include temperature, dews temperature, wind speed, and wind direction.Standard errors, clustered at the grid level, are in parenthesis. *, **, and *** indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

Table B6: Effects of Biogas Power Plants on Agricultural Fires (Excluding Hotspots < 50% Confidence)

	Number of agricultural fires			Number of different types of fires		
	All months	Burn season	Outside burn	Rice fires	Sugarcane fires	Corn fires
Treatment	-0.020**	-0.020**	0.0001	-0.025***	-0.026***	-0.027**
	(0.009)	(0.009)	(0.001)	(0.009)	(0.009)	(0.009)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	Yes
Control mean	0.22	0.22	0.006	0.22	0.21	0.22
Observations	52785	52785	52785	52785	52785	52785

Note: The unit of observation is at the grid-year level, with each grid cell representing a 2.25 km x 2.25 km area (5.06 kilometer square). All the fires outcomes in columns (1) - (6) exclude low-confidence incidence (confidence levels lower than 50 percent). The outcome variables in columns (1) - (3) represent the total number of agricultural fires within a 5km radius of the plants for all months, the burning season from November to March, and the non-burning season from April to October, respectively. Columns (4) - (6) explore rice fires, sugarcane fires, and corn fires. I construct a measure of rice fires as the number of agricultural fires occurring within grids that contain rice cultivation areas. Sugarcane fires are measured as the number of agricultural fires in grids with sugarcane cultivation. Corn fires are defined in the same way, based on the number of agricultural fires within grids containing corn cultivation. All regressions include plant fixed effects, grid cell fixed effects, and year fixed effects. Weather controls include temperature, dews temperature, wind speed, and wind direction.Standard errors, clustered at the grid level, are in parenthesis. *, **, and *** indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

Table B7: Effects of Biogas Power Plants on Fires without Controls

	Number of agricultural fires			Number of different types of fires		
	All months	Burn season	Outside burn	Rice fires	Sugarcane fires	Corn fires
Treatment	-0.022**	-0.021**	-0.001	-0.027**	-0.029***	-0.030***
	(0.010)	(0.010)	(0.002)	(0.010)	(0.010)	(0.010)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	No	No	No	No	No	No
Control mean	0.26	0.25	0.009	0.28	0.27	0.28
Observations	52785	52785	52785	52785	52785	52785

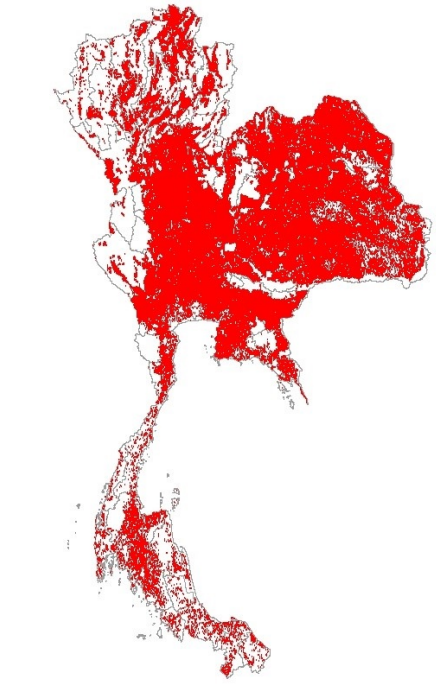
Note: The unit of observation is at the grid-year level, with each grid cell representing a 2.25 km x 2.25 km area (5.06 kilometer square). The outcome variables in columns (1) - (3) represent the total number of agricultural fires within a 5km radius of the plants for all months, the burning season from November to March, and the non-burning season from April to October, respectively. Columns (4) - (6) explore rice fires, sugarcane fires, and corn fires. I construct a measure of rice fires as the number of agricultural fires occurring within grids that contain rice cultivation areas. Sugarcane fires are measured as the number of agricultural fires in grids with sugarcane cultivation. Corn fires are defined in the same way, based on the number of agricultural fires within grids containing corn cultivation. All regressions include plant fixed effects, grid cell fixed effects, and year fixed effects. Standard errors, clustered at the grid level, are in parenthesis. *, **, and *** indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

Table B8: Effects of Biogas Power Plants on Air Pollution without Controls

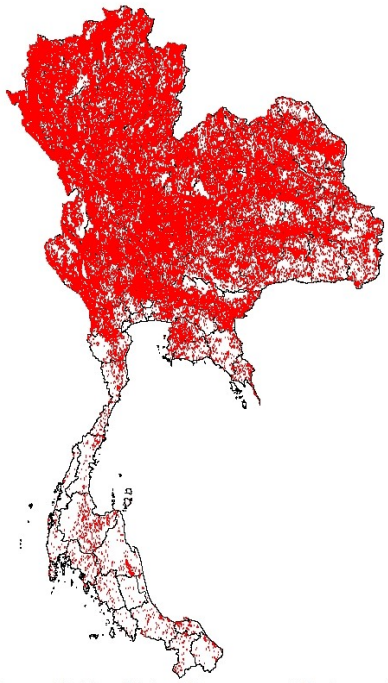
	PM2.5 Pollution						
	All months	Burn season	Nearby urban centers	Nearby urban centers during burn season	Downwind areas	Downwind areas during burn season	Upwind areas
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment	-0.667***	-0.657***	-1.390***	-1.345***	-0.544***	-0.563***	0.347
	(0.0794)	(0.0796)	(0.310)	(0.337)	(0.0898)	(0.0912)	(0.267)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Weather controls	No	No	No	No	No	No	No
Control mean	26.98	27.00	20.42	19.65	26.90	26.93	26.12
Observations	45333	44373	20332	20332	34330	33712	1176

Note: The unit of observation is at the grid-year level, with each grid cell representing a 2.25 km x 2.25 km area (5.06 kilometer square). The outcome variable measures PM2.5 pollution within 5km of biogas plants across different subsamples: (1) full sample; (2) burning season only (October-March); (3-4) urban centers during all periods and burning season; (5-6) downwind areas during all periods and burning season; (7) upwind areas. Upwind areas are defined as grid cells within 45 degrees of the prevailing wind direction (fixed octants calculated from wind rose); downwind areas are the opposite. All regressions include plant fixed effects, grid cell fixed effects, and year fixed effects. Standard errors, clustered at the grid level, are in parenthesis. *, **, and *** indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

Figure B1: Distribution of fires during the sample period



(a) Agricultural fires



(b) All fires (agricultural fires + forest fires)

Figure B2: Location of biogas power plants

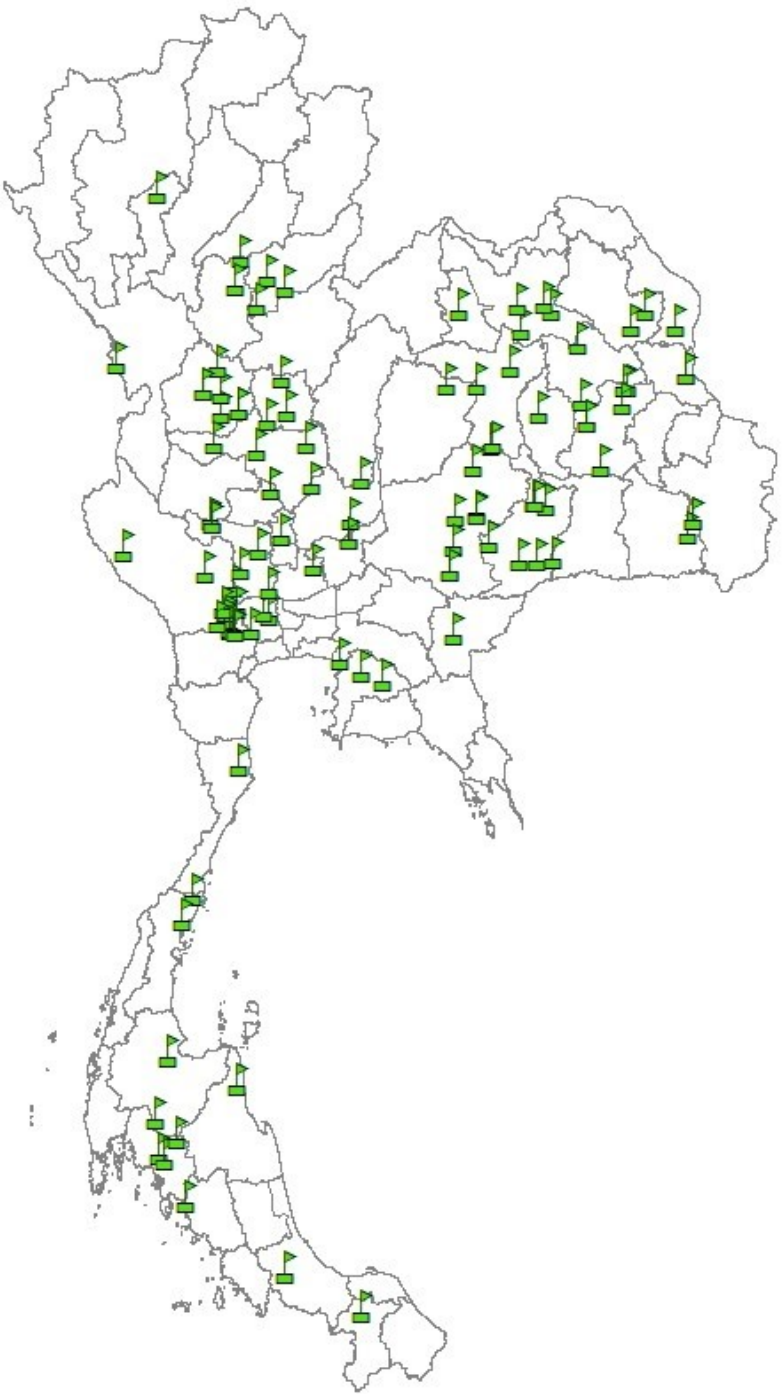
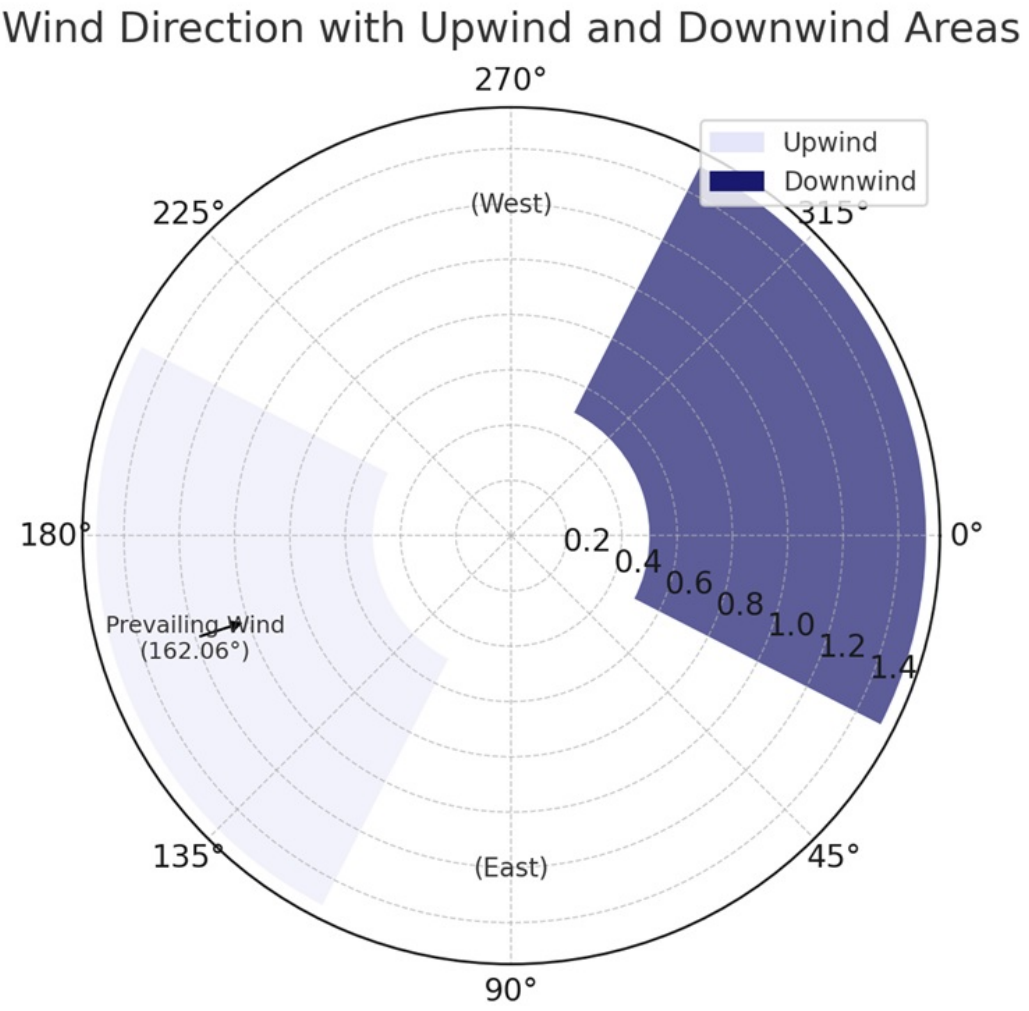
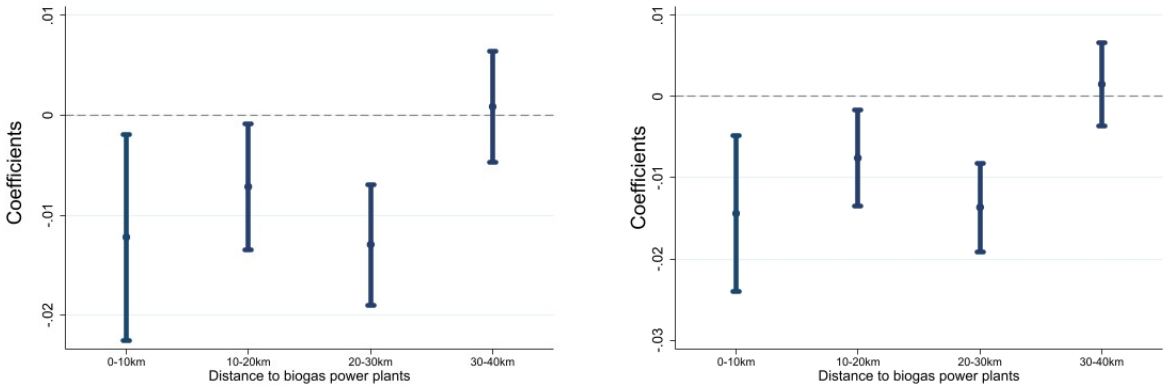


Figure B3: Illustration of wind direction with upwind and downwind areas



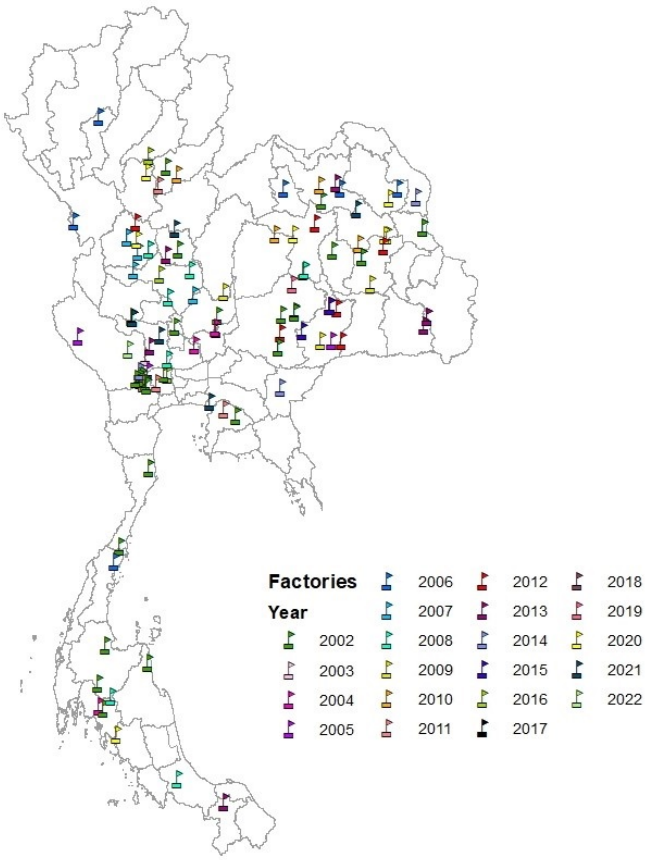


(a) Agricultural Fires with Confidence Level Above 30%

(b) Agricultural Fires with Confidence Level Above 50%

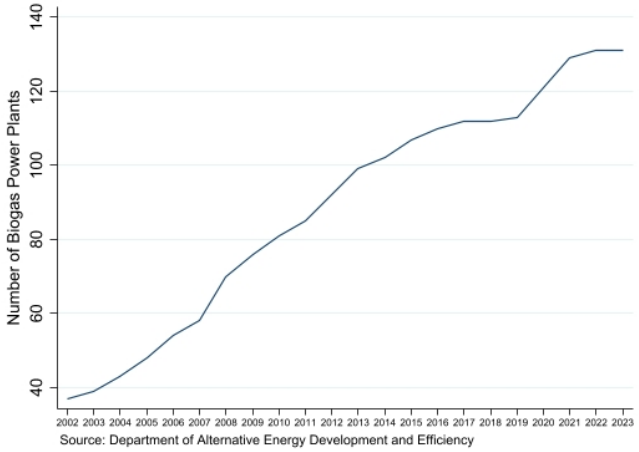
Figure B4: Effects of Biogas Power Plants on Agricultural Fires by Distance, for Fire Detections Above 30% and 50% Confidence Levels

Figure B5: Variations in the timing of the establishment of biogas power plants



Source: Ministry of Natural Resources and Environment

(a) Variations in the timining of biogas power plants entry



(a) Number of biogas power plants by year

Figure B7: Urban areas

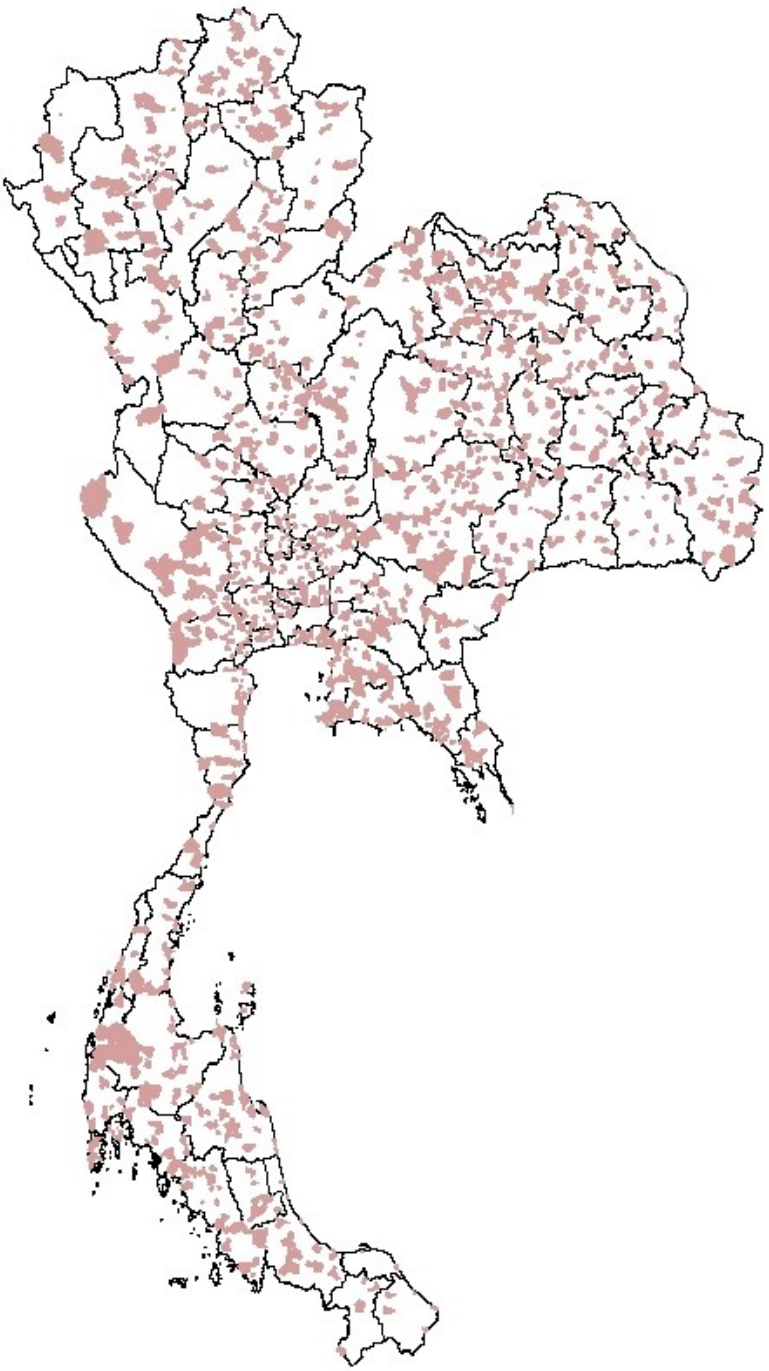
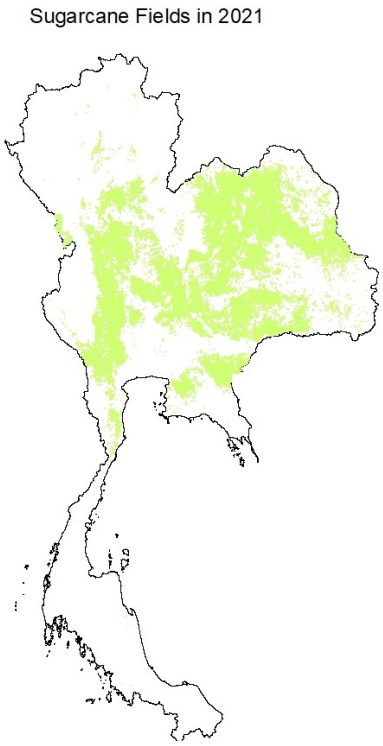


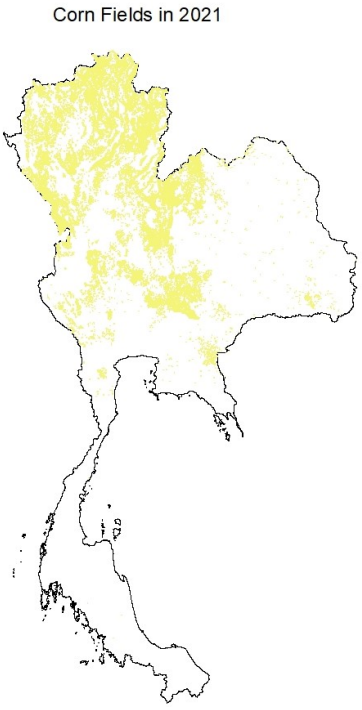
Figure B8: Crop fields



(a) Sugarcane fields

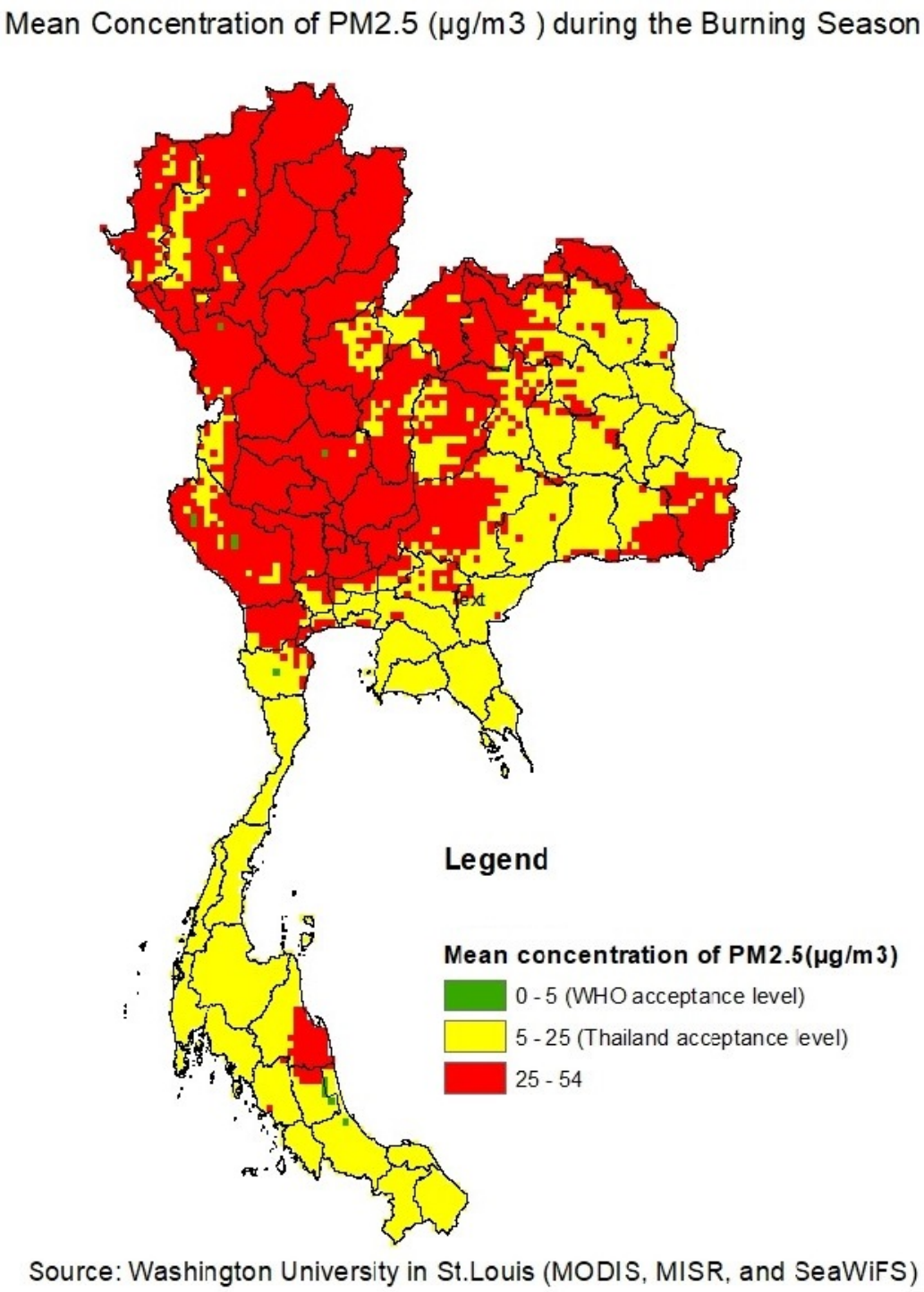


(b) Rice fields



(a) Corn fields

Figure B10: Pollution during the burning season



Appendix C

Appendix for Chapter 3

C.1 Additional Tables and Figures

Figure C1: Active areas of major ethnic armed groups in Myanmar

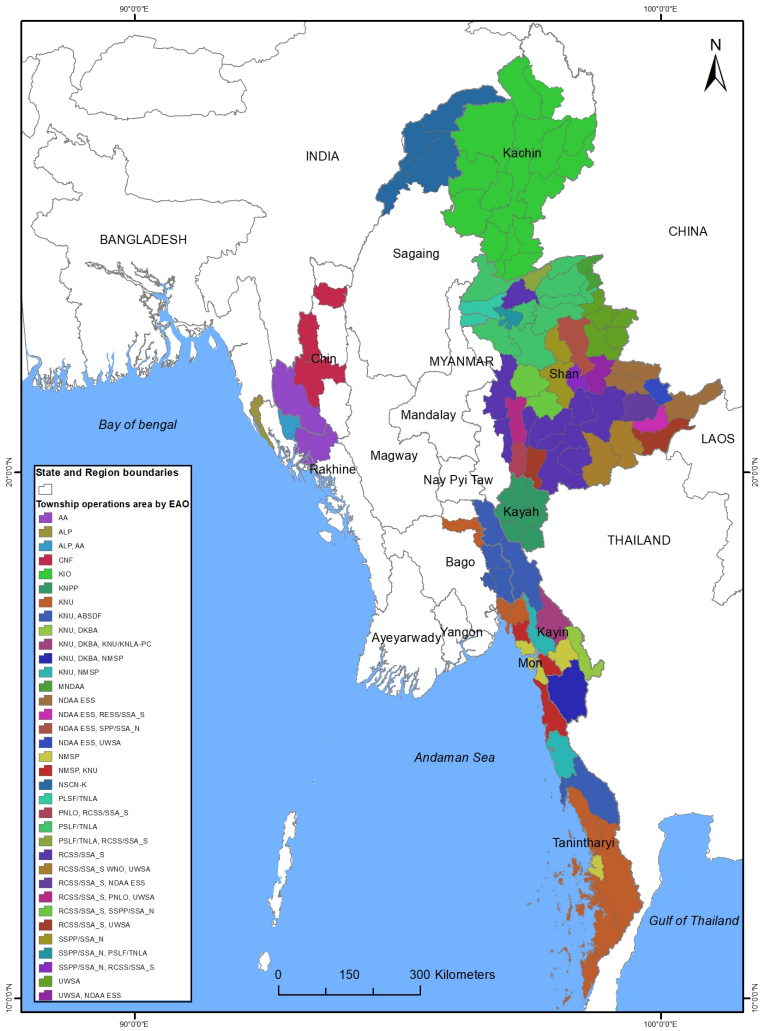
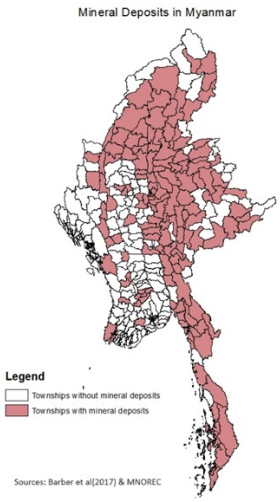
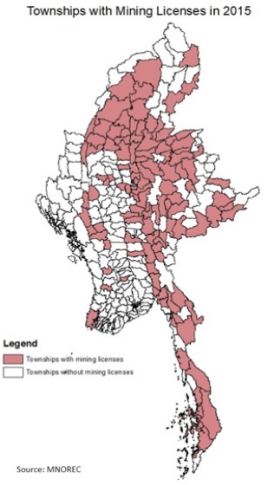


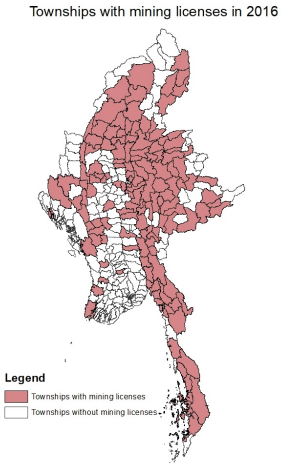
Figure C2: Distribution of mineral deposits, mining licenses, and commodities



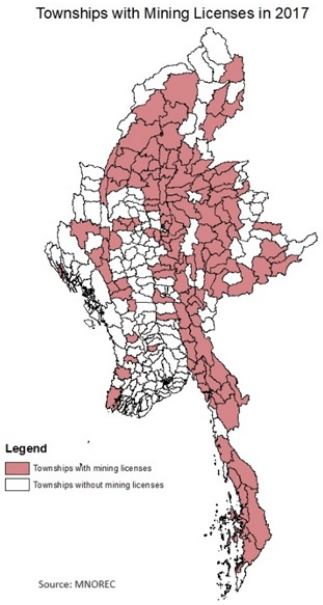
Mineral deposits



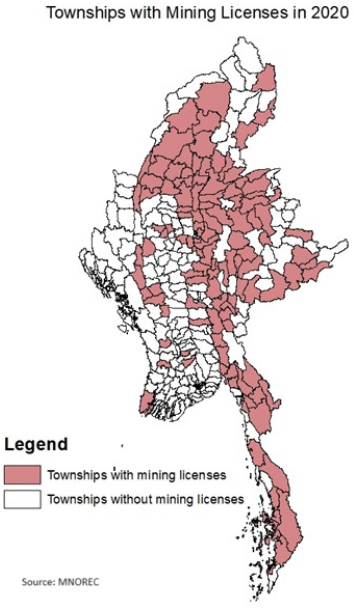
Mining licenses (2015)



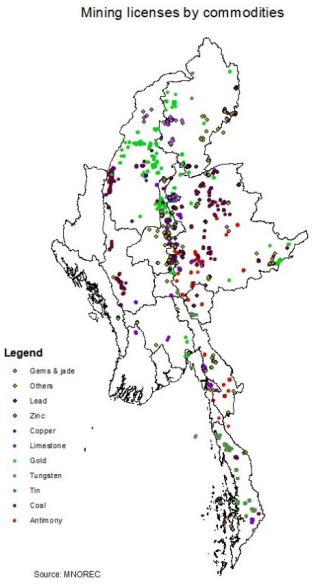
Mining licenses (2016)



Mining licenses (2017)

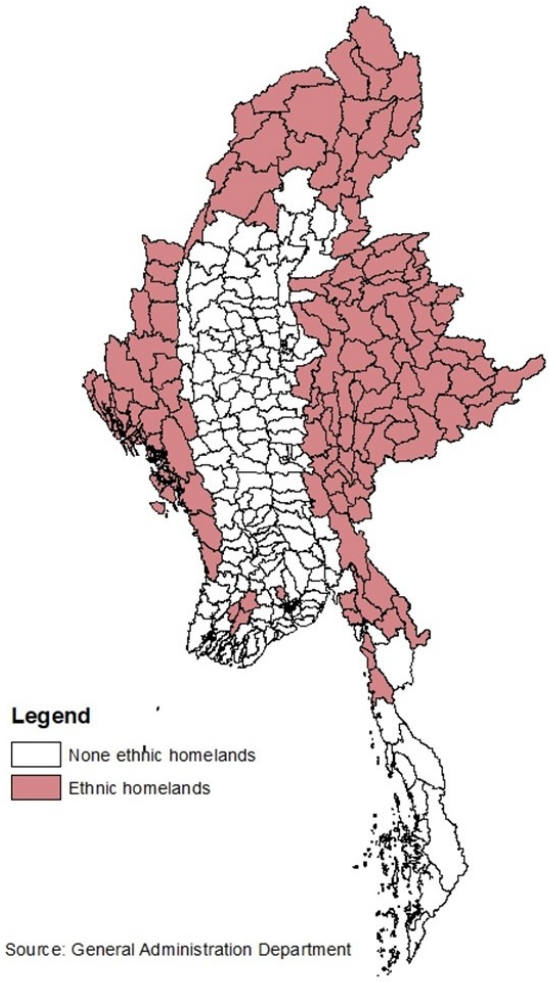


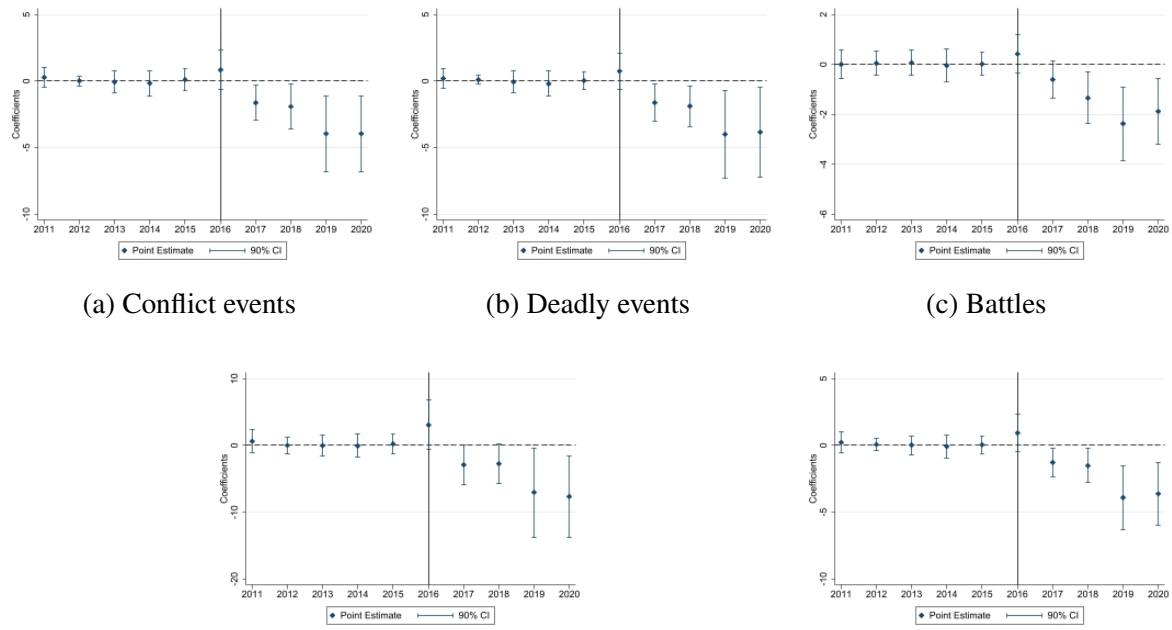
Mining licenses (2020)



Commodities

Figure C3: Ethnic Homelands





(a) Conflict events (b) Deadly events (c) Battles

(d) Violent events (e) State-perpetrated violence

Figure C4: Mining Reform and Conflict: Event-Study Estimates. The graphs plot coefficients from Synthetic DID.

Figure C5: World mineral prices

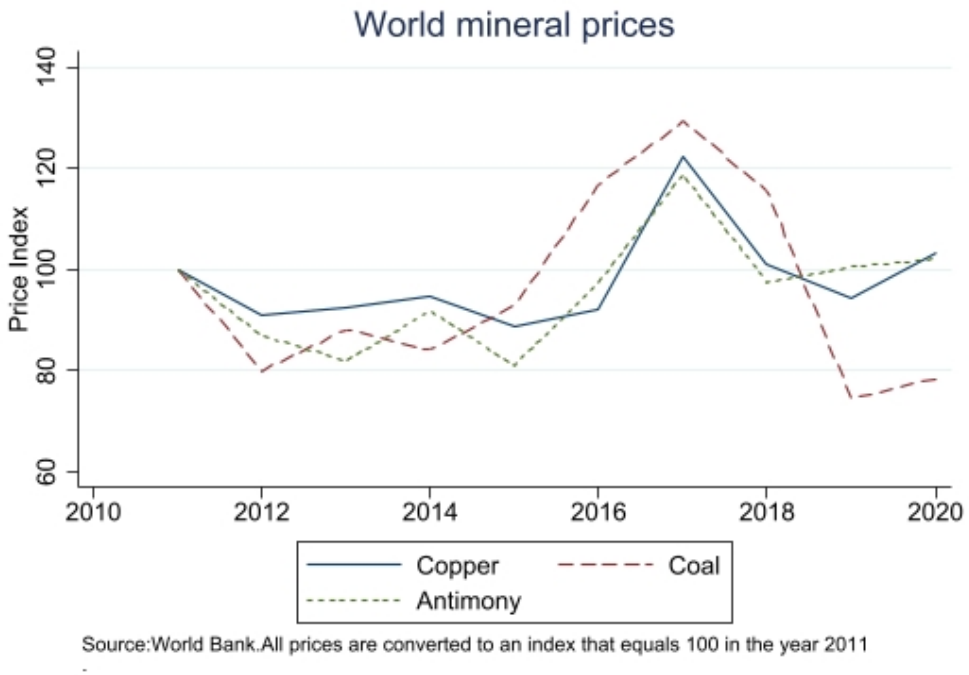


Table C1: Summary statistics for additional variables

	Mean	P50.	Std.Dev.	Min.	Max.	Obs.
Conflict events (ACLED dataset)						
Conflict in ethnic homelands	12.48	1	34.45	0	299	1260
Conflict in non-ethnic homelands	1.46	0	3.95	0	48	2040
Conflict in poor townships	12.22	1	36.10	0	299	860
Conflict in non-poor townships	3.36	0	13.59	0	199	2440
Conflict in remote townships	8.97	0	29.30	0	299	1649
Conflict in non-remote townships	2.38	0	10.12	0	220	1651
Conflict in townships with high coethnic representation	3.62	0	19.35	0	299	1625
Conflict in townships with low coethnic representation	7.66	0	24.43	0	248	1675
Deadly events (ACLED dataset)						
Deadly events in ethnic homelands	11.80	0	34.17	0	299	1260
Deadly events in non-ethnic homelands	0.33	0	1.99	0	44	2040
Deadly events in poor townships	11.66	0	35.97	0	299	860
Deadly events in non-poor townships	2.26	0	13.02	0	199	2440
Deadly events in remote townships	8.40	0	29.08	0	299	1649
Deadly events in non-remote townships	1.02	0	9.29	0	219	1651
Deadly events in townships with high coethnic representation	2.41	0	18.96	0	299	1625
Deadly events in townships with low coethnic representation	6.94	0	24.20	0	247	1675
Battles (ACLED dataset)						
Battles in ethnic homelands	7.00	0	20.89	0	172	1260
Battles in non-ethnic homelands	0.13	0	1.34	0	34	2040
Battles in poor townships	6.94	0	21.77	0	172	860
Battles in non-poor townships	1.28	0	8.16	0	134	2440
Battles in remote townships	5.16	0	17.99	0	172	1649
Battles in non-remote townships	0.35	0	4.77	0	170	1651
Battles in townships with high coethnic representation	1.07	0	9.37	0	172	1625
Battles in townships with low coethnic representation	4.39	0	16.18	0	170	1675
Violent events (ACLED dataset)						
Violent events in ethnic homelands	11.44	0	34.66	0	299	1260
Violent events in non-ethnic homelands	0.21	0	2.01	0	44	2040
Violent events in poor townships	11.10	0	36.29	0	299	860
Violent events in non-poor townships	2.17	0	13.38	0	199	2440
Violent events in remote townships	8.06	0	29.40	0	299	1649
Violent events in non-remote townships	0.94	0	9.61	0	220	1651
Violent events in townships with high coethnic representation	2.38	0	19.19	0	299	1625
Violent events in townships with low coethnic representation	6.56	0	24.52	0	248	1675
State-perpetrated violence (ACLED)						
State-perpetrated violence in ethnic homelands	5.09	0	15.40	0	139	1260
State-perpetrated violence in non-ethnic homelands	0.19	0	1.01	0	22	2040
State-perpetrated violence in poor townships	5.06	0	16.24	0	139	860
State-perpetrated violence in non-poor townships	1.00	0	5.82	0	103	2440
State-perpetrated violence in remote townships	3.65	0	13.14	0	139	1649
State-perpetrated violence in non-remote townships	0.47	0	4.02	0	102	1651
State-perpetrated violence in townships with high coethnic representation	1.12	0	8.53	0	139	1625
State-perpetrated violence in townships with low coethnic representation	2.98	0	10.89	0	120	1675
Ethnic homelands and poor	0.51	1	0.50	0	1	1260
Non-ethnic homelands and poor	0.11	0	0.31	0	1	2040
Ethnic homelands and remote	0.85	1	0.36	0	1	1260
Non-ethnic homelands and remote	0.28	0	0.45	0	1	2040
Copper price (USD/ton)	176.07	0	1002.94	0	7215.41	3300
Coal price (USD/ton)	9.16	0	25.87	0	99.26	3300
Antimony price (USD/ton)	8712.01	7960	1889.79	6700	13000	3300
GDP per capita (kyat)	1549299.21	1164157	2248621.92	197242	31627167	3300
Population density (squared kilometer)	1581.47	105.98	5183.29	1.64	39796.26	3300
Vote share for National League for Democracy	0.68	1	0.47	0	1	3300
Townships with Community Driven Development (CDD) projects	0.02	0	0.15	0	1	3300
Log total employment	12.6	12.81	0.92	8.05	14.31	650
Log share employment in agriculture	3.65	3.99	1.05	0.28	4.47	650
Log share employment in service	3.46	3.45	0.49	1.26	4.46	650
Log share employment in manufacture	2.07	2.18	0.82	-1.29	3.59	650
Gini coefficient	0.16	0.14	0.11	0.00	0.54	3300
Coethnic representation	1467.01	164.54	2948.50	0	19652.36	3250

Note: 1 USD is equal to 2,099 Myanmar Kyat

Table C2: Long-term effects of mining reform on conflict events

	No. of conflict events	No. of deadly events	No. of battles	No. of violent events	No. of state-violence
	(1)	(2)	(3)	(4)	(5)
Mining licenses ×Year ≥ 2017	-5.964***	-5.825***	-3.572***	-5.858***	-2.794***
	(1.814)	(1.810)	(1.007)	(1.818)	(0.789)
Mining licenses ×Year ≥ 2018	-6.282***	-6.108***	-4.034***	-6.045***	-3.004***
	(2.104)	(2.109)	(1.204)	(2.095)	(0.927)
Mining licenses ×Year ≥ 2019	-7.391**	-7.181**	-4.227***	-7.248**	-3.572***
	(2.871)	(2.879)	(1.536)	(2.902)	(1.276)
Fixed Effects	Yes	Yes	Yes	Yes	Yes
Controls × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Mean of Dependent Variable	5.67	4.70	2.75	4.50	2.06
Observation	3300	3300	3300	3300	3300

Notes: The unit of observation is the township level, and the study period covers 2011 to 2020. This table shows that the mining ban reduces conflict events from 2011 to 2020. Conflict events include all types of events, including battles, explosions, strategic developments, violence against civilians (e.g.,extrajudicial killings of unarmed prisoners of war and shooting), protests,and riots. Deadly conflict events include all types of events except protests and riots. Battles include clashes between Myanmar's military forces (the Tatmadaw) and ethnic militias, as well as clashes between different ethnic militias. Violence events are defined as incidents that result in at least one fatality. State-perpetrated violence are incidents initiated by the Tatmadaw and police forces. All regressions control for township fixed effects, year fixed effects and the interaction between year fixed effects and the following baseline characteristics: GDP per capita and population density. Standard errors, clustered at the township level, are in parenthesis. *, **, and *** indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

Table C3: Synthetic DID: Mining reform and conflict events

	No. of conflict events	No. of deadly events	No. of battles	No. of violent events	No. of state-violence
	(1)	(2)	(3)	(4)	(5)
Mining licenses × Year ≥ 2016	-3.600*	-3.628**	-2.373**	-3.448*	-1.874**
	(1.842)	(1.760)	(0.989)	(1.787)	(0.734)
Fixed Effects	Yes	Yes	Yes	Yes	Yes
Controls × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Mean of Dependent Variable	5.67	4.70	2.75	4.50	2.06
Observations	3300	3300	3300	3300	3300

Notes: The unit of observation is the township level, and the study period covers 2011 to 2020. Using synthetic DID, this table shows that the mining ban reduces conflict events from 2011 to 2020. Conflict events include all types of events, including battles, explosions, strategic developments, violence against civilians (e.g.,extrajudicial killings of unarmed prisoners of war and shooting), protests,and riots. Deadly conflict events include all types of events except protests and riots. Battles include clashes between Myanmar's military forces (the Tatmadaw) and ethnic militias, as well as clashes between different ethnic militias. Violence events are defined as incidents that result in at least one fatality. State-perpetrated violence are incidents initiated by the Tatmadaw and police forces. All regressions control for the interaction between year fixed effects and the following baseline characteristics: GDP per capita and population density. Standard errors, clustered at the township level, are in parenthesis. *, **, and *** indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

Table C4: Outliers

	No. of conflict events	No. of deadly events	No. of battles	No. of violent events	No. of state-violence
	(1)	(2)	(3)	(4)	(5)
Mining Licenses x Year ≥ 2016	-1.298***	-1.070***	-0.685***	-1.006***	-0.438***
	(0.404)	(0.334)	(0.194)	(0.367)	(0.119)
Fixed Effects	Yes	Yes	Yes	Yes	Yes
Controls × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Mean of Dependent Variable	2.97	1.90	0.96	1.64	0.75
Observation	3300	3300	3300	3300	3300

Notes: The unit of observation is the township level, and the study period covers 2011 to 2020. All conflict outcomes have been winsorized at 5%. Conflict events include all types of events, including battles, explosions, strategic developments, violence against civilians (e.g.,extrajudicial killings of unarmed prisoners of war and shooting), protests,and riots. Deadly conflict events include all types of events except protests and riots. Battles include clashes between Myanmar's military forces (the Tatmadaw) and ethnic militias, as well as clashes between different ethnic militias. Violence events are defined as incidents that result in at least one fatality. State-perpetrated violence are incidents initiated by the Tatmadaw and police forces. All regressions control for township fixed effects, year fixed effects and the interaction between year fixed effects and the following baseline characteristics: GDP per capita and population density. Standard errors, clustered at the township level, are in parenthesis. *, **, and *** indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

Table C5: Mining reform and conflict events without controls

	Overall conflict events	Extreme conflict events				Non-extreme conflict events
	No. of conflicts	No. of deadly events	No. of battles	No. of violence	No. of state-violence	No. of protests
	(1)	(2)	(3)	(4)	(5)	(6)
Mining licenses x Year ≥ 2016	-3.938**	-3.855**	-2.508***	-3.760**	-1.939***	-0.0836
	(1.572)	(1.553)	(0.850)	(1.582)	(0.637)	(0.165)
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Controls × Year Fixed Effects	No	No	No	No	No	No
Mean of Dependent Variable	5.67	4.70	2.75	4.50	2.06	0.96
Observation	3300	3300	3300	3300	3300	3300

Notes: The unit of observation is the township level, and the study period covers 2011 to 2020. This table shows that the mining ban reduces conflict events from 2011 to 2020. Conflict events include all types of events, including battles, explosions, strategic developments, violence against civilians (e.g.,extrajudicial killings of unarmed prisoners of war and shooting), protests,and riots. Deadly conflict events include all types of events except protests and riots. Battles include clashes between Myanmar's military forces (the Tatmadaw) and ethnic militias, as well as clashes between different ethnic militias. Violence events are defined as incidents that result in at least one fatality. State-perpetrated violence are incidents initiated by the Tatmadaw and police forces. All regressions control for township fixed effects, year fixed effects and the interaction between year fixed effects and the following baseline characteristics: GDP per capita and population density. Standard errors, clustered at the township level, are in parenthesis. *, **, and *** indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

Table C6: District-level analysis

	No. of conflict events	No. of deadly events	No. of battles	No. of violent events	No. of state-violence
	(1)	(2)	(3)	(4)	(5)
Mining Licenses × Year ≥ 2016	-24.48*	-24.43*	-13.18**	-24.42*	-11.95**
	(13.38)	(13.32)	(6.536)	(12.98)	(5.620)
Fixed Effects	Yes	Yes	Yes	Yes	Yes
Controls × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Mean of Dependent Variable	25.32	21.02	12.29	20.09	9.20
Observation	739	739	739	739	739

Notes: The analysis is conducted at the district level, with all outcome variables aggregated by district. This table shows that the mining ban reduces conflict events from 2011 to 2020. Conflict events include all types of events, including battles, explosions, strategic developments, violence against civilians (e.g.,extrajudicial killings of unarmed prisoners of war and shooting), protests,and riots. Deadly conflict events include all types of events except protests and riots. Battles include clashes between Myanmar's military forces (the Tatmadaw) and ethnic militias, as well as clashes between different ethnic militias. Violence events are defined as incidents that result in at least one fatality. State-perpetrated violence are incidents initiated by the Tatmadaw and police forces. All regressions control for township fixed effects, year fixed effects and the interaction between year fixed effects and the following baseline characteristics: GDP per capita and population density. Standard errors, clustered at the district level, are in parentheses. *, **, and *** indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

Table C7: Excluding townships affected by Rohingya crisis

	No. of conflict events	No. of deadly events	No. of battles	No. of violent events	No. of state-violence
	(1)	(2)	(3)	(4)	(5)
Mining Licenses × Year ≥ 2016	-2.538*	-2.462*	-1.897**	-2.363*	-1.319**
	(1.361)	(1.340)	(0.769)	(1.371)	(0.527)
Fixed Effects	Yes	Yes	Yes	Yes	Yes
Controls × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Mean of Dependent Variable	5.16	4.20	2.57	3.99	1.84
Observation	3270	3270	3270	3270	3270

Notes: The unit of observation is the township level, and the study period covers 2011 to 2020. The sample excludes three townships with the highest Rohingya populations: Buthidaung, Maungtaw, and Yathedaung. Conflict events include all types of events, including battles, explosions, strategic developments, violence against civilians (e.g.,extrajudicial killings of unarmed prisoners of war and shooting), protests,and riots. Deadly conflict events include all types of events except protests and riots. Battles include clashes between Myanmar's military forces (the Tatmadaw) and ethnic militias, as well as clashes between different ethnic militias. Violence events are defined as incidents that result in at least one fatality. State-perpetrated violence are incidents initiated by the Tatmadaw and police forces. All regressions control for township fixed effects, year fixed effects and the interaction between year fixed effects and the following baseline characteristics: GDP per capita and population density. Standard errors, clustered at the township level, are in parenthesis. *, **, and *** indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

Table C8: Excluding townships affected by Rohingya crisis without controls

	No. of conflict events	No. of deadly events	No. of battles	No. of violent events	No. of state-violence
	(1)	(2)	(3)	(4)	(5)
Mining Licenses × Year ≥ 2016	-2.542*	-2.458*	-1.893**	-2.359*	-1.318**
	(1.358)	(1.338)	(0.768)	(1.368)	(0.526)
Fixed Effects	Yes	Yes	Yes	Yes	Yes
Controls × Year Fixed Effects	No	No	No	No	No
Mean of Dependent Variable	5.16	4.20	2.57	3.99	1.84
Observation	3270	3270	3270	3270	3270

Notes: The unit of observation is the township level, and the study period covers 2011 to 2020. The sample excludes three townships with the highest Rohingya populations: Buthidaung, Maungtaw, and Yathedaung. Conflict events include all types of events, including battles, explosions, strategic developments, violence against civilians (e.g.,extrajudicial killings of unarmed prisoners of war and shooting), protests,and riots. Deadly conflict events include all types of events except protests and riots. Battles include clashes between Myanmar's military forces (the Tatmadaw) and ethnic militias, as well as clashes between different ethnic militias. Violence events are defined as incidents that result in at least one fatality. State-perpetrated violence are incidents initiated by the Tatmadaw and police forces. All regressions control for township fixed effects, year fixed effects and the interaction between year fixed effects and the following baseline characteristics: GDP per capita and population density. Standard errors, clustered at the township level, are in parenthesis. *, **, and *** indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

Table C9: Illegal mining

	No. of conflict events	No. of deadly events	No. of battles	No. of violent events	No. of state-violence
	(1)	(2)	(3)	(4)	(5)
Mining Licenses × Year ≥ 2016	-3.812**	-3.812**	-2.288**	-3.700**	-1.961***
	(1.642)	(1.628)	(0.886)	(1.672)	(0.650)
Fixed Effects	Yes	Yes	Yes	Yes	Yes
Controls × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Mean of Dependent Variable	5.25	4.29	2.45	4.09	1.85
Observations	2972	2972	2972	2972	2972

Notes: The unit of observation is the township level, and the study period covers 2011 to 2020. This table shows that the mining ban reduces conflict events from 2011 to 2020, when excluding easily looted minerals such as jade, gold, gem, and copper. Conflict events include all types of events, including battles, explosions, strategic developments, violence against civilians (e.g.,extrajudicial killings of unarmed prisoners of war and shooting), protests,and riots. Deadly conflict events include all types of events except protests and riots. Battles include clashes between Myanmar's military forces (the Tatmadaw) and ethnic militias, as well as clashes between different ethnic militias. Violence events are defined as incidents that result in at least one fatality. State-perpetrated violence are incidents initiated by the Tatmadaw and police forces. All regressions control for township fixed effects, year fixed effects and the interaction between year fixed effects and the following baseline characteristics: GDP per capita and population density. Standard errors, clustered at the township level, are in parenthesis. *, **, and *** indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

Table C10: Illegal mining without controls

	No. of conflict events	No. of deadly events	No. of battles	No. of violent events	No. of state-violence
	(1)	(2)	(3)	(4)	(5)
Mining Licenses × Year ≥ 2016	-3.815**	-3.803**	-2.281**	-3.692**	-1.958***
	(1.638)	(1.624)	(0.883)	(1.668)	(0.649)
Observations	2972	2972	2972	2972	2972
Fixed Effects	Yes	Yes	Yes	Yes	Yes
Controls × Year Fixed Effects	No	No	No	No	No
Mean of Dependent Variable	5.25	4.29	2.45	4.09	1.85
Observations	2972	2972	2972	2972	2972

Notes: The unit of observation is the township level, and the study period covers 2011 to 2020. This table shows that the mining ban reduces conflict events from 2011 to 2020, when excluding easily looted minerals such as jade, gold, gem, and copper. Conflict events include all types of events, including battles, explosions, strategic developments, violence against civilians (e.g.,extrajudicial killings of unarmed prisoners of war and shooting), protests,and riots. Deadly conflict events include all types of events except protests and riots. Battles include clashes between Myanmar's military forces (the Tatmadaw) and ethnic militias, as well as clashes between different ethnic militias. Violence events are defined as incidents that result in at least one fatality. State-perpetrated violence are incidents initiated by the Tatmadaw and police forces. All regressions control for township fixed effects, year fixed effects and the interaction between year fixed effects and the following baseline characteristics: GDP per capita and population density. Standard errors, clustered at the township level, are in parenthesis. *, **, and *** indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

Table C11: UCDP conflict dataset

	No. of conflict events	No. of conflict events
	(1)	(2)
Mining Licenses × Year ≥ 2016	-0.495**	-0.497**
	(0.231)	(0.232)
Fixed Effects	Yes	Yes
Controls × Year FE	No	Yes
Mean of Dependent Variable	0.38	0.38
Observations	3300	3300

Notes: The unit of observation is the township level, and the study period covers 2011 to 2020. This table shows that the mining ban reduces conflict events from 2011 to 2020. Conflict data is from the UCDP dataset (Sundberg & Melander 2013). All regression control for township fixed effects and year fixed effects. Column (2) additionally interacts year fixed effects with baseline GDP per capita and population density. Standard errors, clustered at the township level, are in parentheses. *, **, and *** indicate statistical significance at the 10%, 5%, and 1% levels, respectively.

Table C12: Testing for spillovers in neighboring mining townships without controls

	No. of conflict events	No. of deadly events	No. of battles	No. of violent events	No. of state-violence
	(1)	(2)	(3)	(4)	(5)
Mining licenses × Year ≥ 2016	-5.443***	-5.409***	-3.285***	-5.284***	-2.583***
	(2.000)	(1.983)	(1.088)	(2.004)	(0.830)
Townships without mining next to	-5.804***	-5.946***	-2.841***	-5.798***	-2.412***
another mining townships × Year ≥ 2016	(1.836)	(1.825)	(1.008)	(1.823)	(0.793)
Fixed Effects	Yes	Yes	Yes	Yes	Yes
Controls × Year Fixed Effects	No	No	No	No	No
Mean of Dependent Variable	5.67	4.70	2.75	4.50	2.06
Observation	3300	3300	3300	3300	3300

Notes: The unit of observation is the township level, and the study period covers 2011 to 2020. This table shows that the mining ban reduces conflict events in neighboring mining townships that do not have mining licenses. Townships that neighbor with mining townships but do not have mining licenses is a dummy taking the value 1. Conflict events include all types of events, including battles, explosions, strategic developments, violence against civilians (e.g., extrajudicial killings of unarmed prisoners of war and shooting), protests,and riots. Deadly conflict events include all types of events except protests and riots. Battles include clashes between Myanmar's military forces (the Tatmadaw) and ethnic militias, as well as clashes between different ethnic militias. Violence events are conflict events that result in at least one fatality. State-perpetrated violence are incidents initiated by the Tatmadaw and police forces. All regressions control for township fixed effects and year fixed effects. Standard errors, clustered at the township level, are in parenthesis. *, **, and *** indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

Table C13: Heterogeneity effects across different conflict measures without controls

	Ethnic Homeland		Poor Townships		Road Density		Co-ethnic Represent	
	Yes	No	Yes	No	High	Low	High	Low
Panel A: Conflict Events								
Mining licenses × Year ≥ 2016	-10.83***	-0.314	-15.46***	-0.670	-1.058	-8.683***	-4.254**	-2.798
	(4.066)	(0.311)	(5.614)	(1.149)	(0.905)	(3.206)	(1.822)	(2.556)
p-value of difference	0.01		0.01		0.02		0.64	
Panel B: Deadly Events								
Mining Licenses × Year ≥ 2016	-10.85***	-0.109	-15.18***	-0.627	-1.078	-8.403***	-3.635**	-2.963
	(4.052)	(0.200)	(5.622)	(1.108)	(0.898)	(3.187)	(1.788)	(2.522)
p-value of difference	0.009		0.01		0.02		0.83	
Panel D: Battles								
Mining Licenses x Year ≥ 2016	-6.664***	-0.104	-8.007**	-0.858	-0.524	-5.223***	-1.865**	-2.497
	(2.237)	(0.135)	(3.136)	(0.587)	(0.483)	(1.792)	(0.892)	(1.556)
p-value of difference	0.004		0.02		0.01		0.73	
Panel E: Violent Events								
Mining licenses × Year ≥ 2016	-10.55**	-0.116	-14.70**	-0.614	-0.978	-8.182**	-3.527**	-2.804
	(4.115)	(0.220)	(5.632)	(1.185)	(0.908)	(3.218)	(1.742)	(2.617)
p-value of difference	0.01		0.01		0.03		0.82	
Panel F: State-perpetrated violence								
Mining licenses × Year ≥ 2016	-5.179***	-0.114	-6.524***	-0.597	-0.476	-3.987***	-1.819**	-1.484
	(1.688)	(0.100)	(2.397)	(0.423)	(0.378)	(1.352)	(0.827)	(0.985)
p-value of difference	0.003		0.01		0.01		0.80	
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls × Year Fixed Effects	No	No	No	No	No	No	No	No
Observations	1260	2040	860	2440	1650	1649	1625	1675

Notes: The unit of observation is the township level, and the study period covers 2011 to 2020. Ethnic homelands equals to 1 if less than 50% of the population are reported to belong to the other ethnic groups, rather than the dominant Burma ethnic identity. Poor townships equal to 1 if townships' GDP falls below the 20th percentile of the distribution. High road density is equal to 1 if a township's road density is greater than or equal to the median value. Co-ethnic representation is equal to 1 if a township's co-ethnic representation in parliament is greater than or equal to the median. Conflict events include all types of events, including battles, explosions, strategic developments, violence against civilians (e.g., extrajudicial killings of unarmed prisoners of war and shooting), protests,and riots. Deadly conflict events include all types of events except protests and riots. Battles include clashes between Myanmar's military forces (the Tatmadaw) and ethnic militias, as well as clashes between different ethnic militias. Violence events are defined as conflict events that result in at least one fatality. State-perpetrated violence are conflict events initiated by the Tatmadaw and police forces. All regressions control for township fixed effects, year fixed effects, and the interactions between year fixed effects and the following baseline characteristics: GDP per capita and population density. Standard errors, clustered at the township level, are in parentheses. *, **, and *** indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

Table C14: Mineral prices without controls

	No. of conflicts	No. of deadly events	No. of battles	No. of violence	No. of state-violence
	(1)	(2)	(3)	(4)	(5)
Mining Licenses × Year ≥ 2016	-3.979**	-3.878**	-2.533***	-3.780**	-1.928***
	(1.586)	(1.567)	(0.859)	(1.596)	(0.644)
Copper Price × Copper Deposit	0.0001	0.0003	-0.00007	0.0002	-0.00004
	(0.0004)	(0.0003)	(0.0001)	(0.0003)	(0.0001)
Antimony Price × Antimony Deposit	0.0002	0.0002	0.0001	0.0003	0.0001
	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0001)
Coal Price × Coal Deposit	-0.003	-0.0030	-0.001	-0.003	-0.0002
	(0.004)	(0.004)	(0.002)	(0.004)	(0.0003)
Fixed Effects	Yes	Yes	Yes	Yes	Yes
Controls × Year Fixed Effects	No	No	No	No	No
Mean of Dependent Variable	5.67	4.70	2.75	4.50	2.06
Observation	3300	3300	3300	3300	3300

Note: The unit of observation is the township level, and the study period covers 2011 to 2020. This table shows that the mining ban reduces conflict events from 2011 to 2020, when controlling for the potential effects of mineral prices. Conflict events include all types of events, including battles, explosions, strategic developments, violence against civilians (e.g., extrajudicial killings of unarmed prisoners of war and shooting), protests,and riots. Deadly conflict events include all types of events except protests and riots. Battles include clashes between Myanmar's military forces (the Tatmadaw) and ethnic militias, as well as clashes between different ethnic militias. Violence events are defined as conflict events that result in at least one fatality. State-perpetrated violence are conflict events initiated by the Tatmadaw and police forces. All regressions control for township fixed effects and year fixed effects. Standard errors, clustered at the township level, are in parenthesis. *, **, and *** indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

Table C15: Transmission mechanisms

	Log share agri	Log share service	Log share manufacture	Produc of high value commodities	Gini coefficient
	(1)	(2)	(3)	(4)	(5)
Mining Licenses × Year ≥ 2016	0.043**	-0.104***	0.092*	-0.012*	-0.011**
	(0.019)	(0.031)	(0.051)	(0.007)	(0.005)
Mining Licenses × Year = 2017				-0.012*	0.000
				(0.006)	(0.002)
Mining Licenses × Year = 2018				-0.012*	-0.004**
				(0.006)	(0.002)
Mining Licenses × Year = 2019				-0.011*	-0.003
				(0.006)	(0.003)
Fixed Effects	Yes	Yes	Yes	Yes	Yes
Controls × Year Fixed Effects	Yes	Yes	Yes	Yes	Yes
Mean of Dependent Variable	3.65	3.46	2.07	0.005	0.16
Observations	640	640	640	3300	3300

Notes: Log_share_agri is the log share of agricultural employment at the district level, based on 2014 Census and 2018 Census data. Log_share_service is the log share of service sector employment at the district level using 2014 Census and 2018 Census data. Log_share_manufacture is the log share of manufacturing sector at the district level, based on 2014 Census and 2018 Census data. The manufacturing sector includes small and medium enterprises (SMEs). Produc of high value commodities is the intensity of high-value minerals calculated using mineral deposits and their respective world mineral prices. All regressions control for township fixed effects, year fixed effects and the interaction between year fixed effects and the following baseline characteristics: GDP per capita and population density. Standard errors, clustered and the following baseline characteristics: GDP per capita and population density. Standard errors, clustered at the township level, are in parenthesis. *, **, and *** indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

Table C16: Transmission mechanisms without controls

	Log share agri	Log share service	Log share manufacture	Produc of high value commodities	Gini coefficient
	(1)	(2)	(3)	(4)	(5)
Mining Licenses × Year ≥ 2016	0.049**	-0.112***	0.127**	-0.013*	-0.013**
	(0.019)	(0.032)	(0.051)	(0.008)	(0.006)
Mining Licenses × Year = 2017				-0.012*	- 0.000
				(0.006)	(0.002)
Mining Licenses × Year = 2018				-0.012*	-0.004**
				(0.006)	(0.002)
Mining Licenses × Year = 2019				-0.011*	-0.003
				(0.006)	(0.003)
Fixed Effects	Yes	Yes	Yes	Yes	Yes
Controls × Year Fixed Effects	No	No	No	No	No
Mean of Dependent Variable	3.65	3.46	2.07	0.005	0.16
Observations	640	640	640	3300	3300

Notes: Log_share_agri is the log share of agricultural employment at the district level, based on 2014 Census and 2018 Census data. Log_share_service is the log share of service sector employment at the district level using 2014 Census and 2018 Census data. Log_share_manufacture is the log share of manufacturing sector at the district level, based on 2014 Census and 2018 Census data. The manufacturing sector includes small and medium enterprises (SMEs). Produc of high value commodities is the intensity of high-value minerals calculated using mineral deposits and their respective world mineral prices. All regressions control for township fixed effects and year fixed effects. Standard errors, clustered at the township level, are in parenthesis. *, **, and *** indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

Table C17: Alternative accounts without controls

	No. of conflicts	No. of deadly events	No. of battles	No. of violence	No. of state-violence
	(1)	(2)	(3)	(4)	(5)
Panel A: Support for National League for Democracy (NLD)					
Mining Licenses × Year ≥ 2016	-4.471***	-4.406***	-2.791***	-4.330***	-2.163***
	(1.605)	(1.589)	(0.893)	(1.619)	(0.665)
Vote share for NLD × Year ≥ 2016	-9.927***	-9.708***	-4.311***	-9.255***	-3.573***
	(2.688)	(2.682)	(1.476)	(2.694)	(1.145)
Panel B: Townships with Community Driven Development Projects					
Mining Licenses × Year ≥ 2016	-4.069***	-4.011***	-2.616***	-3.946**	-2.017***
	(1.559)	(1.540)	(0.855)	(1.569)	(0.631)
CDD Townships × Year ≥ 2016	-0.813	-1.362	-0.920	-2.055	-0.733
	(2.620)	(2.591)	(1.606)	(2.661)	(1.208)
Fixed Effects	Yes	Yes	Yes	Yes	Yes
Controls × Year Fixed Effects	No	No	No	No	No
Mean of Dependent Variable	5.67	4.70	2.75	4.50	2.06
Observations	3300	3300	3300	3300	3300

Notes: The unit of observation is the township level, and the study period covers 2011 to 2020. Panel A explores NLD government's vote share and Panel B looks at Townships with Community Driven Development (CDD) program. Conflict events include all types of events, including battles, explosions, strategic developments, violence against civilians (e.g., extrajudicial killings of unarmed prisoners of war and shooting), protests,and riots. Deadly conflict events include all types of events except protests and riots. Battles include clashes between Myanmar's military forces (the Tatmadaw) and ethnic militias, as well as clashes between different ethnic militias. Violence events are defined as conflict events that result in at least one fatality. State-perpetrated violence are conflict events initiated by the Tatmadaw and police forces. All regressions control for township fixed effects, year fixed effects, and the interactions between year fixed effects and the following baseline characteristics: GDP per capita and population density. Standard errors, clustered at the township level, are in parentheses. *, **, and *** indicate statistical significant at the 1%, 5%, and 10% levels, respectively.

C.2 Details on Data Construction

Ethnicity Data I obtained unique data from the Ministry of Home Affairs to compute a variable for ethnic homelands for heterogeneity analysis. Ethnic homelands are defined based on the share of the Burma ethnic majority in a given township: a township is considered an ethnic homeland if less than 50% of the population belongs to other ethnic groups, rather than the dominant Burma ethnic identity. This analytical construct is designed with the assumption that conflict events may vary in townships with a more dominant Burmese ethnic majority compared to those with more prevalent ethnic minorities.

Average Income per Capita, Population Density Data Data on average income per capita for 2015 came from the Ministry of Home Affairs. I calculated the population density for 2014 (number of people per square kilometer of land area) using the data for the population and land area of the Ministry of Home Affairs for 2014. The average income per capita and population density are used as control variables. Based on the average income per capita, I define poor townships as those with a GDP below the 25th percentile of the distribution to explore whether conflict events may differ between poor and non-poor townships.

Road Density Data I utilized data on road density from the Ministry of Home Affairs. This data is used to explore whether conflict events may differ between remote townships with low road density and more connected townships with higher road density.

Mineral Prices Information on world mineral prices between 2011 and 2020 was obtained from the World Bank Commodity Prices dataset. I use this information to control the potential effects of movements in mineral prices. In addition, I calculate the value of commodities using mineral deposits and their respective world mineral prices for the mechanism test.

Employment, Gini Coefficient, and Co-ethnic Representation Data These data were used to test transmission mechanisms. Employment data at the district level come from the Myanmar 2014 and 2018 censuses. The data are categorized by sector: the agriculture sector

comprises both livestock and crop farming, the service sector includes activities such as trading, and the manufacturing sector covers industrial production as well as small-scale or handmade goods.

The Gini coefficient at the district level is computed based on GDP per capita at the township level of the Ministry of Home Affairs. Using data on the ethnicity of elected representatives from Amyotha Hluttaw (upper house), Pyithu Hluttaw (lower house) and State and Region Hluttaw in November 2010 and November 2015 from the Union Election Commission (UEC), I construct the variable for co-ethnic representation. This measures political exclusion based on the ethnic composition of the population and the share of elected representatives by ethnicity in each township. To measure how closely the ethnic composition of the parliament aligns with the demographic composition of the overall population in each township (co-ethnic representation), I calculate the squared differences between the population share and the share of members of parliament for each ethnicity. I then sum these squared differences for each township. A higher summed value signifies a greater degree of disparity in co-ethnic representation.

Data on Vote Share for National League for Democracy (NLD) and Community Driven Development (CDD) projects These data were used to test alternative accounts. The NLD vote share data came from the Union Election Commission (UEC) for the November 2010 and November 2015 general elections. Data on whether a township has Community Driven Development (CDD) projects came from the Ministry of Livestock, Fisheries and Rural Development. The CDD projects aim to improve access to basic infrastructure and services such as roads, schools, and water.