# Bioenergy Expansion and Spatially Unequal Environmental Impacts

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January 2026

**Abstract**

Renewable energy transitions promise long-run environmental benefits, yet in the short-run they can generate unequal local and nonlocal environmental effects. This paper studies the global impacts of bioenergy expansion by combining worldwide plant-level data, satellite-based measures of air pollution and land use, and international trade flows. I document three main findings. First, bioenergy expansion accelerates coal phase-out and improves local air quality. An annual increase of 1 MW per operating bioenergy plant raises the probability that a coal plant is retired by 1.74 percentage points and, among remaining active plants, reduces surrounding $SO_2$ and AOD by 1.35 percent and 0.24 percent relative to their means. Second, bioenergy expansion increases upstream wood demand, with the same capacity increase raising wood product imports by 0.17 percent. Third, exploiting nationwide biomass policy shocks in Japan and Korea, I show that rising wood exports induce persistent deforestation in Indonesia, Thailand, and Vietnam, implying cumulative forest loss of 18,000 $km^2$ over the eight-year post-policy period. My findings highlight a tradeoff in the energy transition that bioenergy policies deliver local environmental gains while inducing environmental damage upstream through international supply chains.

JEL Classifications: Q42, Q23, F63, Q56

Keywords: Energy transition, bioenergy, coal phase-out, deforestation, air pollution

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# 1 Introduction

The global transition toward renewable energy is a central pillar of climate mitigation policy. Achieving international targets consistent with limiting global warming to 2°C relative to pre-industrial levels requires a rapid and large-scale replacement of fossil fuel electricity generation with low-carbon alternatives over the coming decades. Between 2010 and 2022, global renewable electricity capacity more than tripled to over 3,700 GW, with annual investment exceeding $500 billion (Ashraf and Sagheer, 2025). While these investments promise great long-run benefits through reductions in greenhouse gas emissions and improvements in local air quality, large-scale deployment also entails extensive material requirements and capital turnover along global supply chains, including upstream manufacturing, mining, and resource extraction. As renewable technologies become embedded in international supply chains, climate policy may generate spatially displaced environmental externalities, whereby downstream environmental improvements coincide with upstream environmental damages, complicating the evaluation of aggregate welfare impacts.

Bioenergy occupies a distinctive position within this transition. Unlike solar and wind power, which rely primarily on ambient energy flows, biomass-based electricity generation depends on continuous physical inputs, most commonly wood pellets and other forest products. As a result, bioenergy expansion directly links electricity generation to forest extraction and land use change, tightly coupling energy markets with land markets. Global trade in industrial wood pellets increased more than sixfold between 2010 and 2022, reaching over 40 million metric tons annually, with Asia—driven primarily by Japan and Korea—accounting for one-third of global import demand (International Energy Agency, 2024). This rapid expansion implies that bioenergy policies in importing countries increasingly shape forest management and land use decisions in distant exporting regions. Although bioenergy is often treated as carbon neutral in policy evaluation, growing evidence suggests that biomass demand can induce forest harvesting and land conversion (e.g., Hall, 2002; Abt et al., 2012), potentially offsetting local environmental gains through carbon leakage and ecosystem degradation. Whether bioenergy expansion ultimately delivers net environmental benefits therefore remains an open empirical question, hinging critically on the magnitude, persistence, and spatial distribution of these upstream responses.

This paper studies the global environmental impacts of large-scale bioenergy expansion, with a particular focus on its spatially unequal effects across electricity-generating and resource-extracting regions. To do so, I combine worldwide plant-level data on 4,537 bioenergy

plants and 14,357 coal-fired generating units, satellite-based measures of air pollution and vegetation, detailed international trade flows, and port-level shipping records to quantify both the local environmental benefits and the nonlocal environmental costs of bioenergy deployment. The empirical analysis proceeds in two steps. First, I conduct a global panel to estimate how bioenergy expansion affects coal plant retirement and surrounding air pollution, thereby identifying the local environmental gains from bioenergy adoption. Second, I exploit two large nationwide biomass policy shocks in Japan and Korea, two of the world's largest biomass importers, to trace how bioenergy-induced trade flows propagate upstream along international supply chains, transmitting environmental impacts into major biomass-exporting countries.

The global analysis reveals three central findings. First, bioenergy expansion generates large and economically meaningful local environmental benefits along both extensive and intensive margins. The estimated annual increase in operating bioenergy capacity is 3,365 MW, equivalent to 1.7 MW per operating plant. This capacity expansion increases the probability that a coal plant is retired by the end of the year by 3.0 percentage points, 14.7 percent relative to the baseline retired share. Among non-retired units, conditional on continued operation, bioenergy expansion also reduces coal plant utilization: surrounding sulfur dioxide ($SO_2$) concentrations and aerosol optical depth (AOD) decline by 2.3 percent and 0.4 percent relative to their respective means. Aggregated across space, these extensive and intensive margin responses imply large reductions in coal-fired electricity generation and associated emissions.

Second, these local benefits are highly uneven across regions. They are concentrated in developed economies like Europe and North America where regulatory stringency, grid flexibility, and pre-existing excess coal capacity facilitate rapid adjustment along both extensive and intensive margins. In contrast, coal retirement responses are not significant in Latin America and Africa, consistent with slower coal phase-out and weaker regulatory incentives in developing economies.

Third, I examine the costs of bioenergy deployment in terms of electricity system performance and upstream input demand. I find no detectable impact on transmission and distribution losses, indicating that bioenergy expansion does not compromise grid reliability. Electricity access declines slightly, but the magnitude is economically negligible, amounting to less than 0.05 percentage points per year relative to baseline access rates exceeding 90 percent. In contrast, bioenergy expansion greatly increases upstream biomass demand. The same 1.7 MW annual capacity expansion per bioenergy plant raises national wood product imports by 0.29 percent, corresponding to an additional 0.18 million $m^3$ of wood products annually.

This sharp divergence between modest local system costs and large upstream input responses highlights the tight linkage between downstream electricity generation and upstream forestry markets.

These patterns raise concerns about environmental impacts in biomass-exporting regions. To identify causal upstream effects, I exploit two major policy-driven expansions in bioenergy demand: Japan's 2012 Feed-in Tariff reform and Korea's Renewable Portfolio Standard. Together, these policies led to multi-gigawatt expansions in bioenergy capacity and nearly tripled wood pellet imports within a decade. Replicating the global analysis in the context of these nationwide policy shocks, I document sharp reductions in coal-related air pollution within Japan and Korea, confirming sizable domestic environmental gains. At the same time, I observe large and persistent surges in wood imports, particularly from Southeast Asia, with import volumes from Indonesia, Vietnam, and Thailand increasing by over 60 percent relative to pre-policy trends.

I then zoom in on Indonesia, Vietnam, and Thailand, three major biomass-exporting countries that collectively supply more than half of Japan and Korea's upstream wood imports. Using detailed port-level shipping data, I construct spatial exposure measures that capture differential access to Japanese and Korean import markets. Comparing highly exposed grids near export ports to less exposed regions, I document large and persistent declines in forest cover and vegetation indices following the policy shocks. Aggregating across space and time, the estimated cumulative forest loss reaches about 18,000 $km^2$ over the eight-year post-policy period. These effects are strongest for forest cover, relative to savanna, shrubland, and grassland, consistent with the much higher biomass density and carbon stocks of forest ecosystems. I also find no evidence of post-shock recovery in forest cover, suggesting that bioenergy-induced deforestation represents a persistent rather than transitory land use response.

This paper contributes to four strands of the literature. The first is the environmental and amenity impacts of renewable energy expansion. Existing studies document how renewable energy projects affect land cover (Hernandez et al., 2015; Song et al., 2023; Gao et al., 2023), property values (Haan and Simmler, 2018; Guo et al., 2024; Mei et al., 2024; Jarvis, 2025; Li et al., 2024), agricultural activity (Sampson et al., 2020; Kaffine, 2019), and biodiversity (Meng et al., 2025; Li et al., 2025; Wang et al., 2025), with a primary focus on local outcomes near renewable energy installations. My paper contributes to this literature by shifting the focus beyond local impacts to cross-border spillovers. Moreover, within this literature, most attention has been devoted to solar and wind energy, likely due to their rapid deployment, large spatial footprint, and prominent public opposition. By contrast, the environmental

consequences of bioenergy expansion remain relatively understudied, despite its growing role in decarbonization strategies and heavy reliance on land-intensive inputs.

The second literature studies environmental spillovers driven by international trade, particularly through pollution leakage and the pollution haven effect. This work shows that trade reallocation can shift pollution and environmental damages across countries via comparative advantage, consumption patterns, and production specialization (Ederington et al., 2005; Levinson and Taylor, 2008; Shapiro, 2016). Papers have shown how environmental regulation and trade openness affect the location of pollution-intensive production, emphasizing firm relocation, outsourcing, and cross-border production shifting (Copeland and Taylor, 2004, 2005; Bombardini and Li, 2020). More recent work extends this perspective to natural resource sectors, documenting how agricultural trade and climate policy affect tropical deforestation (Hsiao, 2025). Existing studies primarily focus on spillovers arising from manufacturing production, final-goods consumption, or agricultural commodity demand. Much less is known about how energy transition policies—especially those promoting land-intensive renewable technologies—generate environmental spillovers through upstream input markets. This paper fills this gap by identifying bioenergy expansion as a new and quantitatively important channel of environmental displacement: while bioenergy policies accelerate coal phase-out and reduce local air pollution, they simultaneously increase deforestation and ecosystem degradation abroad by raising demand for biomass inputs.

The third strand of literature studies the economics of deforestation. Existing work quantifies the environmental and health consequences of forest loss and on identifying its key drivers. Regarding the former, previous research documents that forest cover plays a critical role in regulating precipitation and local climate (Han et al., 2024; Grosset-Touba et al., 2024), mitigating air pollution (Nowak et al., 2014; Xing et al., 2023; Du et al., 2024), sustaining water supply and hydropower generation (Araujo, 2024), and reducing infectious disease transmission while improving human health (Berazneva and Byker, 2017; Garg, 2019; Jones and Goodkind, 2019; Berazneva and Byker, 2024). Regarding the latter, studies emphasize agricultural expansion (Burgess et al., 2012; Assunção et al., 2015; Carreira et al., 2024), infrastructure investment (Pfaff, 1999; Pfaff et al., 2007; Baehr et al., 2021; Araujo et al., 2023), trade liberalization and foreign demand (Dominguez-Iino, 2021; Harstad, 2024; Farrokhi et al., 2025; Hsiao, 2025), and institutional constraints (Assunção and Rocha, 2019) as central drivers of deforestation. This paper contributes to the latter by uncovering a previously underexplored driver of forest loss—bioenergy expansion in advanced economies—which induces persistent deforestation in developing countries through upstream demand responses.

The fourth related literature examines environmental justice and the unequal distribution of environmental harms. Existing studies primarily focus on disparities in pollution exposure across socioeconomic and demographic groups (Banzhaf et al., 2019; Currie, 2011; Tessum et al., 2021; Jbaily et al., 2022; Currie et al., 2023; Cain et al., 2024), driven by the spatial distribution of polluting activities and residential sorting (Shadbegian et al., 2010; Hausman and Stolper, 2021; Bakkensen and Ma, 2020). By contrast, far less is known about inequality in access to environmental amenities, such as green space and forests, particularly across countries, despite growing evidence in the urban and geographic sciences (e.g., Frey, 2017; Fernández et al., 2023; Foster et al., 2024; Li and Li, 2025). This paper highlights a new dimension of environmental injustice: bioenergy expansion in advanced economies exports environmental damages upstream, inducing deforestation and ecosystem degradation in developing countries and generating cross-border inequalities in natural amenities and ecosystem services.

From a policy perspective, the results reveal a tradeoff in the global energy transition. While bioenergy policies deliver great local benefits through accelerated coal phase-out and improved air quality, they simultaneously export environmental damages upstream through international trade, generating persistent deforestation and ecosystem degradation abroad. Ignoring these cross-border spillovers can largely overstate the net environmental benefits of bioenergy expansion and lead to inefficient climate policy design.

More broadly, my findings underscore the importance of incorporating global supply chain externalities into the evaluation of renewable energy policies. Renewable technologies differ sharply in their environmental footprint depending on their reliance on land- and resource-intensive inputs, with critical implications for the composition of efficient and equitable energy transition pathways. My findings highlight the potential role of sustainability certification, trade-based environmental standards, border adjustments, and international coordination, to mitigate upstream environmental damages while preserving local climate and air quality gains.

## 2 Background

### 2.1 Energy transition and bioenergy expansion

The global transition toward low-carbon energy systems has been driven primarily by advanced economies, where climate mitigation objectives, public health concerns, and energy security considerations have motivated large-scale policy interventions to promote renewable energy deployment and accelerate the phase-out of coal-fired power generation (Borenstein, 2012;

Newell et al., 2013; Yolcan, 2023). Coal combustion remains among the largest sources of anthropogenic carbon dioxide emissions and local air pollution, accounting for nearly one-third of global energy-related $CO_2$ emissions and a dominant share of ambient sulfur dioxide and fine particulate matter concentrations. The resulting health damages are large, contributing to millions of premature deaths annually worldwide and imposing large economic costs (Pope III et al., 2011; Hannun and Razzaq, 2022).

In response, many countries have adopted industrial policy packages combining carbon pricing, renewable portfolio standards, feed-in tariffs, production subsidies, investment tax credits, and direct regulatory mandates to stimulate renewable energy investment and induce early retirement of coal capacity (Gerarden et al., 2025). These policy instruments have produced rapid growth in renewable generation capacity, particularly in solar, wind, and bioenergy, reshaping electricity markets and accelerating the decarbonization of power systems.

Within this broader energy transition, bioenergy occupies a distinctive role. Unlike intermittent renewable sources such as solar and wind, bioenergy is fully dispatchable, compatible with existing thermal generation infrastructure, and capable of providing stable baseload and load-following electricity (Bioenergy, 2009; Denholm et al., 2009). These technological characteristics make biomass particularly attractive for replacing coal-fired generation, district heating systems, and industrial energy demand, where reliability, ramping capability, and system flexibility are highly valued. Moreover, bioenergy facilities can often be integrated into existing coal plants through retrofitting, co-firing, or full fuel switching, largely lowering capital adjustment costs and political resistance associated with coal phase-out (Tillman, 2000; Dai et al., 2008). These engineering and institutional advantages have reinforced the appeal of bioenergy within renewable policy portfolios.

Reflecting these features, bioenergy has been widely promoted through feed-in tariffs, renewable portfolio standards, production subsidies, long-term procurement contracts, and capacity market participation. Globally, bioenergy constitutes the largest source of renewable energy in total primary energy supply, accounting for over half of renewable energy production and about six percent of total primary energy consumption. Since the early 2000s, installed bioenergy capacity has expanded rapidly, particularly in high-income economies such as Japan, Korea, the European Union, and North America, driven by a combination of climate policy, grid reliability considerations, and industrial policy objectives (Kim, 2021; Bogdanov et al., 2023; Avitabile et al., 2023). In East Asia, bioenergy has played a central role in post-Fukushima energy strategies, where concerns about nuclear safety and energy security reinforced incentives for dispatchable renewable generation.

From a climate accounting perspective, bioenergy is commonly treated as a low-carbon or carbon-neutral energy source because carbon released during biomass combustion is, in principle, offset by carbon uptake during biomass regrowth (Searchinger et al., 2009; Cherubini et al., 2009). This assumption underlies most life-cycle assessments and national greenhouse gas inventories, which typically assign zero net emissions to biomass combustion at the point of use. However, this accounting framework critically depends on strong assumptions regarding sustainable forest management, land use neutrality, and rapid biomass regeneration. A growing body of engineering and environmental science literature emphasizes that sustained increases in biomass demand can induce significant land use change, forest degradation, and carbon stock depletion, potentially offsetting or even reversing the climate benefits of bioenergy deployment (Searchinger et al., 2009; Mitchell et al., 2012). These mechanisms raise concerns about the net climate effectiveness of large-scale bioenergy expansion once global land use adjustments and supply chain feedbacks are fully internalized.

### 2.2 Biomass plants and wood inputs

Unlike solar and wind power, which harness ambient energy flows, biomass electricity generation relies on the direct combustion of solid woody fuels. At utility scale, bioenergy plants primarily burn industrial wood pellets, together with wood chips, sawmill residues, and forest harvesting residues, which are processed into standardized fuels suitable for large-scale boilers (Bioenergy, 2009). Raw timber and forestry residues are harvested, chipped, dried, ground, and pelletized before being transported to power plants and combusted in dedicated biomass boilers or co-fired with coal in conventional thermal units. From fuel procurement to combustion, the typical supply cycle spans several months to one year, implying that changes in electricity generation translate rapidly into upstream biomass demand. These processing steps generate tightly integrated supply chains that directly connect downstream electricity production to upstream forestry management and land use decisions (Lamers et al., 2015; Matzenberger et al., 2015). The scale of these material flows is large: a single utility-scale bioenergy plant can consume several hundred thousand tons of solid biomass annually, generating persistent and spatially concentrated demand for forest-based inputs (Sikkema et al., 2011; Lamers et al., 2015).

In many high-income economies, domestic biomass supply is constrained by limited land availability, environmental regulations, competing land uses, high labor costs, and sustainability standards (Avitabile et al., 2023). In Japan and Korea, steep terrain, fragmented land ownership, and forest conservation priorities sharply limit economically viable timber

extraction, rendering domestic biomass resources insufficient to sustain large-scale bioenergy deployment. Similar constraints exist across much of Western Europe, where biodiversity protection, ecosystem service preservation, and carbon stock conservation restrict the intensification of forest harvesting. As a result, bioenergy expansion in advanced economies has increasingly depended on imported biomass, particularly wood pellets and wood chips sourced from forest-rich regions in Southeast Asia, Latin America, Eastern Europe, and the southeastern United States (Lamers et al., 2015; Matzenberger et al., 2015).

This growing reliance on international biomass supply chains implies that renewable energy policies implemented in importing countries can induce large land use responses abroad. Rising biomass demand increases returns to timber extraction, plantation establishment, and forest conversion, potentially accelerating deforestation, forest degradation, and land use intensification in exporting regions. These adjustments may operate along extensive margins through forest clearing and conversion, as well as intensive margins through increased harvesting rates, shortened rotation cycles, and shifts toward monoculture plantations. Because forest regeneration is slow, uncertain, and spatially heterogeneous, biomass-induced land use change can generate persistent environmental impacts, including carbon stock depletion, biodiversity loss, hydrological disruption, soil erosion, and heightened vulnerability to fire and extreme climatic events (Pan et al., 2011; Seymour and Busch, 2016). These global production linkages imply that the environmental consequences of bioenergy expansion cannot be assessed solely within national borders. Instead, downstream energy policies and upstream land use outcomes are jointly determined through international trade networks, transportation costs, institutional constraints, and geographic endowments.

# 3 Conceptual framework

This section develops a framework in which bioenergy expansion affects welfare over different horizons. Specifically, it describes how policy-driven increases in bioenergy generation displace coal and improve local air quality in the short run, and how an accelerated energy transition combined with reduced forest carbon sinks affects global welfare in the long run.

## 3.1 Electricity generation in importing regions

Suppose a representative importing country whose electricity generation includes both coal-fired power plants and bioenergy plants. Electricity demand in period $t$ depends on the

electricity price:

$$Q_t = Q(P_t), \qquad Q'(P_t) < 0 \tag{1}$$

where $P_t$ is the market-clearing electricity price. On the supply side, total electricity supply is the sum of coal and bioenergy generation:

$$Q_t = \sum_i q_{it} + \sum_b q_{bt}^B \tag{2}$$

From the producer's perspective, coal plant $i$ produces $q_{it}$ units of electricity at marginal cost $c_i$ and pays a fixed operating cost $F_i$. Bioenergy plant $b$ produces $q_{bt}^B$ units of electricity using biomass inputs. Its marginal cost is specified as:

$$mc_{bt}^B = \kappa p_t^w + \tilde{c}_b - s_t \tag{3}$$

where $p_t^w$ is the wood price, $\kappa$ measures biomass input intensity, $\tilde{c}_b$ captures non-wood operating costs, and $s_t$ represents policy support.

Given the global trends of coal phase-out and renewable expansion, an increase in policy support makes bioenergy production more profitable. Bioenergy generation expands, coal generation contracts, and electricity prices fall:

$$\frac{\partial q_{bt}^B}{\partial s_t} > 0, \qquad \frac{\partial q_{it}}{\partial s_t} < 0, \qquad \frac{\partial P_t}{\partial s_t} < 0 \tag{4}$$

Coal plant profits are:

$$\pi_{it} = (P_t - c_i)q_{it} - F_i \tag{5}$$

A coal plant continues operating as long as revenues cover operating and retirement costs. Plant $i$ exits when its continuation value satisfies:

$$V_{it} < -K_i \tag{6}$$

where $K_i$ is the one-time cost of retirement.

From the perspective of the overall energy sector, coal plants are a major source of local air pollution. Local pollution damages are assumed to be proportional to coal output:

$$D_t^{air} = \sum_i \theta_i q_{it}, \qquad \theta_i > 0 \tag{7}$$

Coal plants face different levels of competition from nearby bioenergy facilities. Exposure to bioenergy competition is measured as:

$$E_{it} = \sum_b \omega(d_{ib}) \cdot Cap_{bt}, \qquad \omega'(d) < 0 \tag{8}$$

where $d_{ib}$ is the distance between coal plant $i$ and bioenergy plant $b$. Thus, coal plants with greater exposure experience larger reductions in output and higher exit rates:

$$\frac{\partial q_{it}}{\partial E_{it}} < 0, \qquad \frac{\partial \Pr(\text{exit}_{it})}{\partial E_{it}} > 0 \tag{9}$$

For bioenergy generation, plants require biomass inputs such as wood pellets. Aggregate wood demand in the importing country is specified as:

$$M_t^w = \kappa \sum_b q_{bt}^B, \qquad \frac{\partial M_t^w}{\partial s_t} > 0 \tag{10}$$

Because biomass markets are globally integrated, higher demand raises the wood price:

$$p_t^w = p^w(M_t^w), \qquad \frac{\partial p_t^w}{\partial M_t^w} > 0 \tag{11}$$

### 3.2 Exporting regions and forest dynamics

Now suppose that biomass used for bioenergy production is sourced from exporting regions that differ in forest endowments and access to international markets. Exporting locations are indexed by grid $g$ and are characterized by initial forest cover $F_{g0}$. When biomass prices rise, producers in exporting regions increase wood harvesting, especially in locations that are closer to ports or have better market access. Wood harvesting responds to the wood price and market access as follows:

$$h_{gt} = h(p_t^w, Access_g), \qquad \frac{\partial h_{gt}}{\partial p_t^w} > 0, \qquad \frac{\partial h_{gt}}{\partial Access_g} > 0 \tag{12}$$

Forest cover evolves over time as harvesting reduces forest area and natural regeneration partially offsets these losses:

$$F_{g,t+1} = F_{gt} - \lambda h_{gt} + R_{gt}, \qquad \lambda > 0 \tag{13}$$

where $R_{gt}$ captures forest regeneration.

Over the medium run, forest regeneration is slow relative to harvesting, so increases in wood extraction translate into persistent reductions in forest cover:

$$\frac{\partial R_{gt}}{\partial t} \approx 0 \tag{14}$$

As a result, bioenergy-driven increases in biomass demand reduce forest carbon stocks in exporting regions, particularly in locations with high exposure to biomass trade.

### 3.3 Short-run welfare

I now evaluate short-run welfare from the perspective of the importing country. Short-run welfare depends on electricity market outcomes, local income effects, local air quality, and the fiscal cost of bioenergy policy:

$$W_t^{SR} = CS_t(P_t) + PS_t^C + PS_t^B + Y_t^{loc} - D_t^{air} - S_t \tag{15}$$

Producer surplus from coal and bioenergy generation reflects revenues net of operating costs:

$$PS_t^C = \sum_i \left[(P_t - c_i)q_{it} - F_i\right], \qquad PS_t^B = \sum_b (P_t - mc_{bt}^B)q_{bt}^B \tag{16}$$

Bioenergy deployment generates local income through construction activity, plant operation, and related supply chains:

$$Y_t^{loc} = \omega_1 \sum_b Cap_{bt} + \omega_2 \sum_b q_{bt}^B \tag{17}$$

At the same time, bioenergy policies involve fiscal expenditures that scale with bioenergy output:

$$S_t = s_t \sum_b q_{bt}^B \tag{18}$$

In the short run, increased bioenergy generation displaces coal, reduces local air pollution, and raises local income, generating welfare gains in importing regions:

$$\frac{\partial D_t^{air}}{\partial s_t} < 0, \qquad \frac{\partial Y_t^{loc}}{\partial s_t} \geq 0 \tag{19}$$

### 3.4 Long-run global welfare and empirical predictions

Coal phase-out not only improves local air quality but also accelerates the energy transition, which leads to long-run global welfare gains. However, the large increase in wood demand leads to a loss of forest stock, which reduces long-run carbon sinks and generates welfare losses. Long-run welfare is evaluated at the global level and incorporates both downstream climate benefits and upstream environmental costs.

Specifically, long-run global welfare aggregates discounted short-run welfare and long-run environmental damages:

$$W^{LR} = \sum_{t=0}^{\infty} \beta^t \left( W_t^{SR} - D_t^{clim} - D_t^{for} \right), \qquad \beta \in (0,1) \tag{20}$$

Climate damages depend on fossil fuel use and the pace of the energy transition:

$$D_t^{clim} = \psi \left( \sum_i \gamma_i q_{it} - \sum_b \delta q_{bt}^B \right), \qquad \psi > 0 \tag{21}$$

Forest-related damages capture losses in forest carbon stocks and biodiversity resulting from biomass harvesting and land conversion:

$$D_t^{for} = \sum_g \left( \chi_1 \Delta F_{gt} + \chi_2 \Delta B_{gt} \right) \tag{22}$$

An accelerated energy transition reduces climate damages through sustained coal phase-out, while increased biomass demand raises forest-related damages by reducing forest carbon sinks. The net effect on long-run global welfare depends on the relative magnitude of these opposing forces:

$$\frac{\partial W^{LR}}{\partial s_t} = -\frac{\partial D_t^{clim}}{\partial s_t} - \frac{\partial D_t^{for}}{\partial s_t} - \frac{\partial S_t}{\partial s_t} \tag{23}$$

This stylized model implies that the long-run welfare effects of bioenergy expansion are ambiguous. I use empirical data to test several predictions. First, coal generation and coal plant survival decline more in locations with greater exposure to nearby bioenergy facilities, and these changes are accompanied by improvements in local air quality. Second, bioenergy expansion increases biomass demand and wood prices in importing countries. Third, higher biomass prices induce greater forest loss in exporting regions with better market access and weaker land-use constraints. The empirical analysis examines these predictions to assess how short-run welfare gains in importing regions compare with long-run global welfare trade-offs.

# 4 Data

## 4.1 Energy tracker

Data on global power plant characteristics are obtained from the Global Energy Monitor (GEM) Energy Tracker database. It provides plant-level information on electricity generation facilities worldwide, including location, fuel type, installed capacity, commissioning year, operational status, and retirement year. The Energy Tracker integrates data from regulatory filings, company disclosures, satellite imagery, and systematic manual verification, yielding consistent global coverage across countries and time.

For bioenergy plants, the database reports detailed information on biomass-based electricity generation facilities, including plant capacity, fuel classification, operational status, and geographic coordinates. I use the Global Bioenergy Power Tracker (GBPT), which records all utility-scale bioenergy power plants with a minimum capacity threshold, allowing me to construct annual measures of operating bioenergy capacity and plant entry over time. For coal-fired power plants, I use the Global Coal Plant Tracker (GCPT), which documents the universe of coal power units worldwide. The GCPT provides plant-level data on installed capacity, commissioning year, retirement year, unit-level operating status, and geographic location.

## 4.2 Land use

To examine how wood exports affect vegetation and land cover, I rely on two global remote sensing products. The first is the MODIS global land cover product MCD12Q1 Version 6.1, which reports annual land cover classifications at a 0.05 degree resolution from 2001 onward. The MODIS scheme distinguishes seventeen land cover categories, including evergreen needleleaf forest, evergreen broadleaf forest, deciduous broadleaf forest, deciduous needleleaf forest, mixed forest, woody savanna, savanna, shrubland, and grassland. These classifications allow me to construct measures of forest cover, tree-dominated landscapes, and total vegetated area. Forest share is defined as the combined area of the forest classes. Broad tree share expands this to include woody savanna and savanna. Vegetation share encompasses all forest, woody savanna, savanna, shrubland, and grassland categories, providing a broad measure of terrestrial vegetation.

The second source is the Landsat 7 Surface Reflectance dataset produced by the United States Geological Survey (USGS). It provides 30-meter spatial resolution imagery at a 16-day revisit frequency. From these observations I construct the normalized difference vegetation index

(NDVI),

$$NDVI = \frac{NIR - Red}{NIR + Red}$$

which is derived from the near-infrared (NIR) and red spectral bands and captures variation in canopy greenness and surface biomass associated with photosynthetic activity.

### 4.3 Air pollution

To measure air pollution, I use two global satellite-based datasets that provide uniform spatial coverage and consistent retrieval protocols over time. This avoids the challenges associated with ground-based monitoring, which is highly uneven across countries and often subject to variation in reporting quality, calibration, and maintenance. Both satellite products are fully comparable across space and time and are completely independent of local reporting practices.

The first pollution measure is the MERRA-2 aerosol optical depth (AOD) produced by NASA's Global Modeling and Assimilation Office. MERRA-2 is a reanalysis product that integrates satellite radiances, ground observations, and atmospheric transport models to generate daily global aerosol fields at a resolution of 0.5 by 0.625 degrees.

The second measure is sulfur dioxide ($SO_2$). I use satellite-based retrievals from the Ozone Monitoring Instrument (OMI) onboard NASA's Aura satellite. OMI provides daily global coverage of atmospheric trace gases using ultraviolet and visible spectrometry. I employ the OMSO2e Level-3 planetary boundary layer $SO_2$ column product, which isolates near-surface $SO_2$ concentrations most directly linked to fossil fuel combustion and industrial emissions. The OMI $SO_2$ product is constructed by applying spectral fitting algorithms to backscattered solar radiation, followed by corrections for atmospheric scattering, surface reflectance, and cloud effects. These retrievals generate spatially continuous global fields at a resolution of 0.25 by 0.25 degrees and daily temporal frequency.

### 4.4 Trade

International trade data are obtained from the United Nations Comtrade Database, which reports bilateral trade flows at the importer–exporter–product–year–month level. I focus on imports and exports of wood-based products used as the primary feedstocks for utility-scale bioenergy generation, including fuelwood, wood chips, wood residues, and processed wood pellets. These products are identified using HS 6-digit codes 440110, 440111, 440112, 440121, 440122, 440130, 440131, 440132, 440139, 440140, 440141, and 440149, covering fuelwood, wood

chips and particles, sawdust, wood waste and scrap, and agglomerated wood residues, as well as HS 121110, 121120, 121130, 121140, 121150, 121160, and 121190, which capture industrial plant materials commonly used as biomass inputs.

To isolate bioenergy-driven demand from broader trade dynamics, I additionally construct a set of non-biofuel control products, including cereals (HS 10), minerals (HS 25), fertilizers (HS 31), iron and steel (HS 72), machinery (HS 84), electrical equipment (HS 85), and vehicles (HS 87). These categories span agricultural, industrial, and manufactured goods, allowing me to net out confounding shocks related to macroeconomic conditions, trade liberalization, and sector-specific demand fluctuations.

### 4.5 Ports

Data on global port locations and shipping flows are obtained from the World Port Index (WPI) compiled by the US National Geospatial-Intelligence Agency. The WPI provides detailed information on the geographic coordinates and country affiliations of major commercial ports worldwide, covering both coastal and river ports that serve as key nodes in international trade networks.

To measure international shipping activity, I combine the port location data with port-level and port-pair level shipping flow information. These data report annual cargo outflows aggregated at the port level, as well as bilateral shipping volumes between origin and destination port pairs. The port-pair data allow me to construct spatially detailed measures of trade connectivity and transportation intensity between exporting and importing regions.

### 4.6 Electricity stability

To measure electricity system stability, I use annual country-level indicators from the World Development Indicators (WDI) compiled by the World Bank. These data provide consistent cross-country coverage and harmonized definitions. I focus on two primary measures. The first is the electricity access rate, defined as the percentage of the population with access to electricity. This variable captures the extensive margin of electricity service provision and reflects overall system reliability, infrastructure coverage, and service availability. The second measure is transmission and distribution (T&D) losses, expressed as the percentage of electricity output lost during transmission and distribution. T&D losses reflect grid efficiency, infrastructure quality, and technical performance of electricity networks.

Both measures are available annually for a broad set of countries since before 2000s. Electricity access data are derived from household surveys, utility records, and national statistical systems, harmonized by the World Bank to ensure comparability. Transmission and distribution losses are constructed from national electricity production and consumption accounts reported by energy authorities.

# 5 Global analysis: local and import effects of biomass plants

## 5.1 Empirical strategy

I study the local effects of bioenergy expansion on coal plant outcomes using a panel regression at the global coal plant-year level. My analysis focuses on two margins: coal plant retirement and short-run changes in surrounding air pollution. These two outcomes capture, respectively, the extensive margin exit response and the intensive margin environmental adjustment induced by bioenergy-driven competition in electricity markets. My baseline specification is:

$$Y_{it} = \rho \cdot D_{it} + \alpha_i + \gamma_t + \varepsilon_{it} \tag{24}$$

where $i$ denotes coal plants and $t$ denotes time. The coefficient of interest, $\rho$, measures the effect of exposure to nearby operating bioenergy capacity on coal plant outcomes.

I first analyze coal plant retirement using an annual panel covering all coal plants worldwide that were operating prior to 2007. In this specification, the dependent variable $Y_{it}$ equals one if plant $i$ has retired by year $t$, including retirement in and before year $t$, and zero otherwise. This allows me to examine whether proximity to expanding bioenergy capacity accelerates coal plant exit through intensified local competition in electricity generation.

Second, I study short-run environmental responses using a monthly panel of coal-fired power plants over 2007-2019, restricting the sample to plants that remain in continuous operation throughout the period. In this specification, $Y_{it}$ measures ambient air pollution concentrations within a 50 km buffer surrounding each plant, including sulfur dioxide ($SO_2$) and aerosol optical depth (AOD). This design isolates intensive-margin adjustments among incumbent plants, capturing changes in fuel input mix, combustion intensity, and abatement effort, rather than extensive-margin responses driven by plant entry or exit.

The key treatment variable, $D_{it}$, captures coal plant exposure to nearby operating bioenergy

capacity within the same country:

$$D_{it} = \sum_{b \in \mathcal{B}_{c(i)}} \frac{Cap_{bt} \cdot \mathbf{1}[Operate_{bt} = 1]}{1 + DistKM_{ib}} \tag{25}$$

where $\mathcal{B}_{c(i)}$ denotes the set of bioenergy plants located in the same country as coal plant $i$, $Cap_{bt}$ is the operating capacity of bioenergy plant $b$ at time $t$, and $DistKM_{ib}$ is the distance in kilometers between coal plant $i$ and bioenergy plant $b$. This inverse-distance weighting scheme reflects localized competition in electricity markets, transmission constraints, and grid congestion, under which bioenergy generation primarily displaces coal output from nearby plants. As a result, coal plants located closer to expanding bioenergy facilities face larger demand and price shocks, leading to stronger incentives for operational adjustment and earlier retirement.

All specifications include coal plant fixed effects $\alpha_i$, which absorb time-invariant plant characteristics such as baseline technology, efficiency, scale, and location, as well as time fixed effects $\gamma_t$, which control for common global shocks, including changes in energy demand, fuel prices, climate conditions, and macroeconomic fluctuations. Identification therefore comes from within-plant variation in exposure driven by differential spatial proximity to bioenergy expansion over time. Standard errors are clustered at the coal plant level.

### 5.2 Coal phase-out

Table 1 reports the global effects of bioenergy expansion on coal plant retirement. Panel A presents baseline results and heterogeneity by alternative fuel feasibility. In Column (1), pooling all coal plants worldwide, I find that greater exposure to nearby bioenergy capacity significantly increases the probability of coal plant retirement. In terms of magnitude, increasing capacity by 100 MW at every bioenergy plant increases the mean value of the treatment variable by 29.8. Plugging in the point estimate, this results in an increase in the retirement probability of 0.0295, or 14.6 percent relative to the sample mean. This magnitude indicates a sizable displacement effect of bioenergy expansion on coal generation at the global scale.

Columns (2) and (3) explore heterogeneity by alternative fuel feasibility. I separately estimate the effect of bioenergy exposure for coal plants whose alternative fuel is bioenergy and for those using other fuels. The underlying intuition is that coal plants that can readily switch to bioenergy retain asset value and operational flexibility, making them less likely to retire. Consistent with this mechanism, Column (2) shows a much smaller and statistically

insignificant effect for plants with bioenergy as an alternative fuel. In contrast, Column (3) indicates a large and precisely estimated effect for other coal plants, implying that the pooled retirement response is primarily driven by plants without easy access to bioenergy substitution. These results highlight the importance of technological compatibility and asset specificity in shaping coal plant exit decisions.

Table 1 Panel B examines regional heterogeneity across five major regions. The estimated effects are largest in Oceania, followed by Asia, North America, and Europe, while the effects are close to zero and statistically insignificant in Latin America and Africa. This pattern is consistent with several structural factors. Developed regions tend to exhibit greater policy support for renewable energy, higher regulatory stringency, and more redundant coal capacity, all of which facilitate coal retirement in response to bioenergy expansion. In addition, these regions typically possess better-developed biomass supply chains and lower adjustment costs. In contrast, the absence of coal-to-bioenergy effects in Latin America and Africa suggests that energy transition dynamics are constrained by limited infrastructure, weaker policy incentives, and tighter capacity margins, implying that global decarbonization pressures disproportionately translate into coal phase-out in more developed economies.

### 5.3 Air pollution

This section focuses on the intensive margin response of coal plants. Among plants that remain active, operation may decline, leading to lower emissions of air pollution. Table 2 Panel A reports estimation results using $SO_2$ as the dependent variable. In Column (1), negative and significant estimates indicate that $SO_2$ concentrations decrease as bioenergy capacity expands. Given current coal and bioenergy plant locations, a uniform expansion of bioenergy capacity by 100 MW leads to a reduction in $SO_2$ of 0.175 units, equivalent to over 130 percent of the mean and 79.2 percent of the standard deviation. This highlights the double dividend of bioenergy in reducing short-run air pollution and facilitating long-run energy transition.

In Table 2 Panel B, I instead use aerosol optical depth as the dependent variable. As global bioenergy capacity increases uniformly by 100 MW, AOD concentrations surrounding coal plants decrease by 0.063 units, equivalent to 20.2 percent of the mean and 30.3 percent of the standard deviation. The larger reduction in $SO_2$ relative to AOD suggests that some operating coal plants continue to use high-sulfur-content fuels.

In both panels, I separately estimate effects for coal plants that can use bioenergy as an alternative fuel and those that cannot in Columns (2) and (3). The effects are mainly driven

by plants without bioenergy as an alternative fuel, suggesting larger reductions in operation among these plants.

### 5.4 Electricity stability

One potential concern is that large-scale bioenergy expansion may compromise electricity system stability. Table S1 directly addresses this issue using country-year level data on electricity access and transmission and distribution losses. I find no detectable effects of bioenergy development on transmission and distribution losses, regardless of whether bioenergy is measured by installed capacity or plant count. This suggests that bioenergy expansion does not materially affect grid congestion, network reliability, or system-wide transmission efficiency. A likely explanation is that bioenergy plants are typically deployed in a decentralized manner and connected to existing distribution networks, thereby avoiding the large-scale grid stress associated with centralized generation sources. Moreover, biomass-based generation provides dispatchable baseload power, which helps stabilize supply rather than introduce intermittency.

In contrast, I observe a small but statistically significant decline in electricity access. However, the magnitude of this effect is economically modest and much smaller than the estimated improvements in air quality and reductions in coal reliance. This pattern is consistent with bioenergy capacity partially displacing coal generation in regions with pre-existing electrification, while expansion into new grid connections remains limited. Overall, these results suggest that bioenergy development does not compromise grid stability and that its modest impact on access is unlikely to offset its environmental and health benefits.

### 5.5 Wood import

While many countries possess abundant domestic biomass resources, others rely heavily on international trade to satisfy the rapid expansion of bioenergy capacity. To quantify these nonlocal demand responses, I examine how bioenergy development affects imports of wood products, which serve as the primary feedstock for biomass power generation. I aggregate bioenergy expansion to the importer-country level and study its effects on wood imports using a balanced importer–product–year–month panel over 2007–2019.

Table 3 Panel A reports estimates using only wood products. Across specifications, the coefficients on bioenergy capacity are positive and highly significant. The results remain stable after controlling for country–product fixed effects, which absorb time-invariant import preferences and comparative advantage across importer–product pairs. My preferred specification implies

that a uniform 100 MW increase in bioenergy capacity raises wood imports by 0.168 log points, corresponding to an 18.3 percent increase relative to the mean. This large elasticity highlights the strong upstream demand response generated by bioenergy expansion.

Panel B further strengthens identification by incorporating a broad set of non-wood control products, including cereals, minerals, fertilizers, metals, machinery, electrical equipment, and vehicles (HS 10, 25, 31, 72, 84, 85, and 87), and estimating a difference-in-differences specification. Focusing on the interaction between bioenergy capacity and a wood product indicator, I again find positive and precisely estimated effects. The magnitude is similar to that in Panel A, indicating that wood imports increase sharply relative to products unrelated to biomass energy. This pattern confirms that the observed import response is not driven by general trade expansion or macroeconomic shocks, but instead reflects a targeted increase in biomass feedstock demand induced by bioenergy policies.

### 5.6 Magnitude

To understand the economic magnitude of my estimates, I scale all effects by the observed intensive margin expansion of operating bioenergy plants. Globally, operating bioenergy capacity increases by 3,365 MW per year on average, which corresponds to 1.7 MW of additional capacity per operating plant per year. I therefore interpret the coefficients in terms of a 1.7 MW expansion, which represents a realistic annual adjustment at the plant level. Under this scaling, a 1.7 MW increase in each bioenergy plant's capacity increases the probability that a coal plant is retired by the end of the year by 3.0 percentage points. While this annual effect is modest at the plant level, it accumulates persistently over time, implying large long-run coal displacement in regions with sustained bioenergy expansion. These results highlight that bioenergy policies operate primarily through gradual but persistent capacity reallocation rather than abrupt one-time shocks.

Among coal plants that remain active, a 1.7 MW increase in each bioenergy plant's capacity reduces surrounding $SO_2$ concentrations by 0.003 units, corresponding to 2.3 percent of the mean and 1.4 percent of a standard deviation, and lowers aerosol optical depth by 0.001 units, equivalent to 0.4 percent of the mean and 0.5 percent of a standard deviation. These effects indicate meaningful short-run improvements in local air quality, operating through intensive margin responses such as reduced utilization rates, cleaner fuel mixes, and enhanced pollution control.

At the international trade margin, a 1.7 MW increase in each bioenergy plant's capacity raises

wood product imports by 0.0029 log points, or 0.29 percent. While small in annual terms, this effect compounds over time, generating sizable cumulative demand shocks in global wood markets. Combined with the spatial concentration of biomass sourcing, this mechanism helps explain the large deforestation responses observed in major exporting countries.

# 6 Biomass subsidies and mandates

## 6.1 Policy background and empirical strategy

In this section, instead of exploiting annual variation in each country's bioenergy capacity, I take advantage of two nationwide biomass-favorable policies in Japan and Korea as sharp and plausibly exogenous shocks to examine the impacts of bioenergy expansion on local pollution around coal plants and the nonlocal land use consequences transmitted through international biomass trade. The first policy comes from biomass subsidies in Japan. Japan implemented a nationwide Feed-in Tariff (FIT) program in July 2012 under the Act on Special Measures Concerning Renewable Energy, which required electric utilities to purchase renewable electricity at fixed government-set prices through long-term contracts. Biomass electricity generation was explicitly covered under the FIT, with contract durations typically extending to 20 years. By guaranteeing stable revenue streams, reducing market risk, and lowering financing constraints, the policy greatly improved the profitability and bankability of biomass power projects, triggering a large and rapid expansion of bioenergy investment nationwide.

Consistent with these incentives, bioenergy capacity in Japan increased sharply after 2012, as shown in Figure S1. Prior to the FIT introduction, biomass power generation shows slow growth, reflecting weak investment incentives under the pre-reform regulatory regime. Immediately following the policy implementation, operating bioenergy capacity began to rise steeply, more than doubling within a few years. In contrast, for coal power capacity, despite continued growth, the gap between bioenergy and coal remained large and broadly parallel before the policy, and began to narrow after the policy implementation.

The second bioenergy policy comes from Korea. In January 2012, Korea introduced a nationwide Renewable Portfolio Standard (RPS), requiring large electricity generators to meet an increasing and binding share of renewable electricity generation. Compliance can be achieved either through direct renewable production or through the purchase of Renewable Energy Certificates (RECs) in a centralized market. Biomass electricity is fully eligible under the RPS and receives favorable REC weightings, generating strong implicit subsidies for biomass

investment relative to other renewable technologies. Similar to Japan, the Korea policy was implemented uniformly nationwide, leading to a large and persistent increase in bioenergy capacity.

Despite large domestic expansion in bioenergy generation, both Japan and Korea possess limited domestic biomass resources relative to policy-induced demand. Domestic forest stocks, harvesting capacity, and land availability constrain the scale of locally sourced biomass feedstocks. As a result, biomass power plants in both countries rely heavily on imported wood pellets, chips, and other solid biomass products. This dependence on international supply chains directly links domestic renewable energy policies to upstream trade flows and environmental impacts in exporting regions.

I first focus on the local environmental effects of bioenergy expansion. I use a coal plant-year-month level panel and estimate the following specification:

$$Y_{it} = \beta \cdot BioenergyExposure_{it} + Plant_i + Time_t + \varepsilon_{it}$$

where $Y_{it}$ denotes coal plant $i$'s surrounding air pollution within 50 km buffers in year-month $t$. My analysis focuses exclusively on coal plants that remain active and continuously operating throughout the sample period 2007-2019. I do not study coal plant retirement in this setting because coal retirement is limited in both Japan and Korea during the sample period. As a result, environmental adjustments primarily operate through intensive margin responses, such as changes in fuel mix, combustion efficiency, and pollution control effort, rather than extensive margin plant closures.

On the right-hand side, I measure bioenergy exposure of each coal plant $i$ based on spatial proximity to pre-existing bioenergy plants:

$$BioenergyExposure_i = \frac{1}{\min_b\{DistKM_{ib}\} + 1}$$

where $\min_b\{DistKM_{ib}\}$ denotes the distance between coal plant $i$ and the nearest bioenergy plant $b$ that was already active before 2007. The assumption is that pre-policy plants benefit from the FIT program and may expand more than newly built plants. Pre-policy plants also serve as a proxy for regions favorable to bioenergy combustion and may be correlated with future policy-induced plant entry. Given localized energy supply conditions, coal plants located near bioenergy plants are more likely to be affected by the FIT than those farther away.

For additional controls, I include plant fixed effects that absorb time-invariant plant char-

acteristics, including baseline technology, location, and regulatory environment. I also include year-month fixed effects to control for common national trends in energy markets, environmental regulation, fuel prices, and macroeconomic conditions.

### 6.2 Local environmental effects in Japan and Korea

Table S2 Panel A reports the effect of bioenergy exposure on $SO_2$ and AOD in Japan. In Columns (1) and (2), using $SO_2$ as the dependent variable, the negative estimates on $Post$ suggest a nationwide reduction in $SO_2$ concentrations across all coal plants after July 2012, after controlling for monthly quadratic time trends. The magnitude of reduction is 0.021 units, equivalent to 32.8% of the outcome mean and 0.25 standard deviations. In contrast, the additional local effect associated with bioenergy exposure is small, although the point estimate is negative.

In Columns (4) to (6), AOD also shows a nationwide reduction, along with an additional decline near bioenergy-exposed coal power plants, captured by negative and statistically significant estimates on $Post \times Exposure$. Evaluated at the interquartile range of exposure (0.028), the average coal plant experiences a reduction in AOD of 0.042 units, corresponding to 15.6% of the mean and 0.48 standard deviations. Overall, these results are similar to the global findings, where bioenergy expansion leads to localized air quality improvements near plants.

In Panel B, I find similarly strong reductions in AOD in Korea. Columns (4) to (6) show negative and statistically significant estimates on both $Post$ and $Post \times Exposure$. Coal plants located closer to pre-existing bioenergy plants experience larger declines in particulate pollution after the policy introduction. Using the interquartile range of exposure of 0.0052, the implied total reduction in AOD equals 0.029 units, corresponding to an 8.1% decline, or 0.23 standard deviations, magnitudes largely similar to those observed in Japan.

The smaller reduction in $SO_2$ likely reflects the use of low-sulfur coal and the near-universal adoption of end-of-pipe sulfur control technologies in both Japan and Korea. In Korea, stringent air quality regulations restrict coal-fired power plants to burning low-sulfur coal and mandate advanced flue gas desulfurization (FGD) systems, largely compressing baseline sulfur emissions. Similarly, Japan enforces some of the world's strictest $SO_2$ emission standards for coal-fired power generation, supported by near-universal installation of FGD systems and long-standing reliance on low-sulfur imported coal (International Energy Agency, 2016; Ministry of Economy, Trade and Industry of Japan, 2022). These regulatory and technological constraints largely limit baseline $SO_2$ concentrations, leaving limited scope for additional sulfur abatement

through marginal operational adjustments induced by bioenergy expansion, compared with coal plants in other countries. As a result, I observe only modest incremental reductions in $SO_2$, even when broader particulate pollution, captured by AOD, declines largely.

### 6.3 Wood exports to Japan and Korea

I next examine the impacts of biomass subsidies and mandates on wood imports in Japan and Korea. Both countries have limited domestic forest resources relative to the scale of policy-induced biomass demand, making them highly reliant on imported wood feedstocks. I therefore compare changes in exporters' shipments of wood to Japan and Korea with their exports of other goods before and after policy implementation. As controls, I use a broad set of non-wood products unlikely to be directly affected by biomass expansion, including cereals, minerals, fertilizers, metals, machinery, electrical equipment, and vehicles (HS 10, 25, 31, 72, 84, 85, and 87). Using treated and control products, I construct a balanced exporter–product–year–month panel over 2007-2019, separately for Japan and Korea. This design isolates differential changes in wood imports within exporters over time, netting out exporter-specific supply shocks and common trade trends.

Table 4 Panel A reports difference-in-differences estimates for Japan, pooling all exporting countries. The single term $Treated$ is absorbed by product fixed effects, and $Post$ is absorbed by year-month fixed effects. Across all specifications, estimates on $Post \times Treated$ remain positive and significant, suggesting that wood exports to Japan increase sharply relative to control products following the introduction of the Feed-in Tariff in July 2012. The effects are highly stable across alternative fixed effects specifications, with almost no change in point estimates. The results suggest exports of wood to Japan increase by 19% relative to non-wood products.

In Table S3 Panel A, I explore heterogeneity across exporting countries by restricting the sample to three Southeast Asian exporters, Indonesia, Thailand, and Vietnam. The effects are much larger than the pooled results. Wood exports to Japan increase by two to three times relative to control products in the post-regulation period. These stronger responses are consistent with abundant forest resources, lower transportation costs due to geographic proximity, and weaker deforestation regulations, which together lower the marginal cost of expanding wood production and export capacity.

In Table 4 Panel B, I present a similar difference-in-differences estimate for Korea following the introduction of the Renewable Portfolio Standard in January 2012. Estimates on $Post \times Treated$ are positive and significant, suggesting that exports of wood to Korea increase by 16.5%

relative to control products, with results again highly robust across specifications.

In Table S3 Panel B, similar to Japan, heterogeneous effects are much stronger among Southeast Asian exporters, with particularly large responses observed for Vietnam. Three factors may explain why Vietnam shows a larger export response to Korea relative to Japan. First, Vietnam enjoys dense maritime connectivity and short shipping distances to Korean ports, resulting in much lower transportation costs than those of alternative exporters. Second, Korea's biomass demand relies heavily on standardized wood pellets, for which Vietnam has developed specialized production capacity and dedicated export infrastructure, allowing for rapid supply expansion. Third, long-term supply contracts and vertically integrated pellet supply chains between Vietnamese producers and Korean utilities further amplify Vietnam's responsiveness to Korea's policy-induced demand shock.

To further assess the dynamic responses, Figure 1 shows the event-study estimates of exports to Japan and Korea before and after each country's policy shocks. Specifically, it plots quarter-specific treatment effects using the exporter–product–year–month panel, with export quantity as the outcome. Estimates are centered around zero and statistically insignificant throughout the pre-policy period, indicating no evidence of differential pre-trends between wood and non-wood products. In the post-policy period, wood exports begin to increase about one year after policy implementation, with the effects growing steadily over time. Figure S2 zooms in on the first eight post-policy quarters, highlighting the sharp divergence in wood exports shortly after the first year. Two years after policy adoption, the magnitude of the trade response becomes very large. This delayed adjustment likely reflects the time required for biomass power investments to scale up and for international trade relationships to adapt, including contract negotiation, production expansion, and shipping capacity adjustments between exporters and importers.

### 6.4 Empirical strategy in exporting regions

I next examine the local land use responses in exporting regions, focusing on Indonesia, Thailand, and Vietnam. Motivated by the large and heterogeneous trade responses documented above, I study whether biomass policy shocks in Japan and Korea induce spatially heterogeneous deforestation patterns within these exporting countries. The baseline specification for the Japan FIT shock is:

$$Y_{it} = \beta \cdot PostJapan_t \times ExposureJapan_i + \alpha_i + \gamma_t + \varepsilon_{it} \tag{26}$$

where the sample spans 2007-2019 and is constructed separately for Indonesia, Thailand, and Vietnam. The outcome variable $Y_{it}$ measures local vegetation cover, including forest share and vegetation indices, in 0.1-degree grid $i$. For vegetation indices, $t$ denotes year-month, and for specific land use shares, $t$ denotes year. I include grid fixed effects $\alpha_i$ to absorb time-invariant spatial characteristics and time fixed effects $\gamma_t$ to control for common temporal shocks. I conduct a similar analysis for Korea:

$$Y_{it} = \beta \cdot PostKorea_t \times ExposureKorea_i + \alpha_i + \gamma_t + \varepsilon_{it} \tag{27}$$

The key explanatory variable is each grid's exposure to the biomass policy shocks in Japan and Korea. I construct exposure using pre-policy port-level trade flows and spatial proximity, capturing how strongly each inland location is connected to international export channels. Focusing on Indonesia as an example, exposure to the Japan policy shock is defined as:

$$ExposureJapan_i = PreForest_i \times \sum_{p \in \mathcal{P}} (InverseDist_{i,p} \cdot FlowJapan_p) \tag{28}$$

where $PreForest_i$ is the average forest share in grid $i$ over 2001-2005, capturing baseline biomass endowments, namely the extent to which trees may be converted to non-tree land uses and exported to Japanese biomass plants. $InverseDist_{i,p} = 1/(1 + dist_{i,p})$ is a distance-based weight between grid $i$ and port $p$, with $dist_{i,p}$ measured in kilometers. $FlowJapan_p$ denotes port $p$'s share of Indonesia's total wood outflow to Japan, measuring this port's importance in exports to Japan across all Indonesian ports, constructed from port-pair trade data. This measure assigns higher exposure to forest-rich grids that are spatially close to ports heavily engaged in trade with Japan. As a robustness check, I alternatively use absolute port outflows instead of shares.

I apply the same construction to Thailand and Vietnam and analogously define exposure to Korea using Korean port-level trade flows. This approach generates large spatial variation in exposure both across and within countries, reflecting heterogeneity in forest endowments, port connectivity, and importer-specific transportation networks. Figure 2 visualizes the resulting exposure maps for Japan across Indonesia, Thailand, and Vietnam. While exposure is generally higher in coastal regions due to naturally shorter distances to ports, there are also inland grids with high exposure, likely reflecting high tree endowments. Within both coastal and inland areas, there is large variation in exposure, providing identifying variation for estimating localized deforestation responses.

### 6.5 Deforestation in exporting regions

Table 5 presents the difference-in-differences estimation results. In Panel A, I use forest share (between 0 and 1) as the dependent variable. Estimates on $Post \times Exposure$ are negative and statistically significant, indicating a reduction in forest share in grids more exposed to Japan's biomass policy shock relative to less exposed grids. Column (1) shows that exposed grids experience a larger decline than non-exposed grids. Taking all Indonesian grids together, the average exposure is 0.0001831, which corresponds to a reduction in forest share of 0.844 percentage points, or 4.08 percent relative to the mean. In Column (2), adding ADM1-specific linear time trends has little impact on the point estimates.

In Column (3), instead of using continuous exposure, I replace it with quartile indicators, omitting the lowest exposure quartile as the reference group. The results show a monotonic gradient, with forest share decreasing by 2.69 percentage points in the highest exposure quartile after the Japan policy, 1.49 percentage points in the third quartile, and 0.478 percentage points in the second quartile, relative to the lowest quartile. This pattern is consistent with the estimates using continuous exposure.

In Panel B, I use broad tree share as the dependent variable, which includes forest, woody savanna, and savanna. The sample mean increases from 20.7 percent for forest share to 28.2 percent for broad tree share. However, the estimated effects decline relative to those in Panel A. Specifically, at the mean exposure level, the implied reduction in broad tree share is 0.21 percentage points, or 0.75 percent relative to the mean. This suggests that forest loss is more pronounced than reductions in lower-density tree cover, consistent with the fact that biomass energy production primarily relies on high-density wood inputs rather than short savanna vegetation with limited pellet or combustible biomass content.

In Panel C, I further broaden the definition of vegetation by including shrubland and grassland. The estimated effects decline slightly relative to Panel B, and the exposure-gradient pattern in Column (3) becomes less steep. At the mean exposure level, the implied post-policy reduction in vegetation share is 0.19 percentage points, corresponding to a 6.98 percent decline relative to the mean vegetation share.

I explore the dynamic pattern in Figure 3, using forest share as the dependent variable. In the left panel, I focus on Indonesia and plot the estimated coefficients on exposure interacted with year dummies, relative to the baseline year 2011. In the pre-policy period, the estimates are small and statistically insignificant, suggesting that highly and weakly exposed grids exhibit parallel trends in forest share over 2008-2011. After the implementation of the FIT

policy, I observe a large and persistent decline in forest share that intensifies over time and does not reverse. Note that the magnitude of the point estimates appears large because the exposure variable is small in absolute value. The sustained post-policy decline is consistent with irreversible tree cutting and wood extraction for export to Japan, with little evidence of restoration or reforestation. This pattern highlights concerns about unsustainable deforestation practices and underscores the potential for long-term environmental externalities induced by bioenergy policies.

I estimate the same specification focusing on Thailand's response to the Japan policy, with results reported in Table S4. The outcome means are smaller, reflecting lower forest endowments in Thailand relative to the tropical forest abundance in Indonesia. In Panel A, I again find negative and statistically significant estimates on $Post \times Exposure$. At the mean exposure level of 0.0001817, forest share declines by 0.125 percentage points, or 1.83 percent relative to the mean. While smaller in magnitude than the corresponding estimates for Indonesia, the results are again robust to alternative time trends and to discretizing exposure into quartiles. In Column $(3)$, the effects are primarily driven by the highest exposure quartile, while most other grids experience little deforestation.

In Panel B, I again observe reductions in broad tree share. At the mean exposure level, broad tree share declines by 0.09 percentage points, or 0.62 percent relative to the mean. The magnitude is smaller than in Panel A, reflecting the lower biomass content of savanna relative to forest. In Column $(3)$, the effects are again concentrated in the highest exposure quartile. In Panel C, I find no statistically significant change in overall vegetation share when forest, savanna, shrubland, and grassland are aggregated, highlighting that the land use response is concentrated in tree cover.

The dynamic patterns for Thailand in response to Japan's FIT policy are reported in the right panel of Figure 3. Consistent with the Indonesian results, I find no evidence of differential pre-trends prior to policy implementation, further validating the difference-in-differences design and confirming that the exposure measure does not capture confounding factors unrelated to export connectivity with Japan's biomass market. In the post-policy period, the estimated effects are initially small in 2012 and then decline gradually over the subsequent eight years. This smooth adjustment contrasts with a sharp immediate response and likely reflects the gradual nature of biomass investment expansion and trade reallocation in Thailand. In particular, Thailand's export response appears to operate through progressive capacity adjustments, including the expansion of logging activities, processing infrastructure, and port logistics, rather than abrupt supply shifts. Moreover, institutional and regulatory frictions in

land conversion, as well as slower adjustment of plantation forestry, likely contribute to the delayed response.

Table S5 presents the land use effects in Vietnam in response to Japan's biomass FIT policy. Similar to Indonesia and Thailand, I observe significant reductions in forest share in more exposed grids, with the strongest effects concentrated in the highest exposure quartile. At the same time, the impacts on savanna are smaller, and the effects on shrubland and grassland are even more limited. At the mean exposure level, grids exposed to Japan's biomass policy experience a reduction in forest share of 0.535 percentage points, corresponding to a 5.88 percent decline relative to the mean.

I obtain similar results for Korea. Tables S6, S7, and S8 report the corresponding estimates for Indonesia, Thailand, and Vietnam in response to Korea's biomass policy. Across all three countries, I find negative and statistically significant effects on forest cover, with magnitudes and spatial patterns closely comparable to those observed for Japan. As a robustness check, I further re-estimate all specifications using absolute port-level outflows instead of normalized flow shares to construct exposure. The results, reported in Section C, remain highly similar, confirming that my findings are not sensitive to the specific normalization of trade flows.

In addition to land use shares, I also use vegetation indices as alternative outcome variables. Unlike discrete land use classifications, vegetation indices provide continuous measures of vegetation density and quality, allowing us to capture within-land use type changes. They are also available at the monthly frequency, allowing us to capture seasonal variation and improve statistical precision. Results for Japan's biomass policy shocks are reported in Table S9. In Panel A, focusing on Indonesia, the average NDVI across all grids is 0.728. I find that more exposed grids experience higher reductions in NDVI relative to less exposed grids. At the mean exposure level, the post-July 2012 decline in NDVI is 0.003 units, corresponding to a 0.41 percent reduction relative to the mean and a 2.46 percent decline relative to the standard deviation. These estimates remain stable when controlling for ADM1-specific monthly trends. In Column (3), the results further show similar effects in the second and third exposure quartiles, and much larger declines in the highest exposure quartile.

Panels B and C show similar reductions in vegetation indices for Thailand and Vietnam following Japan's FIT policy, with effects concentrated in more exposed grids. For Thailand, at the mean exposure level, NDVI declines by 0.0022 units, corresponding to a 0.36 percent reduction relative to the mean and a 1.36 percent decline relative to the standard deviation. For Vietnam, the average reduction in NDVI is 0.0041 units, equivalent to a 0.63 percent decrease relative to the mean and a 2.59 percent decline relative to the standard deviation. Table S10

reports consistent reductions in NDVI across all three exporting countries in response to Korea's biomass policy, with the largest effects concentrated in the highest exposure quartile.

### 6.6 Magnitude

I next quantify the magnitude of the deforestation impacts implied by my estimates. Using the baseline coefficients and evaluating exposure at country-specific mean levels, I translate the estimated treatment effects into changes in forest share and aggregate forest loss for Indonesia, Thailand, and Vietnam. For the Japan biomass policy, the implied reduction in forest share at the average exposure level equals 0.84 percentage points in Indonesia, 0.12 percentage points in Thailand, and 0.54 percentage points in Vietnam. Aggregating these grid-level effects across space yields a total forest loss of 15,969 $km^2$ in Indonesia, 658 $km^2$ in Thailand, and 1,843 $km^2$ in Vietnam. For the Korea biomass policy, the corresponding reductions in forest share equal 0.82 percentage points in Indonesia, 0.13 percentage points in Thailand, and 0.54 percentage points in Vietnam, implying aggregate forest losses of 15,555 $km^2$, 675 $km^2$, and 1,851 $km^2$, respectively.

These magnitudes are economically large. For Indonesia, the implied forest losses correspond to a large fraction of the country's annual deforestation during the 2010s, indicating that foreign renewable energy policies can meaningfully shift domestic land use outcomes through trade channels. In Thailand and Vietnam, while the absolute forest losses are smaller, the estimated impacts remain sizable relative to national forest baselines, highlighting the sensitivity of land use in smaller forest economies to external demand shocks.

## 7 Discussion and conclusion

This paper shows bioenergy expansion reallocates environmental burdens across space. While bioenergy expansion delivers sizable local gains by accelerating coal phase-out and improving air quality, it also shifts land use pressure upstream through international biomass supply chains, inducing persistent deforestation in exporting regions. This spatial displacement reveals a central tension in renewable energy policy: policies that reduce domestic pollution can generate environmental costs abroad.

My results yield three insights. First, energy transitions should consider global production networks when assessing overall welfare effects. The environmental footprint of renewable deployment depends not only on downstream electricity generation but also on upstream

input markets, logistics, and land use responses. Evaluations that ignore these supply chain channels systematically understate total environmental impacts. Second, land use responses have strong persistence. The absence of post-shock recovery in forest cover indicates that bioenergy-induced deforestation represents a long-run ecological cost rather than a transitory adjustment, with implications for carbon stocks, biodiversity, and ecosystem services. Third, cross-country heterogeneity in impacts highlights the central role of geographic endowments, port connectivity, and pre-existing trade relationships in shaping environmental spillovers.

These findings have direct policy implications. Conventional life-cycle assessments and carbon accounting frameworks typically treat biomass as carbon-neutral and focus on combustion-stage emissions. My results show that this approach understates the environmental costs of bioenergy by omitting induced land use change abroad. Accounting for global land use spillovers would yield more accurate assessments of the net climate and environmental benefits of renewable energy policies. More broadly, international coordination, sustainability certification, and supply chain traceability are likely necessary to limit cross-border displacement of environmental damage.

Finally, my findings point to a distinction across renewable technologies. Unlike solar and wind, bioenergy is intrinsically land-intensive, linking energy production directly to agricultural and forestry systems. As a result, bioenergy policies are uniquely prone to generating land use externalities. Renewable portfolios that emphasize land-neutral technologies may therefore achieve decarbonization with lower ecological cost. When bioenergy is deployed, complementary land use regulation and import standards become essential to prevent climate mitigation efforts from accelerating global forest loss.

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Table 1: Global effects of bioenergy expansion on coal plant retirement

| | Panel A: Pooled analysis | | |
|---|---|---|---|
| | Retirement dummy | | |
| | All plants | Bioenergy feasible | Other plants |
| | (1) | (2) | (3) |
| Bioenergy exposure | 0.00099*** | 0.00004 | 0.00111*** |
| | (0.00035) | (0.00090) | (0.00035) |
| Observations | 77311 | 2821 | 74490 |
| R-square | 0.707 | 0.639 | 0.708 |
| Y-mean | 0.202 | 0.098 | 0.205 |
| Y-sd | 0.401 | 0.298 | 0.404 |

| | Panel B: Heterogeneity across regions | | | | |
|---|---|---|---|---|---|
| | Retirement dummy | | | | |
| | North America | Europe | Asia | Oceania | Latin America and Africa |
| | (1) | (2) | (3) | (4) | (5) |
| Bioenergy exposure | 0.00293* | 0.00215*** | 0.00278*** | 0.59695*** | 0.00462 |
| | (0.00170) | (0.00035) | (0.00058) | (0.18378) | (0.00341) |
| Observations | 15574 | 18707 | 39026 | 1378 | 2626 |
| R-square | 0.649 | 0.713 | 0.752 | 0.661 | 0.252 |
| Y-mean | 0.263 | 0.183 | 0.198 | 0.229 | 0.007 |
| Y-sd | 0.440 | 0.387 | 0.398 | 0.421 | 0.085 |
| Plant FEs | Y | Y | Y | Y | Y |
| Year FEs | Y | Y | Y | Y | Y |

*Notes:* The analysis is conducted at the coal plant-year level using a balanced panel from 2007-2019. The outcome variable equals one if a plant has already retired by a given year and zero otherwise. The sample includes only coal plants that were active prior to 2007. Standard errors are clustered at the plant level.

Table 2: Global effects of bioenergy expansion on coal plant air pollution

| | Panel A: $SO_2$ | | |
|---|---|---|---|
| | All plants | Bioenergy feasible | Other plants |
| | (1) | (2) | (3) |
| Bioenergy exposure | -0.00666*** | -0.00014 | -0.00845*** |
| | (0.00074) | (0.00011) | (0.00081) |
| Observations | 631737 | 27433 | 604304 |
| R-square | 0.454 | 0.158 | 0.467 |
| Y-mean | 0.134 | 0.068 | 0.137 |
| Y-sd | 0.221 | 0.154 | 0.223 |
| | Panel B: AOD | | |
| | All plants | Bioenergy feasible | Other plants |
| Bioenergy exposure | -0.00241*** | -0.00017** | -0.00308*** |
| | (0.00027) | (0.00008) | (0.00029) |
| Observations | 653172 | 28704 | 624468 |
| R-square | 0.794 | 0.669 | 0.796 |
| Y-mean | 0.313 | 0.221 | 0.318 |
| Y-sd | 0.209 | 0.136 | 0.210 |
| Plant FEs | Y | Y | Y |
| Year-month FEs | Y | Y | Y |

*Notes:* The analysis is conducted at the coal plant-year-month level using a balanced panel from 2007-2019. Outcome variables are average $SO_2$ and AOD concentration within 50 km buffers around coal plants. The sample includes only coal plants that remain active throughout the sample period. Standard errors are clustered at the plant level.

Table 3: Global effects of bioenergy expansion on wood imports

| | Panel A: Single-difference, wood only | |
|---|---|---|
| | ln(Quantity) | |
| | (1) | (2) |
| Bioenergy exposure | 0.00033*** | 0.00033*** |
| | (0.00011) | (0.00011) |
| Observations | 812448 | 812448 |
| R-square | 0.408 | 0.667 |
| Y-mean | 1.374 | 1.374 |
| Y-sd | 3.734 | 3.734 |
| | Panel B: Double-difference, wood vs. non-wood | |
| | ln(Quantity) | |
| | (1) | (2) |
| Treated × Exposure | 0.00064** | 0.00055*** |
| | (0.00029) | (0.00014) |
| Exposure | -0.00022* | -0.00016*** |
| | (0.00013) | (0.00005) |
| Observations | 1121952 | 1121952 |
| R-square | 0.373 | 0.673 |
| Y-mean | 0.995 | 0.995 |
| Y-sd | 3.236 | 3.236 |
| Country FEs | Y | |
| Product FEs | Y | |
| Country-product FEs | | Y |
| Year-month FEs | Y | Y |

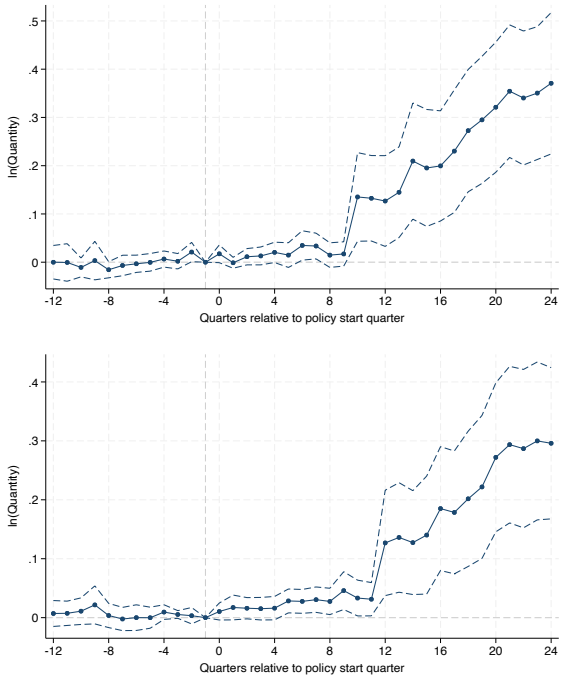
*Notes:* The analysis is conducted at the importer-product-year-month level using a balanced panel over 2007-2019. Panel A includes only wood products, identified using HS 6-digit codes 440110, 440111, 440112, 440121, 440122, 440130, 440131, 440132, 440139, 440140, 440141, 440149, 121110, 121120, 121130, 121140, 121150, 121160, and 121190. Panel B includes wood and non-wood products, including cereals (HS 10), minerals (HS 25), fertilizers (HS 31), iron and steel (HS 72), machinery (HS 84), electrical equipment (HS 85), and vehicles (HS 87). Standard errors are clustered at the importer level.

Table 4: Wood exports to Japan and Korea

| | Panel A: Japan ln(Quantity) | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Post × Treated | 0.18976*** | 0.18976*** | 0.18976*** | 0.18976*** |
| | (0.03987) | (0.03987) | (0.03987) | (0.03988) |
| Observations | 692172 | 692172 | 692172 | 692172 |
| R-square | 0.109 | 0.492 | 0.171 | 0.141 |
| Y-mean | 0.134 | 0.134 | 0.134 | 0.134 |
| Y-sd | 1.298 | 1.298 | 1.298 | 1.298 |
| Exporter FEs | Y | | | Y |
| Product FEs | Y | | Y | Y |
| Year-month FEs | Y | Y | | Y |
| Exporter-product FEs | | Y | | |
| Exporter-year-month FEs | | | Y | |
| Exporter-specific trends | | | | Y |
| | Panel B: Korea ln(Quantity) | | | |
| | (1) | (2) | (3) | (4) |
| Post × Treated | 0.16500*** | 0.16500*** | 0.16500*** | 0.16500*** |
| | (0.03735) | (0.03735) | (0.03734) | (0.03735) |
| Observations | 650832 | 650832 | 650832 | 650832 |
| R-square | 0.099 | 0.347 | 0.184 | 0.147 |
| Y-mean | 0.091 | 0.091 | 0.091 | 0.091 |
| Y-sd | 1.010 | 1.010 | 1.010 | 1.010 |
| Exporter FEs | Y | | | Y |
| Product FEs | Y | | Y | Y |
| Year-month FEs | Y | Y | | Y |
| Exporter-product FEs | | Y | | |
| Exporter-year-month FEs | | | Y | |
| Exporter-specific trends | | | | Y |

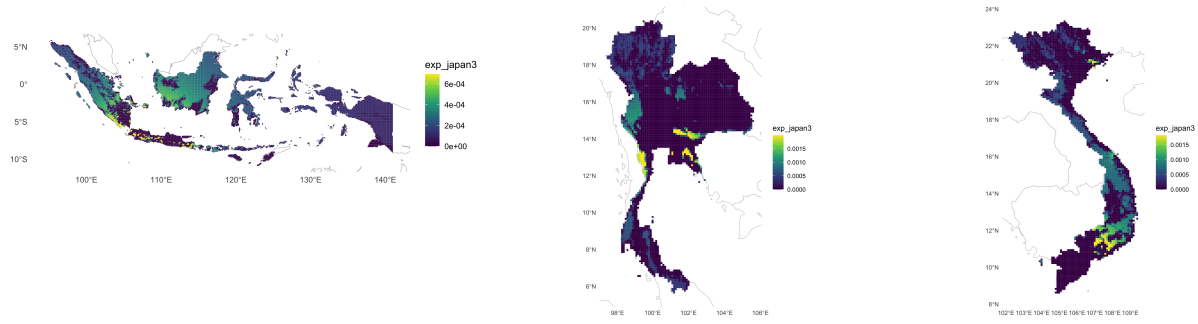
*Notes:* The analysis is conducted at the exporter-product-year-month level using a balanced panel from 2007-2019. For Japan, the sample includes only exporters that ever export treated or control products to Japan; for Korea, the sample includes only exporters that ever export treated or control products to Korea. Standard errors are clustered at the exporter level.

Figure 1: Biomass policies on wood exports to Japan and Korea




*Notes:* This figure plots event-study estimates of the effects of biomass policy shocks in Japan (top) and Korea (bottom) on exporters' wood exports, using a balanced exporter–product–year–month panel from 2007-2019. The event window spans three years before and six years after the policy implementation. All specifications include exporter fixed effects, product fixed effects, and year–month fixed effects. Standard errors are clustered at the exporter level.

Figure 2: Exposure to biomass policy shocks in exporting regions



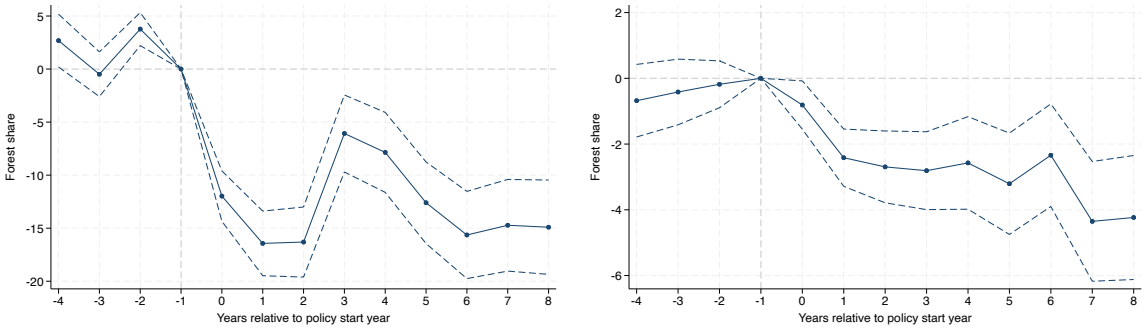

*Notes:* This figure maps grid-level exposure to biomass policy shocks in Japan across Indonesia, Thailand, and Vietnam. Exposure is constructed using baseline forest cover, distance-weighted proximity to ports, and port-level export flows to each destination.

Table 5: Land use effects in Indonesia in response to Japan biomass policy

| | Panel A: Forest share | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Post × Exposure | -46.105732*** | -44.822334*** | |
| | (3.282568) | (3.273183) | |
| Post × Exposure Q2 | | | -0.004778*** |
| | | | (0.000685) |
| Post × Exposure Q3 | | | -0.014895*** |
| | | | (0.000902) |
| Post × Exposure Q4 | | | -0.026901*** |
| | | | (0.001066) |
| Observations | 199927 | 199927 | 199927 |
| R-square | 0.948 | 0.949 | 0.949 |
| Y-mean | 0.207 | 0.207 | 0.207 |
| Y-sd | 0.147 | 0.147 | 0.147 |
| | Panel B: Broad tree share | | |
| Post × Exposure | -8.487228*** | -11.545355*** | |
| | (1.184633) | (1.375375) | |
| Post × Exposure Q2 | | | -0.005914*** |
| | | | (0.000674) |
| Post × Exposure Q3 | | | -0.006687*** |
| | | | (0.000699) |
| Post × Exposure Q4 | | | -0.006399*** |
| | | | (0.000671) |
| Observations | 199927 | 199927 | 199927 |
| R-square | 0.959 | 0.960 | 0.959 |
| Y-mean | 0.282 | 0.282 | 0.282 |
| Y-sd | 0.105 | 0.105 | 0.105 |
| | Panel C: Vegetation share | | |
| Post × Exposure | -7.983753*** | -10.827935*** | |
| | (1.128060) | (1.318378) | |
| Post × Exposure Q2 | | | -0.005517*** |
| | | | (0.000657) |
| Post × Exposure Q3 | | | -0.006472*** |
| | | | (0.000663) |
| Post × Exposure Q4 | | | -0.006004*** |
| | | | (0.000640) |
| Observations | 199927 | 199927 | 199927 |
| R-square | 0.963 | 0.963 | 0.963 |
| Y-mean | 0.284 | 0.284 | 0.284 |
| Y-sd | 0.103 | 0.103 | 0.103 |
| Grid FEs | Y | Y | Y |
| Year FEs | Y | Y | Y |
| ADM1-specific trends | | Y | |

*Notes:* The analysis is conducted at the 0.1-degree grid-year level over 2007-2019. Standard errors are clustered at the grid level.

Figure 3: Forest share responses to Japan biomass policy in Indonesia and Thailand

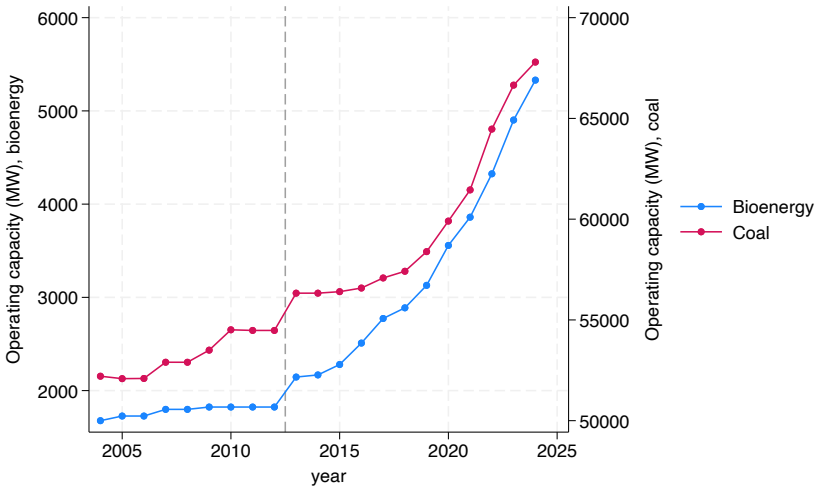



*Notes:* This figure plots event-study estimates of the effects of Japan's biomass policy on forest share at the 0.1-degree grid-year level over 2007-2019. The left panel shows Indonesia, and the right panel shows Thailand. All specifications include grid fixed effects, year fixed effects, and ADM1-specific linear time trends. Standard errors are clustered at the grid level.

# Online Appendix

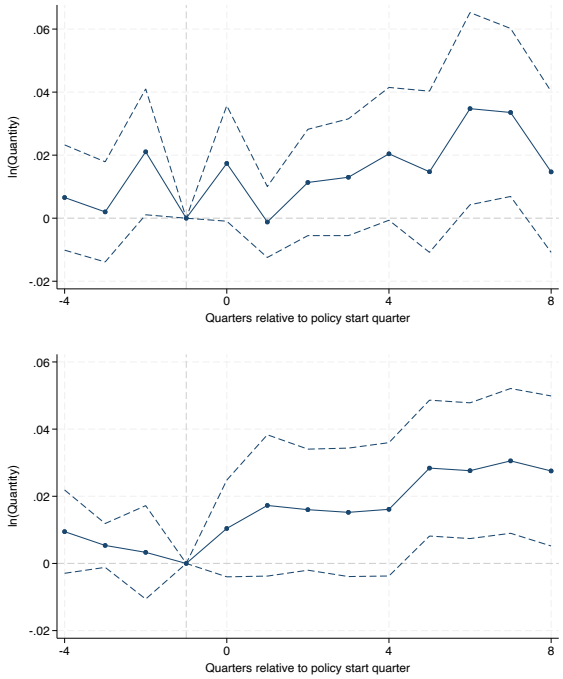
## A Appendix figures

Figure S1: Bioenergy and coal capacity in Japan




*Notes:* This figure shows national operating capacity (MW) of bioenergy (blue, left axis) and coal (red, right axis). The vertical dashed line indicates 2012, the year in which the Feed-in Tariff policy was implemented.

Figure S2: Biomass policies on wood exports to Japan and Korea: short window




*Notes:* This figure plots event-study estimates of the effects of biomass policy shocks in Japan (top) and Korea (bottom) on exporters' wood exports, using a balanced exporter–product–year–month panel from 2007-2019. The event window spans four quarters before and eight quarters after the policy implementation. All specifications include exporter fixed effects, product fixed effects, and year–month fixed effects. Standard errors are clustered at the exporter level.

# B Appendix tables

Table S1: Bioenergy expansion and electricity stability

| | Bioenergy capacity | | Bioenergy plant count | |
|---|---|---|---|---|
| | Electricity access (%) | T&D loss (%) | Electricity access (%) | T&D loss (%) |
| | (1) | (2) | (3) | (4) |
| Bioenergy exposure | -0.00084*** | 0.00014 | -0.01561*** | 0.00210 |
| | (0.00024) | (0.00010) | (0.00508) | (0.00205) |
| Observations | 3417 | 2527 | 3417 | 2527 |
| R-square | 0.977 | 0.865 | 0.977 | 0.865 |
| Y-mean | 81.564 | 13.234 | 81.564 | 13.234 |
| Y-sd | 27.408 | 9.398 | 27.408 | 9.398 |
| Country FEs | Y | Y | Y | Y |
| Year FEs | Y | Y | Y | Y |

*Notes:* The analysis is conducted at the country-year level over 2007-2019. Standard errors are clustered at the country level.

Table S2: Air pollution near coal plants in Japan and Korea

| | Panel A: Japan | | | | | |
|---|---|---|---|---|---|---|
| | $SO_2$ | | | AOD | | |
| | (1) | (2) | (3) | (4) | (5) | (6) |
| Post × Exposure | -0.00569 | -0.00569 | -0.00569 | -0.01148*** | -0.01148*** | -0.01148*** |
| | (0.00424) | (0.00424) | (0.00425) | (0.00318) | (0.00318) | (0.00319) |
| Post | -0.02097*** | -0.01591*** | 0.00000 | -0.04135*** | -0.04130*** | 0.00000 |
| | (0.00300) | (0.00298) | (.) | (0.00135) | (0.00135) | (.) |
| Observations | 31232 | 31232 | 31232 | 38064 | 38064 | 38064 |
| R-square | 0.154 | 0.158 | 0.269 | 0.756 | 0.756 | 0.861 |
| Y-mean | 0.064 | 0.064 | 0.064 | 0.267 | 0.267 | 0.267 |
| Y-sd | 0.085 | 0.085 | 0.085 | 0.087 | 0.087 | 0.087 |
| | Panel B: Korea | | | | | |
| | $SO_2$ | | | AOD | | |
| Post × Exposure | -1.72451 | -1.72451 | -1.72451 | -0.65423** | -0.65423** | -0.65423** |
| | (1.29393) | (1.29398) | (1.30552) | (0.29484) | (0.29485) | (0.29753) |
| Post | 0.05315*** | 0.06661*** | 0.00000 | -0.02581*** | -0.02574*** | 0.00000 |
| | (0.01749) | (0.01721) | (.) | (0.00311) | (0.00311) | (.) |
| Observations | 12544 | 12544 | 12544 | 15288 | 15288 | 15288 |
| R-square | 0.315 | 0.330 | 0.638 | 0.775 | 0.775 | 0.960 |
| Y-mean | 0.090 | 0.090 | 0.090 | 0.359 | 0.359 | 0.359 |
| Y-sd | 0.123 | 0.123 | 0.123 | 0.129 | 0.129 | 0.129 |
| Plant FEs | Y | Y | Y | Y | Y | Y |
| Year, month FEs | Y | Y | | Y | Y | |
| Year-month FEs | | | Y | | | Y |
| Quadratic trends | | Y | | | Y | |

*Notes:* The analysis is conducted at the plant-year-month level over 2007-2019. I use 50 km buffers to measure pollution around coal plants. The sample includes only coal plants that remain operating throughout 2007-2019. Standard errors are clustered at the plant level.

Table S3: Wood exports to Japan and Korea, heterogeneity by exporter

| | Panel A: Japan ln(Quantity) | | | |
|---|---|---|---|---|
| | Pooled | Indonesia | Thailand | Vietnam |
| | (1) | (2) | (3) | (4) |
| Post × Treated | 0.18976*** | 2.14776** | 2.33315** | 2.97981*** |
| | (0.03987) | (0.81065) | (0.91028) | (1.03427) |
| Observations | 692172 | 4524 | 4524 | 4524 |
| R-square | 0.109 | 0.434 | 0.456 | 0.479 |
| Y-mean | 0.134 | 0.897 | 0.975 | 1.245 |
| Y-sd | 1.298 | 3.392 | 3.655 | 4.234 |
| Exporter FEs | Y | | | |
| Product FEs | Y | Y | Y | Y |
| Year-month FEs | Y | Y | Y | Y |
| | Panel B: Korea ln(Quantity) | | | |
| | Pooled | Indonesia | Thailand | Vietnam |
| Post × Treated | 0.16500*** | 2.39872*** | 1.84798** | 3.33048*** |
| | (0.03735) | (0.81706) | (0.70221) | (1.03357) |
| Observations | 650832 | 4368 | 4368 | 4368 |
| R-square | 0.099 | 0.462 | 0.415 | 0.492 |
| Y-mean | 0.091 | 1.054 | 0.812 | 1.464 |
| Y-sd | 1.010 | 3.569 | 3.127 | 4.568 |
| Exporter FEs | Y | | | |
| Product FEs | Y | Y | Y | Y |
| Year-month FEs | Y | Y | Y | Y |

*Notes:* The analysis is conducted at the exporter-product-year-month level using a balanced panel from 2007-2019. For Japan, the sample includes only exporters that ever export treated or control products to Japan; for Korea, the sample includes only exporters that ever export treated or control products to Korea. Standard errors are clustered at the product level.

Table S4: Land use effects in Thailand in response to Japan biomass policy

| | Panel A: Forest share | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Post × Exposure | -6.807651*** | -6.854438*** | |
| | (0.979017) | (0.984219) | |
| Post × Exposure Q2 | | | 0.000000 |
| | | | (.) |
| Post × Exposure Q3 | | | -0.003480 |
| | | | (0.002543) |
| Post × Exposure Q4 | | | -0.010574*** |
| | | | (0.001270) |
| Observations | 56264 | 56264 | 56264 |
| R-square | 0.956 | 0.957 | 0.956 |
| Y-mean | 0.068 | 0.068 | 0.068 |
| Y-sd | 0.119 | 0.119 | 0.119 |
| | Panel B: Broad tree share | | |
| Post × Exposure | -4.423406*** | -4.990896*** | |
| | (0.920201) | (1.070640) | |
| Post × Exposure Q2 | | | 0.000000 |
| | | | (.) |
| Post × Exposure Q3 | | | 0.001415 |
| | | | (0.002150) |
| Post × Exposure Q4 | | | -0.004339*** |
| | | | (0.001139) |
| Observations | 56264 | 56264 | 56264 |
| R-square | 0.960 | 0.963 | 0.960 |
| Y-mean | 0.147 | 0.147 | 0.147 |
| Y-sd | 0.151 | 0.151 | 0.151 |
| | Panel C: Vegetation share | | |
| Post × Exposure | -1.155131 | -2.013107* | |
| | (0.853805) | (1.116783) | |
| Post × Exposure Q2 | | | 0.000000 |
| | | | (.) |
| Post × Exposure Q3 | | | 0.001968 |
| | | | (0.002215) |
| Post × Exposure Q4 | | | -0.000668 |
| | | | (0.001112) |
| Observations | 56264 | 56264 | 56264 |
| R-square | 0.952 | 0.955 | 0.952 |
| Y-mean | 0.162 | 0.162 | 0.162 |
| Y-sd | 0.151 | 0.151 | 0.151 |
| Grid FEs | Y | Y | Y |
| Year FEs | Y | Y | Y |
| ADM1-specific trends | | Y | |

*Notes:* The analysis is conducted at the 0.1-degree grid-year level over 2007-2019. Standard errors are clustered at the grid level.

Table S5: Land use effects in Vietnam in response to Japan biomass policy

| | Panel A: Forest share | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Post × Exposure | -20.809706*** | -20.376995*** | |
| | (2.425499) | (2.338570) | |
| Post × Exposure Q2 | | | 0.000000 |
| | | | (.) |
| Post × Exposure Q3 | | | -0.003978** |
| | | | (0.002017) |
| Post × Exposure Q4 | | | -0.018673*** |
| | | | (0.001954) |
| Observations | 36387 | 36387 | 36387 |
| R-square | 0.951 | 0.954 | 0.951 |
| Y-mean | 0.091 | 0.091 | 0.091 |
| Y-sd | 0.131 | 0.131 | 0.131 |
| | Panel B: Broad tree share | | |
| Post × Exposure | -3.914695** | -5.558420*** | |
| | (1.548105) | (2.034803) | |
| Post × Exposure Q2 | | | 0.000000 |
| | | | (.) |
| Post × Exposure Q3 | | | 0.000663 |
| | | | (0.001955) |
| Post × Exposure Q4 | | | -0.004743*** |
| | | | (0.001530) |
| Observations | 36387 | 36387 | 36387 |
| R-square | 0.948 | 0.950 | 0.948 |
| Y-mean | 0.219 | 0.219 | 0.219 |
| Y-sd | 0.143 | 0.143 | 0.143 |
| | Panel C: Vegetation share | | |
| Post × Exposure | -2.829479* | -3.052374 | |
| | (1.524156) | (2.002811) | |
| Post × Exposure Q2 | | | 0.000000 |
| | | | (.) |
| Post × Exposure Q3 | | | -0.000198 |
| | | | (0.001871) |
| Post × Exposure Q4 | | | -0.003486** |
| | | | (0.001490) |
| Observations | 36387 | 36387 | 36387 |
| R-square | 0.947 | 0.949 | 0.947 |
| Y-mean | 0.226 | 0.226 | 0.226 |
| Y-sd | 0.139 | 0.139 | 0.139 |
| Grid FEs | Y | Y | Y |
| Year FEs | Y | Y | Y |
| ADM1-specific trends | | Y | |

*Notes:* The analysis is conducted at the 0.1-degree grid-year level over 2007-2019. Standard errors are clustered at the grid level.

Table S6: Land use effects in Indonesia in response to Korea biomass policy

| | Panel A: Forest share | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Post × Exposure | -42.323076*** | -43.164637*** | |
| | (2.835201) | (3.030162) | |
| Post × Exposure Q2 | | | -0.005319*** |
| | | | (0.000664) |
| Post × Exposure Q3 | | | -0.014197*** |
| | | | (0.000897) |
| Post × Exposure Q4 | | | -0.026480*** |
| | | | (0.001081) |
| Observations | 199927 | 199927 | 199927 |
| R-square | 0.948 | 0.949 | 0.949 |
| Y-mean | 0.207 | 0.207 | 0.207 |
| Y-sd | 0.147 | 0.147 | 0.147 |
| | Panel B: Broad tree share | | |
| Post × Exposure | -8.125659*** | -11.657294*** | |
| | (1.044564) | (1.238762) | |
| Post × Exposure Q2 | | | -0.006119*** |
| | | | (0.000671) |
| Post × Exposure Q3 | | | -0.006491*** |
| | | | (0.000698) |
| Post × Exposure Q4 | | | -0.006430*** |
| | | | (0.000675) |
| Observations | 199927 | 199927 | 199927 |
| R-square | 0.959 | 0.960 | 0.959 |
| Y-mean | 0.282 | 0.282 | 0.282 |
| Y-sd | 0.105 | 0.105 | 0.105 |
| | Panel C: Vegetation share | | |
| Post × Exposure | -7.686718*** | -10.710666*** | |
| | (0.994704) | (1.189078) | |
| Post × Exposure Q2 | | | -0.005800*** |
| | | | (0.000653) |
| Post × Exposure Q3 | | | -0.006313*** |
| | | | (0.000666) |
| Post × Exposure Q4 | | | -0.005986*** |
| | | | (0.000638) |
| Observations | 199927 | 199927 | 199927 |
| R-square | 0.963 | 0.963 | 0.963 |
| Y-mean | 0.284 | 0.284 | 0.284 |
| Y-sd | 0.103 | 0.103 | 0.103 |
| Grid FEs | Y | Y | Y |
| Year FEs | Y | Y | Y |
| ADM1-specific trends | | Y | |

*Notes:* The analysis is conducted at the 0.1-degree grid-year level over 2007-2019. Standard errors are clustered at the grid level.

Table S7: Land use effects in Thailand in response to Korea biomass policy

| | Panel A: Forest share | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Post × Exposure | -6.925152*** | -6.984262*** | |
| | (0.980262) | (0.986065) | |
| Post × Exposure Q2 | | | 0.000000 |
| | | | (.) |
| Post × Exposure Q3 | | | -0.003570 |
| | | | (0.002539) |
| Post × Exposure Q4 | | | -0.010545*** |
| | | | (0.001271) |
| Observations | 56264 | 56264 | 56264 |
| R-square | 0.956 | 0.957 | 0.956 |
| Y-mean | 0.068 | 0.068 | 0.068 |
| Y-sd | 0.119 | 0.119 | 0.119 |
| | Panel B: Broad tree share | | |
| Post × Exposure | -4.432775*** | -4.944698*** | |
| | (0.921039) | (1.076858) | |
| Post × Exposure Q2 | | | 0.000000 |
| | | | (.) |
| Post × Exposure Q3 | | | 0.001676 |
| | | | (0.002171) |
| Post × Exposure Q4 | | | -0.004421*** |
| | | | (0.001134) |
| Observations | 56264 | 56264 | 56264 |
| R-square | 0.960 | 0.963 | 0.960 |
| Y-mean | 0.147 | 0.147 | 0.147 |
| Y-sd | 0.151 | 0.151 | 0.151 |
| | Panel C: Vegetation share | | |
| Post × Exposure | -1.133431 | -1.923550* | |
| | (0.860051) | (1.120677) | |
| Post × Exposure Q2 | | | 0.000000 |
| | | | (.) |
| Post × Exposure Q3 | | | 0.002230 |
| | | | (0.002236) |
| Post × Exposure Q4 | | | -0.000750 |
| | | | (0.001108) |
| Observations | 56264 | 56264 | 56264 |
| R-square | 0.952 | 0.955 | 0.952 |
| Y-mean | 0.162 | 0.162 | 0.162 |
| Y-sd | 0.151 | 0.151 | 0.151 |
| Grid FEs | Y | Y | Y |
| Year FEs | Y | Y | Y |
| ADM1-specific trends | | Y | |

*Notes:* The analysis is conducted at the 0.1-degree grid-year level over 2007-2019. Standard errors are clustered at the grid level.

Table S8: Land use effects in Vietnam in response to Korea biomass policy

| | Panel A: Forest share | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Post × Exposure | -20.851542*** | -20.213623*** | |
| | (2.451058) | (2.345554) | |
| Post × Exposure Q2 | | | 0.000000 |
| | | | (.) |
| Post × Exposure Q3 | | | -0.003853* |
| | | | (0.002010) |
| Post × Exposure Q4 | | | -0.018773*** |
| | | | (0.001957) |
| Observations | 36387 | 36387 | 36387 |
| R-square | 0.951 | 0.954 | 0.951 |
| Y-mean | 0.091 | 0.091 | 0.091 |
| Y-sd | 0.131 | 0.131 | 0.131 |
| | Panel B: Broad tree share | | |
| Post × Exposure | -3.932527** | -5.592279*** | |
| | (1.547584) | (2.031910) | |
| Post × Exposure Q2 | | | 0.000000 |
| | | | (.) |
| Post × Exposure Q3 | | | 0.000597 |
| | | | (0.001956) |
| Post × Exposure Q4 | | | -0.004691*** |
| | | | (0.001530) |
| Observations | 36387 | 36387 | 36387 |
| R-square | 0.948 | 0.950 | 0.948 |
| Y-mean | 0.219 | 0.219 | 0.219 |
| Y-sd | 0.143 | 0.143 | 0.143 |
| | Panel C: Vegetation share | | |
| Post × Exposure | -2.829614* | -3.090425 | |
| | (1.525112) | (2.002554) | |
| Post × Exposure Q2 | | | 0.000000 |
| | | | (.) |
| Post × Exposure Q3 | | | -0.000239 |
| | | | (0.001871) |
| Post × Exposure Q4 | | | -0.003454** |
| | | | (0.001490) |
| Observations | 36387 | 36387 | 36387 |
| R-square | 0.947 | 0.949 | 0.947 |
| Y-mean | 0.226 | 0.226 | 0.226 |
| Y-sd | 0.139 | 0.139 | 0.139 |
| Grid FEs | Y | Y | Y |
| Year FEs | Y | Y | Y |
| ADM1-specific trends | | Y | |

*Notes:* The analysis is conducted at the 0.1-degree grid-year level over 2007-2019. Standard errors are clustered at the grid level.

Table S9: Vegetation index responses to Japan biomass policy

| | Panel A: Indonesia (NDVI) | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Post × Exposure | -13.278581*** | -16.151788*** | |
| | (1.032287) | (1.018458) | |
| Post × Exposure Q2 | | | -0.005411*** |
| | | | (0.000466) |
| Post × Exposure Q3 | | | -0.003144*** |
| | | | (0.000447) |
| Post × Exposure Q4 | | | -0.009970*** |
| | | | (0.000472) |
| Observations | 507507 | 507507 | 507507 |
| R-square | 0.838 | 0.839 | 0.838 |
| Y-mean | 0.728 | 0.728 | 0.728 |
| Y-sd | 0.121 | 0.121 | 0.121 |
| | Panel B: Thailand (NDVI) | | |
| Post × Exposure | -9.581244*** | -11.960074*** | |
| | (0.739158) | (0.687167) | |
| Post × Exposure Q2 | | | 0.000000 |
| | | | (.) |
| Post × Exposure Q3 | | | -0.001029 |
| | | | (0.001117) |
| Post × Exposure Q4 | | | -0.010792*** |
| | | | (0.000634) |
| Observations | 437128 | 437128 | 437128 |
| R-square | 0.828 | 0.831 | 0.828 |
| Y-mean | 0.601 | 0.601 | 0.601 |
| Y-sd | 0.160 | 0.160 | 0.160 |
| | Panel C: Vietnam (NDVI) | | |
| Post × Exposure | -19.043253*** | -16.008883*** | |
| | (1.329784) | (1.138289) | |
| Post × Exposure Q2 | | | 0.000000 |
| | | | (.) |
| Post × Exposure Q3 | | | -0.005381*** |
| | | | (0.001181) |
| Post × Exposure Q4 | | | -0.020398*** |
| | | | (0.001072) |
| Observations | 204327 | 204327 | 204327 |
| R-square | 0.764 | 0.767 | 0.764 |
| Y-mean | 0.647 | 0.647 | 0.647 |
| Y-sd | 0.158 | 0.158 | 0.158 |
| Grid FEs | Y | Y | Y |
| Year FEs | Y | Y | Y |
| ADM1-specific trends | | Y | |

*Notes:* The analysis is conducted at the 0.1-degree grid-year level over 2007-2019. The dependent variable is NDVI. All specifications include grid fixed effects and year fixed effects. Column (2) additionally controls for ADM1-specific linear time trends. Standard errors are clustered at the grid level.

Table S10: Vegetation index responses to Korea biomass policy

| | Panel A: Indonesia (NDVI) | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Post × Exposure | -16.449986*** | -20.618465*** | |
| | (1.087076) | (1.185231) | |
| Post × Exposure Q2 | | | -0.009136*** |
| | | | (0.000485) |
| Post × Exposure Q3 | | | -0.007480*** |
| | | | (0.000454) |
| Post × Exposure Q4 | | | -0.013441*** |
| | | | (0.000488) |
| Observations | 507507 | 507507 | 507507 |
| R-square | 0.838 | 0.839 | 0.838 |
| Y-mean | 0.728 | 0.728 | 0.728 |
| Y-sd | 0.121 | 0.121 | 0.121 |
| | Panel B: Thailand (NDVI) | | |
| Post × Exposure | -7.228293*** | -9.172782*** | |
| | (0.620456) | (0.579233) | |
| Post × Exposure Q2 | | | 0.000000 |
| | | | (.) |
| Post × Exposure Q3 | | | -0.003462*** |
| | | | (0.001010) |
| Post × Exposure Q4 | | | -0.009678*** |
| | | | (0.000578) |
| Observations | 437128 | 437128 | 437128 |
| R-square | 0.828 | 0.830 | 0.828 |
| Y-mean | 0.601 | 0.601 | 0.601 |
| Y-sd | 0.160 | 0.160 | 0.160 |
| | Panel C: Vietnam (NDVI) | | |
| Post × Exposure | -19.253115*** | -16.235324*** | |
| | (1.386112) | (1.190021) | |
| Post × Exposure Q2 | | | 0.000000 |
| | | | (.) |
| Post × Exposure Q3 | | | -0.006722*** |
| | | | (0.001199) |
| Post × Exposure Q4 | | | -0.020605*** |
| | | | (0.001106) |
| Observations | 204327 | 204327 | 204327 |
| R-square | 0.764 | 0.767 | 0.764 |
| Y-mean | 0.647 | 0.647 | 0.647 |
| Y-sd | 0.158 | 0.158 | 0.158 |
| Grid FEs | Y | Y | Y |
| Year FEs | Y | Y | Y |
| ADM1-specific trends | | Y | |

*Notes:* The analysis is conducted at the 0.1-degree grid-year level over 2007-2019. The dependent variable is NDVI. All specifications include grid fixed effects and year fixed effects. Column (2) additionally controls for ADM1-specific linear time trends. Standard errors are clustered at the grid level.

# C Robustness using ports' absolute outflow

Table S11: Land use effects in Indonesia in response to Japan biomass policy

| | Panel A: Forest share | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Post × Exposure | -0.000039*** | -0.000038*** | |
| | (0.000003) | (0.000003) | |
| Post × Exposure Q2 | | | -0.004778*** |
| | | | (0.000685) |
| Post × Exposure Q3 | | | -0.014895*** |
| | | | (0.000902) |
| Post × Exposure Q4 | | | -0.026901*** |
| | | | (0.001066) |
| Observations | 199927 | 199927 | 199927 |
| R-square | 0.948 | 0.949 | 0.949 |
| Y-mean | 0.207 | 0.207 | 0.207 |
| Y-sd | 0.147 | 0.147 | 0.147 |
| | Panel B: Broad tree share | | |
| Post × Exposure | -0.000007*** | -0.000010*** | |
| | (0.000001) | (0.000001) | |
| Post × Exposure Q2 | | | -0.005914*** |
| | | | (0.000674) |
| Post × Exposure Q3 | | | -0.006687*** |
| | | | (0.000699) |
| Post × Exposure Q4 | | | -0.006399*** |
| | | | (0.000671) |
| Observations | 199927 | 199927 | 199927 |
| R-square | 0.959 | 0.960 | 0.959 |
| Y-mean | 0.282 | 0.282 | 0.282 |
| Y-sd | 0.105 | 0.105 | 0.105 |
| | Panel C: Vegetation share | | |
| Post × Exposure | -0.000007*** | -0.000009*** | |
| | (0.000001) | (0.000001) | |
| Post × Exposure Q2 | | | -0.005517*** |
| | | | (0.000657) |
| Post × Exposure Q3 | | | -0.006472*** |
| | | | (0.000663) |
| Post × Exposure Q4 | | | -0.006004*** |
| | | | (0.000640) |
| Observations | 199927 | 199927 | 199927 |
| R-square | 0.963 | 0.963 | 0.963 |
| Y-mean | 0.284 | 0.284 | 0.284 |
| Y-sd | 0.103 | 0.103 | 0.103 |
| Grid FEs | Y | Y | Y |
| Year FEs | Y | Y | Y |
| ADM1-specific trends | | Y | |

*Notes:* The analysis is conducted at the 0.1-degree grid-year level over 2007-2019. Standard errors are clustered at grid level.

Table S12: Land use effects in Thailand in response to Japan biomass policy

| | Panel A: Forest share | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Post × Exposure | -0.000002*** | -0.000002*** | |
| | (0.000000) | (0.000000) | |
| Post × Exposure Q2 | | | 0.000000 |
| | | | (.) |
| Post × Exposure Q3 | | | -0.003480 |
| | | | (0.002543) |
| Post × Exposure Q4 | | | -0.010574*** |
| | | | (0.001270) |
| Observations | 56264 | 56264 | 56264 |
| R-square | 0.956 | 0.957 | 0.956 |
| Y-mean | 0.068 | 0.068 | 0.068 |
| Y-sd | 0.119 | 0.119 | 0.119 |
| | Panel B: Broad tree share | | |
| Post × Exposure | -0.000001*** | -0.000002*** | |
| | (0.000000) | (0.000000) | |
| Post × Exposure Q2 | | | 0.000000 |
| | | | (.) |
| Post × Exposure Q3 | | | 0.001415 |
| | | | (0.002150) |
| Post × Exposure Q4 | | | -0.004339*** |
| | | | (0.001139) |
| Observations | 56264 | 56264 | 56264 |
| R-square | 0.960 | 0.963 | 0.960 |
| Y-mean | 0.147 | 0.147 | 0.147 |
| Y-sd | 0.151 | 0.151 | 0.151 |
| | Panel C: Vegetation share | | |
| Post × Exposure | -0.000000 | -0.000001* | |
| | (0.000000) | (0.000000) | |
| Post × Exposure Q2 | | | 0.000000 |
| | | | (.) |
| Post × Exposure Q3 | | | 0.001968 |
| | | | (0.002215) |
| Post × Exposure Q4 | | | -0.000668 |
| | | | (0.001112) |
| Observations | 56264 | 56264 | 56264 |
| R-square | 0.952 | 0.955 | 0.952 |
| Y-mean | 0.162 | 0.162 | 0.162 |
| Y-sd | 0.151 | 0.151 | 0.151 |
| Grid FEs | Y | Y | Y |
| Year FEs | Y | Y | Y |
| ADM1-specific trends | | Y | |

*Notes:* The analysis is conducted at the 0.1-degree grid-year level over 2007-2019. Standard errors are clustered at grid level.

Table S13: Land use effects in Vietnam in response to Japan biomass policy

| | Panel A: Forest share | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Post × Exposure | -0.000005*** | -0.000005*** | |
| | (0.000001) | (0.000001) | |
| Post × Exposure Q2 | | | 0.000000 |
| | | | (.) |
| Post × Exposure Q3 | | | -0.003978** |
| | | | (0.002017) |
| Post × Exposure Q4 | | | -0.018673*** |
| | | | (0.001954) |
| Observations | 36387 | 36387 | 36387 |
| R-square | 0.951 | 0.954 | 0.951 |
| Y-mean | 0.091 | 0.091 | 0.091 |
| Y-sd | 0.131 | 0.131 | 0.131 |
| | Panel B: Broad tree share | | |
| Post × Exposure | -0.000001** | -0.000001*** | |
| | (0.000000) | (0.000000) | |
| Post × Exposure Q2 | | | 0.000000 |
| | | | (.) |
| Post × Exposure Q3 | | | 0.000663 |
| | | | (0.001955) |
| Post × Exposure Q4 | | | -0.004743*** |
| | | | (0.001530) |
| Observations | 36387 | 36387 | 36387 |
| R-square | 0.948 | 0.950 | 0.948 |
| Y-mean | 0.219 | 0.219 | 0.219 |
| Y-sd | 0.143 | 0.143 | 0.143 |
| | Panel C: Vegetation share | | |
| Post × Exposure | -0.000001* | -0.000001 | |
| | (0.000000) | (0.000000) | |
| Post × Exposure Q2 | | | 0.000000 |
| | | | (.) |
| Post × Exposure Q3 | | | -0.000198 |
| | | | (0.001871) |
| Post × Exposure Q4 | | | -0.003486** |
| | | | (0.001490) |
| Observations | 36387 | 36387 | 36387 |
| R-square | 0.947 | 0.949 | 0.947 |
| Y-mean | 0.226 | 0.226 | 0.226 |
| Y-sd | 0.139 | 0.139 | 0.139 |
| Grid FEs | Y | Y | Y |
| Year FEs | Y | Y | Y |
| ADM1-specific trends | | Y | |

*Notes:* The analysis is conducted at the 0.1-degree grid-year level over 2007-2019. Standard errors are clustered at grid level.

Table S14: Land use effects in Indonesia in response to Korea biomass policy

| | Panel A: Forest share | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Post × Exposure | -0.000032*** | -0.000033*** | |
| | (0.000002) | (0.000002) | |
| Post × Exposure Q2 | | | -0.005319*** |
| | | | (0.000664) |
| Post × Exposure Q3 | | | -0.014197*** |
| | | | (0.000897) |
| Post × Exposure Q4 | | | -0.026480*** |
| | | | (0.001081) |
| Observations | 199927 | 199927 | 199927 |
| R-square | 0.948 | 0.949 | 0.949 |
| Y-mean | 0.207 | 0.207 | 0.207 |
| Y-sd | 0.147 | 0.147 | 0.147 |
| | Panel B: Broad tree share | | |
| Post × Exposure | -0.000006*** | -0.000009*** | |
| | (0.000001) | (0.000001) | |
| Post × Exposure Q2 | | | -0.006119*** |
| | | | (0.000671) |
| Post × Exposure Q3 | | | -0.006491*** |
| | | | (0.000698) |
| Post × Exposure Q4 | | | -0.006430*** |
| | | | (0.000675) |
| Observations | 199927 | 199927 | 199927 |
| R-square | 0.959 | 0.960 | 0.959 |
| Y-mean | 0.282 | 0.282 | 0.282 |
| Y-sd | 0.105 | 0.105 | 0.105 |
| | Panel C: Vegetation share | | |
| Post × Exposure | -0.000006*** | -0.000008*** | |
| | (0.000001) | (0.000001) | |
| Post × Exposure Q2 | | | -0.005800*** |
| | | | (0.000653) |
| Post × Exposure Q3 | | | -0.006313*** |
| | | | (0.000666) |
| Post × Exposure Q4 | | | -0.005986*** |
| | | | (0.000638) |
| Observations | 199927 | 199927 | 199927 |
| R-square | 0.963 | 0.963 | 0.963 |
| Y-mean | 0.284 | 0.284 | 0.284 |
| Y-sd | 0.103 | 0.103 | 0.103 |
| Grid FEs | Y | Y | Y |
| Year FEs | Y | Y | Y |
| ADM1-specific trends | | Y | |

*Notes:* The analysis is conducted at the 0.1-degree grid-year level over 2007-2019. Standard errors are clustered at grid level.

Table S15: Land use effects in Thailand in response to Korea biomass policy

| | Panel A: Forest share | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Post × Exposure | -0.000004*** | -0.000004*** | |
| | (0.000001) | (0.000001) | |
| Post × Exposure Q2 | | | 0.000000 |
| | | | (.) |
| Post × Exposure Q3 | | | -0.003570 |
| | | | (0.002539) |
| Post × Exposure Q4 | | | -0.010545*** |
| | | | (0.001271) |
| Observations | 56264 | 56264 | 56264 |
| R-square | 0.956 | 0.957 | 0.956 |
| Y-mean | 0.068 | 0.068 | 0.068 |
| Y-sd | 0.119 | 0.119 | 0.119 |
| | Panel B: Broad tree share | | |
| Post × Exposure | -0.000003*** | -0.000003*** | |
| | (0.000001) | (0.000001) | |
| Post × Exposure Q2 | | | 0.000000 |
| | | | (.) |
| Post × Exposure Q3 | | | 0.001676 |
| | | | (0.002171) |
| Post × Exposure Q4 | | | -0.004421*** |
| | | | (0.001134) |
| Observations | 56264 | 56264 | 56264 |
| R-square | 0.960 | 0.963 | 0.960 |
| Y-mean | 0.147 | 0.147 | 0.147 |
| Y-sd | 0.151 | 0.151 | 0.151 |
| | Panel C: Vegetation share | | |
| Post × Exposure | -0.000001 | -0.000001* | |
| | (0.000001) | (0.000001) | |
| Post × Exposure Q2 | | | 0.000000 |
| | | | (.) |
| Post × Exposure Q3 | | | 0.002230 |
| | | | (0.002236) |
| Post × Exposure Q4 | | | -0.000750 |
| | | | (0.001108) |
| Observations | 56264 | 56264 | 56264 |
| R-square | 0.952 | 0.955 | 0.952 |
| Y-mean | 0.162 | 0.162 | 0.162 |
| Y-sd | 0.151 | 0.151 | 0.151 |
| Grid FEs | Y | Y | Y |
| Year FEs | Y | Y | Y |
| ADM1-specific trends | | Y | |

*Notes:* The analysis is conducted at the 0.1-degree grid-year level over 2007-2019. Standard errors are clustered at grid level.

Table S16: Land use effects in Vietnam in response to Korea biomass policy

| | Panel A: Forest share | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Post × Exposure | -0.000008*** | -0.000008*** | |
| | (0.000001) | (0.000001) | |
| Post × Exposure Q2 | | | 0.000000 |
| | | | (.) |
| Post × Exposure Q3 | | | -0.003853* |
| | | | (0.002010) |
| Post × Exposure Q4 | | | -0.018773*** |
| | | | (0.001957) |
| Observations | 36387 | 36387 | 36387 |
| R-square | 0.951 | 0.954 | 0.951 |
| Y-mean | 0.091 | 0.091 | 0.091 |
| Y-sd | 0.131 | 0.131 | 0.131 |
| | Panel B: Broad tree share | | |
| Post × Exposure | -0.000001** | -0.000002*** | |
| | (0.000001) | (0.000001) | |
| Post × Exposure Q2 | | | 0.000000 |
| | | | (.) |
| Post × Exposure Q3 | | | 0.000597 |
| | | | (0.001956) |
| Post × Exposure Q4 | | | -0.004691*** |
| | | | (0.001530) |
| Observations | 36387 | 36387 | 36387 |
| R-square | 0.948 | 0.950 | 0.948 |
| Y-mean | 0.219 | 0.219 | 0.219 |
| Y-sd | 0.143 | 0.143 | 0.143 |
| | Panel C: Vegetation share | | |
| Post × Exposure | -0.000001* | -0.000001 | |
| | (0.000001) | (0.000001) | |
| Post × Exposure Q2 | | | 0.000000 |
| | | | (.) |
| Post × Exposure Q3 | | | -0.000239 |
| | | | (0.001871) |
| Post × Exposure Q4 | | | -0.003454** |
| | | | (0.001490) |
| Observations | 36387 | 36387 | 36387 |
| R-square | 0.947 | 0.949 | 0.947 |
| Y-mean | 0.226 | 0.226 | 0.226 |
| Y-sd | 0.139 | 0.139 | 0.139 |
| Grid FEs | Y | Y | Y |
| Year FEs | Y | Y | Y |
| ADM1-specific trends | | Y | |

*Notes:* The analysis is conducted at the 0.1-degree grid-year level over 2007-2019. Standard errors are clustered at grid level.

Table S17: NDVI responses to Japan biomass policy

| | Panel A: Indonesia | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Post × Exposure | -0.000011*** | -0.000014*** | |
| | (0.000001) | (0.000001) | |
| Post × Exposure Q2 | | | -0.005411*** |
| | | | (0.000466) |
| Post × Exposure Q3 | | | -0.003144*** |
| | | | (0.000447) |
| Post × Exposure Q4 | | | -0.009970*** |
| | | | (0.000472) |
| Observations | 507507 | 507507 | 507507 |
| R-square | 0.838 | 0.839 | 0.838 |
| Y-mean | 0.728 | 0.728 | 0.728 |
| Y-sd | 0.121 | 0.121 | 0.121 |
| | Panel B: Thailand | | |
| Post × Exposure | -0.000003*** | -0.000004*** | |
| | (0.000000) | (0.000000) | |
| Post × Exposure Q2 | | | 0.000000 |
| | | | (.) |
| Post × Exposure Q3 | | | -0.001029 |
| | | | (0.001117) |
| Post × Exposure Q4 | | | -0.010792*** |
| | | | (0.000634) |
| Observations | 437128 | 437128 | 437128 |
| R-square | 0.828 | 0.831 | 0.828 |
| Y-mean | 0.601 | 0.601 | 0.601 |
| Y-sd | 0.160 | 0.160 | 0.160 |
| | Panel C: Vietnam | | |
| Post × Exposure | -0.000004*** | -0.000004*** | |
| | (0.000000) | (0.000000) | |
| Post × Exposure Q2 | | | 0.000000 |
| | | | (.) |
| Post × Exposure Q3 | | | -0.005381*** |
| | | | (0.001181) |
| Post × Exposure Q4 | | | -0.020398*** |
| | | | (0.001072) |
| Observations | 204327 | 204327 | 204327 |
| R-square | 0.764 | 0.767 | 0.764 |
| Y-mean | 0.647 | 0.647 | 0.647 |
| Y-sd | 0.158 | 0.158 | 0.158 |
| Grid FEs | Y | Y | Y |
| Year FEs | Y | Y | Y |
| ADM1-specific trends | | Y | |

*Notes:* The analysis is conducted at the 0.1-degree grid-year level over 2007-2019. Standard errors are clustered at grid level.

Table S18: NDVI responses to Korea biomass policy

| | Panel A: Indonesia | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| Post × Exposure | -0.000013*** | -0.000016*** | |
| | (0.000001) | (0.000001) | |
| Post × Exposure Q2 | | | -0.009136*** |
| | | | (0.000485) |
| Post × Exposure Q3 | | | -0.007480*** |
| | | | (0.000454) |
| Post × Exposure Q4 | | | -0.013441*** |
| | | | (0.000488) |
| Observations | 507507 | 507507 | 507507 |
| R-square | 0.838 | 0.839 | 0.838 |
| Y-mean | 0.728 | 0.728 | 0.728 |
| Y-sd | 0.121 | 0.121 | 0.121 |
| | Panel B: Thailand | | |
| Post × Exposure | -0.000004*** | -0.000006*** | |
| | (0.000000) | (0.000000) | |
| Post × Exposure Q2 | | | 0.000000 |
| | | | (.) |
| Post × Exposure Q3 | | | -0.003462*** |
| | | | (0.001010) |
| Post × Exposure Q4 | | | -0.009678*** |
| | | | (0.000578) |
| Observations | 437128 | 437128 | 437128 |
| R-square | 0.828 | 0.830 | 0.828 |
| Y-mean | 0.601 | 0.601 | 0.601 |
| Y-sd | 0.160 | 0.160 | 0.160 |
| | Panel C: Vietnam | | |
| Post × Exposure | -0.000007*** | -0.000006*** | |
| | (0.000001) | (0.000000) | |
| Post × Exposure Q2 | | | 0.000000 |
| | | | (.) |
| Post × Exposure Q3 | | | -0.006722*** |
| | | | (0.001199) |
| Post × Exposure Q4 | | | -0.020605*** |
| | | | (0.001106) |
| Observations | 204327 | 204327 | 204327 |
| R-square | 0.764 | 0.767 | 0.764 |
| Y-mean | 0.647 | 0.647 | 0.647 |
| Y-sd | 0.158 | 0.158 | 0.158 |
| Grid FEs | Y | Y | Y |
| Year FEs | Y | Y | Y |
| ADM1-specific trends | | Y | |

*Notes:* The analysis is conducted at the 0.1-degree grid-year level over 2007-2019. Standard errors are clustered at grid level.