



Working Paper

The deforestation effect of climate aid

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Octobre 2025

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The deforestation effect of climate aid

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October 10, 2025

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Abstract

Climate aid is an international financial flow that promotes mitigation and adaptation to climate change while supporting local economic development. These flows may have unintended consequences, potentially exacerbating environmental degradation. This study examines the impact of climate aid on deforestation in Africa from 2001 to 2021. Using a novel dataset of geocoded aid projects that we classify as pursuing climate-related objectives by applying a machine learning model, we find evidence of a causal link between climate aid and forest loss. On average, deforestation increases by 94 hectares for every additional 1 million USD of geocoded climate aid projects disbursed. Over the complete period and spatial extent, 5% of deforestation is linked to the disbursement of climate aid projects. These effects are heterogeneous and vary by initial forest cover: aid increases deforestation in densely forested areas, while it appears to reduce deforestation where forest cover was initially sparse. Analysis of the mechanisms suggests that the effects are primarily driven by economic funding for mitigation, production-related activities, and particularly agricultural expansion.

Keywords— mitigation and adaptation; tropical deforestation; land conversion

JEL Codes— Q23; Q56; O13; O55

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1 Introduction

Climate change presents escalating challenges that necessitate coordinated international responses. Forests are central to this issue: they sustain human livelihoods, act as critical carbon sinks, and host much of the world’s biodiversity. Yet they are also under intensifying pressure from land-use change and climate shocks (IPCC, 2019, 2023). In this context, climate finance has emerged as a key tool to address mitigation and adaptation, including forest preservation. High-income countries pledged in Copenhagen in 2009 to mobilize 100 billion USD annually, and climate-related aid flows have expanded in the years since (Roberts et al., 2021; OECD, 2024a). Climate aid—a subset of climate finance defined as financial transfers from high-income to low- and lower-middle-income countries for climate objectives—is of particular interest. It channels resources through development aid systems (Falconer and Buchner, 2022), but its direct impacts on outcomes and forest loss remain poorly understood.

This paper addresses the question: *Does climate aid reduce or exacerbate deforestation in recipient countries?* While many climate aid projects are designed with climate objectives in mind—including programs such as REDD+ (Reducing Emissions from Deforestation and Forest Degradation)—the effectiveness of such aid in shaping land-use outcomes is uncertain. A 2020 World Bank report warned that climate aid may follow existing development mandates rather than being designed for climate needs (World Bank, 2020). More broadly, aid flows are shaped by both donor strategies and recipient conditions, raising the possibility that climate aid could generate unintended consequences for forest conservation. Understanding whether these large financial flows mitigate or accelerate forest loss is therefore crucial for evaluating their effectiveness.

A small but growing literature has investigated the links between climate finance and carbon outcomes. Studies find mixed effects of climate aid on greenhouse gas emissions, often pointing to marginal or inconclusive results (Wu et al., 2021; Kablan and Chouard, 2022; Zhao et al., 2024). Evidence on forest outcomes is even scarcer. While some work finds reduced deforestation associated with environmental aid (Restivo et al., 2018), other studies document increased forest loss following conservation-related projects (Bare et al., 2015). Existing research has emphasized structural drivers of deforestation, such as agricultural expansion, fuelwood demand, and conflict (Curtis et al., 2018; Busch and Ferretti-Gallon, 2023), but little is known about how international transfers affect these dynamics. The absence of systematic evidence on climate aid and deforestation represents a critical gap.

This study aims to contribute to this debate by investigating the impact of climate aid projects on deforestation in Africa from 2001 to 2021, using a novel data source of geocoded aid projects from 19 OECD donor countries and the World Bank. We classify these projects using their titles

and descriptions, replicating a natural language processing (NLP) analysis developed by [Toetzke et al. \(2022\)](#). Despite coverage limitations arising from selection bias in the geocoding process (see Section 3.2.3 for discussion), this new dataset provides an opportunity to analyze the effects of climate projects at a highly disaggregated resolution.

Our focus on Africa is backed by several reasons. This region is the largest recipient of ODA in absolute terms, of which 32% was classified as climate aid in 2021-2022 ([OECD, 2024b](#)). This makes it a key region for assessing the impact of such funding on deforestation dynamics. Africa is also the second-largest region with the most intact natural land, underscoring its critical role in global biodiversity conservation and carbon storage ([Hansen et al., 2022](#)). Moreover, pressures on forest cover are intensifying, alongside other climate change challenges, with Africa being particularly vulnerable to climate change impacts ([IPCC, 2019](#)). Although numerous publications have explored the drivers of deforestation in several African countries, there is still a lack of regional assessments concerning the effects of international transfers ([Busch and Ferretti-Gallon, 2023](#)). Africa’s deforestation patterns are shaped by distinct mechanisms from other tropical regions, such as the Amazonian basin or Southeast Asia ([Curtis et al., 2018](#)). It is therefore essential to analyze Africa separately, ensuring a better understanding of the tradeoffs between economic development and deforestation ([Jack, 2017](#)).

A key methodological challenge lies in the treatment of endogeneity of climate aid with respect to deforestation. Beyond measurement issues of aid, climate aid allocation depends on multiple factors, including governance quality, regional investments, geopolitical preferences, or the persistence of extreme weather events, all of which may also influence land-use change ([Weiler et al., 2018](#); [Bayramoglu et al., 2023](#)). Reverse causality is another concern, as increased deforestation can trigger higher climate aid disbursement. To address these issues, we employ a shift-share instrumental variable approach to instrument the total monetary value of climate aid disbursement, leveraging the time-dependent donor-recipient relationship. In the flavor of the strategy for time-series variation proposed by [Nunn and Qian \(2014\)](#), we interact an exogenous shift—the annual fraction of climate aid disbursement per donor, excluding African countries—with a cell-level measure of the frequency of treatment. The exclusion restriction requires that fluctuations in the fraction of non-African climate aid, conditional on a selection of fixed effects and controls, influence deforestation only through the local presence of climate projects.

Our analysis yields the following results. First, climate aid can have substantial, unintended environmental consequences by accelerating deforestation. Climate aid increases deforestation even after controlling for weather shocks, local activity measures, lagged non-climate aid disbursements, and interactions of weather with historical exposure. Quantitatively, a one-standard-deviation increase in climate aid (2.7 million 2014 USD) corresponds to an increase in deforesta-

tion of 2.5 square kilometers, or roughly one-third of a standard deviation in typical forest loss.

Second, the impact of climate aid on deforestation varies substantially across initial forest cover, climate objectives, and sectoral classification. Interacting climate aid with baseline forest cover shows that areas with low initial forest cover experience reduced deforestation, whereas densely forested areas exhibit strongly positive effects, suggesting that the average effect essentially reflects forest outcomes in heavily forested cells. Considering climate-related objectives, mitigation-linked projects—often involving large infrastructure, land-intensive activities, or land conservation projects—are associated with significant increases in deforestation, while adaptation-focused projects show smaller and mostly insignificant effects. Sectoral analysis using OECD purpose codes indicates that production-related climate aid, targeting agriculture, forestry, mining, and industry, consistently raises deforestation, while multisectoral projects have weaker and more ambiguous effects.

Besides, climate aid may influence deforestation through multiple mechanisms. We provide suggestive evidence on a number of them. First, the economic activity channel appears limited: while parsimonious specifications show a positive association between climate aid and nightlight intensity, this effect becomes statistically insignificant once a broader set of controls or regional fixed effects is included, indicating that local economic stimulation is unlikely to be the main driver of observed deforestation. Second, the agricultural expansion channel provides more consistent evidence: climate aid significantly increases the crop price index used as a proxy of crop markets, particularly in areas with high initial forest cover, supporting the interpretation that aid may incentivize land conversion for agriculture. Third, infrastructure-related channels, proxied by market access, appear less relevant: controlling for time-varying market access does not alter the estimated impact of climate aid on deforestation, suggesting that improvements in connectivity and trade access are not a primary mechanism.

Fourth, to provide a sense of magnitude, we complement our main results with a back-of-the-envelope cost calculation. Translating the estimated deforestation effect of climate aid into carbon emissions, we find that additional aid disbursements are associated with 1.3–4.1 gigatonnes of CO₂-equivalent emissions over the study period, or 0.06–0.19 gigatonnes annually. Valuing these emissions with standard estimates of the Social Cost of Carbon implies that the hidden environmental costs of climate aid-induced deforestation exceed the direct financial resources provided by roughly an order of magnitude. These illustrative figures underscore the potential scale of unintended environmental consequences of climate aid projects.

Related literature and contributions. This study contributes to multiple strands of literature. First, as mentioned above, it builds on the growing body of research investigating the effects of

climate aid on GHG emissions and carbon transitions. This includes studies assessing the impact of specific subsets of climate aid, such as flows allocated to mitigation efforts or renewable energy projects (Wu et al., 2021; Kablan and Chouard, 2022; Zhao et al., 2024; Carfora and Scandurra, 2019). These analyses have been conducted at global and regional scales, including studies on the Belt and Road Initiative countries and the Congo Basin (Zeng et al., 2022; Aquilas and Atemnkeng, 2022). Findings from this literature remain mixed but generally indicate only marginal reductions in GHG emissions. Second, this study is closely related to the literature on deforestation in Africa and its underlying drivers. Climate aid can influence multiple land-use activities contributing to deforestation, including agricultural expansion, timber extraction, fuelwood collection, and artisanal mining (Branthomme, A. et al., 2023; Pendrill et al., 2022; Berman et al., 2023; Girard et al., 2022; Rudel, 2013; Fisher, 2010). Additionally, institutional quality, political instability, and conflicts, which are closely linked to the allocation of climate aid, have significant effects on forest cover (Balboni et al., 2023; Fischer et al., 2020; Wehkamp et al., 2015). The establishment of protected areas also yields heterogeneous effects on deforestation. While some studies document spillover effects leading to increased deforestation outside protected zones, more recent research highlights improvements in conservation outcomes (Meyfroidt et al., 2010; Desbureaux et al., 2025).

Third, this paper connects to the broader debate on the relationship between aid (general aid, or environment-related aid) and deforestation, a topic that has yielded contradictory findings. Few studies exist on ODA and deforestation, and are sometimes hampered by their very weak empirical strategy. Some studies explore the links between ODA allocation and deforestation (Mak Arvin and Lew, 2009), or between World Bank projects and biodiversity conservation through habitat preservation (Buchanan et al., 2016). Other studies, focusing on specific types of aid, show negative effects of aid on deforestation (Hermanrud and de Soysa, 2017; He et al., 2022). In particular, McCarthy et al. (2023) aim to assess the effectiveness of environmental aid on several key environmental outcomes, including CO₂ emissions, deforestation rates, the extent of protected areas, and the implementation of environmental policies. To do so, they focus on a specific subset of OECD aid projects classified as participating in environmental protection. Their approach relies on correlation analysis rather than causal inference, and their findings indicate no statistically significant effect of environmental aid on forest cover. The authors highlight the complexity of isolating the impact of aid, emphasizing the multitude of interacting factors that hamper disentangling a clear relationship between aid and deforestation. More specifically, two studies have examined the impact of climate-related aid on forest loss in the Global South. Restivo et al. (2018) report a lower country-level rate of deforestation between 2001 and 2014 in low- and middle-income countries, causally linked to the allocation of USAID environmental aid

between 1990 and 2000. In contrast, [Bare et al. \(2015\)](#) found that international conservation aid was correlated with increased forest loss after a two-year lag, though this effect did not persist over time in their analysis of 42 African countries between 2000 and 2013.

Compared to the existing literature, this study advances the literature in several ways. Unlike previous research, it utilizes a novel geocoded dataset that precisely locates climate aid projects, allowing for assessment at a within-country level. Additionally, it considers a broader set of climate aid projects beyond conservation-focused projects, incorporating funding from 19 OECD donor countries and the World Bank. This approach allows for a more comprehensive assessment of climate aid's impact on deforestation, providing an updated analysis of its effects.

Results in this paper may extend beyond the African case. Indeed, while our empirical analysis is restricted to Africa, the mechanisms identified—particularly the link between climate aid and agricultural expansion—are not region-specific. Similar aid-induced land-use pressures could plausibly arise in other tropical regions where forests serve both as carbon sinks and as reserves of arable land. However, external validity is limited by contextual factors: Africa's deforestation is more fragmented and smallholder-driven than in the Amazon or Southeast Asia, and the institutional capacity to enforce land-use regulations is generally weaker ([Curtis et al., 2018](#); [Balboni et al., 2023](#)). Thus, our estimates should be interpreted as indicative of a broader tradeoff between climate finance and land-use dynamics, but not as directly transferable across contexts.

This paper is structured as follows. Section 2 examines the key theoretical mechanisms involved and the current empirical evidence supporting them. Section 3 describes the dataset, defines the key variables of interest, and presents descriptive statistics. Section 4 examines the impact of climate aid on deforestation, outlining the empirical model, addressing endogeneity concerns, and presenting the identification strategy. Section 5 presents the baseline results, followed by a heterogeneity analysis, before turning to the investigation of mechanisms. Finally, Section 6 reports the back-of-the-envelope carbon cost of climate aid. Section 7 concludes the study.

2 Theoretical mechanisms

Climate aid projects can influence deforestation through multiple, potentially opposing channels. These channels mainly concentrate around: (i) local income levels, (ii) local production techniques, (iii) infrastructure investments, and, as we are considering climate aid in particular, (iv) the climate-specific objectives of the projects themselves. The net effect is theoretically ambiguous and may vary across regions, projects, and donors.

Climate aid projects are often designed to promote economic development, which may affect deforestation through changes in local income. For instance, such climate projects could consist of

distributing solar cookers in areas with high forest pressure, to prevent deforestation while supporting local economic development and livelihoods. The environmental Kuznets curve (EKC) and forest transition theory suggest an inverse U-shaped relationship between income growth and forest cover: deforestation initially rises with income before declining as economic development proceeds (Grossman and Krueger, 1995; Stern, 2004; Mather, 1992; Barbier et al., 2017). The poverty-environment hypothesis posits that poverty exacerbates environmental degradation, so reducing poverty may decrease deforestation (Baland and Platteau, 1996; Foster and Rosenzweig, 2003). Empirical evidence is mixed: some studies find income increases reduce forest pressure, such as Ferraro and Simorangkir (2020) and Garg and Shenoy (2021), who show that cash transfers or place-based policies improved income without significantly affecting deforestation. Other studies indicate the opposite. For instance, Alix-Garcia et al. (2013), Heß et al. (2021), and Pagel (2022) find that development programs or cash transfers increased deforestation, particularly in poorly connected or isolated areas.

A significant share of climate aid projects targets the land-use sector, and particularly agriculture. On the one hand, agricultural intensification can reduce pressure on forests by increasing yields and decreasing the need for land expansion, consistent with the Borlaug hypothesis (Angelsen and Kaimowitz, 2001; Borlaug, 2007; Phalan et al., 2011) and supported by empirical evidence for different kinds of productivity shocks in several settings (Assunção et al., 2017; Abman and Carney, 2020). However, the Borlaug hypothesis could be reversed if the adoption of yield-enhancing technologies leads to higher agricultural profitability and increased land pressure. Increasing agricultural returns can incentivize deforestation through land expansion, consistent with the Jevons paradox (Angelsen, 1999; Morton et al., 2006; Kremen and Merenlender, 2018). Empirical evidence supports this mechanism for governmental subsidies or agricultural aid, notably *via* seed access enhancement (Bulte et al., 2007; Heß et al., 2021; He et al., 2022; Bernard et al., 2023; Carreira et al., 2024).

Infrastructure can alter land-use dynamics in complex ways. Improved market access can increase deforestation by raising land value and facilitating resource extraction (Copeland and Taylor, 2004; Frankel and Rose, 2005), but infrastructure can also mitigate deforestation by improving access to alternative energy or markets, thereby reducing reliance on forest products. Empirical evidence shows mixed outcomes: highway projects in India accelerated forest loss, while rural road investments had a limited impact (Asher et al., 2020). This may be particularly relevant for climate aid, as a share of mitigation projects is allocated to renewable development, involving the construction of infrastructure such as hydropower dams, solar farms, and associated transmission lines.

Finally, the climate-specific objectives of climate aid projects introduce additional complexities.

Projects targeting mitigation, adaptation, or combined “triple-benefit” by including development outcomes can generate synergies. For example, afforestation and sustainable forest management can enhance both mitigation and development (IPCC, 2019), and agroforestry schemes may provide adaptation benefits, income, and land tenure security (Kalame et al., 2011; Locatelli et al., 2016). However, empirical evidence remains limited and often qualitative. Integrating adaptation and mitigation faces challenges, including competing priorities among practitioners and gaps between scientific knowledge and implementation (Suckall et al., 2015). Meta-analyses suggest that while claims of synergies are common, robust empirical support is weaker (Barbieri et al., 2024).

Overall, multiple mechanisms operate simultaneously and often in opposing directions. The net impact of climate aid on deforestation is theoretically ambiguous and likely heterogeneous across regions, project types, and donor-recipient relationships. To better identify which mechanisms dominate, we explore specific channels empirically in Section 5.3.

3 Data

3.1 Spatial coverage and timeline

We generated a spatial grid covering Africa with a resolution of 0.5° (i.e., pixels of about $55 \text{ km} \times 55 \text{ km}$ at the equator), resulting in 10,677 grid cells. All data were processed at this resolution, mainly through aggregation. This level of spatial aggregation mitigates potential biases arising from local deforestation dynamics, ensuring that the analysis captures broader spatial patterns rather than localized variations while not being too global. Because the deforestation data used do not include annual information on forest gains (e.g., through reforestation or afforestation), we restrict the analysis to cells below a zero forest-cover threshold, hence focusing on areas with sufficient tree density where deforestation is plausible. This restriction mainly excludes deserts (e.g., Sahara, Guban, Danakil, Namib, Kalahari) and large lake areas (e.g., Nyasa, Victoria). This restriction reduces the sample to 5,756 cells.

3.2 Climate aid

3.2.1 Geocoded ODA

Official Development Assistance (ODA) refers to concessional financial flows from high-income to low- and lower-middle-income countries, primarily aimed at promoting economic development. We use data from Bompreszi et al. (2024) and the Geocoded Official Development Aid Dataset (GODAD), which compiles geocoded ODA projects from multiple sources. GODAD

integrates already geocoded projects, including those funded by China, India, the World Bank (via AidData), and the French Development Agency (AFD), as well as newly geocoded OECD Creditor Reporting System (CRS) projects, established in 1976 to standardize ODA allocation for OECD countries. Geographic coordinates were extracted and assigned using a natural language processing model (Bomprezzi et al., 2024). The dataset specifically focuses on bilateral flows from 18 European countries and the USA allocated to specific regions.

Geocoding introduces limitations, mainly due to information loss. Only about 15% of CRS projects can be precisely georeferenced, raising concerns about spatial coverage and representativity. A rigorous assessment of the GODAD database was conducted by Bomprezzi et al. (2024).¹ We also discuss this selection bias in Section 3.2.3. The final dataset includes 909,188 geocoded projects. Our analysis focuses on a subset of this dataset, integrating bilateral aid projects with positive disbursements from 19 OECD donors and the World Bank between 2001 and 2021, aligning with the availability of deforestation data.²

3.2.2 Geocoded climate aid

A portion of geocoded ODA projects from the GODAD dataset can be classified as climate aid, meaning that these projects also incorporate climate-related objectives. To identify and classify the climate aid projects, we applied a natural language processing model developed by Toetzke et al. (2022). This dual-classifier model, called *ClimateFinanceBERT*, has been conceived to automatically identify and categorize climate-related ODA projects from the OECD CRS database.³ We apply the same methodology to the GODAD database, using the translated project titles and descriptions as inputs to the machine learning model. Each project is hence assigned to one of 14 categories,⁴ further grouped into adaptation, mitigation, and nature conservation (see Table A.1). A wide diversity of projects is classified into these labels (projects linked to renewable energy, to sustainable agriculture, to water preservation, etc.). For illustration purposes, Figure A.2 in the Appendix shows four geocoded GODAD examples and the outcomes of the climate-

¹They highlight donor reporting quality and project type (e.g., country-wide budget support) as sources of discrepancies, though sectoral averages remain consistent and no systematic bias in geolocation probability was found.

²Projects with zero or negative disbursements, likely due to coding errors, temporal misallocation of ODA, or grant repayment, are excluded.

³This approach overcomes the main limitations of the Rio Marker methodology commonly used in the literature. The Rio markers, introduced by OECD countries in 1995 to track funding related to the 1992 Rio Conventions, rate projects on a scale from 0 to 2 based on their mitigation or adaptation objectives. The mitigation marker has been self-reported and widely used since 2002, while the adaptation marker was introduced later and broadly applied since 2009 (OECD, 2013). However, because these markers are self-reported by donor countries, they are subject to biases and potential miscoding (Michaelowa and Michaelowa, 2011; Weikmans et al., 2017; Toetzke et al., 2022). Additionally, Rio markers are only available for projects in the OECD CRS database, and adaptation markers are only available from 2010 onward. This restricts analyses both in time and donor coverage, excluding projects from non-OECD countries, the World Bank, and those before 2010.

⁴The climate finance categories created by Toetzke et al. (2022) are: adaptation, solar-energy, biofuel-energy, geothermal-energy, marine-energy, renewables-multiple, hydro-energy, energy-efficiency, wind-energy, other mitigation projects, nature conservation, sustainable land-use, biodiversity, and other environment-protection projects.

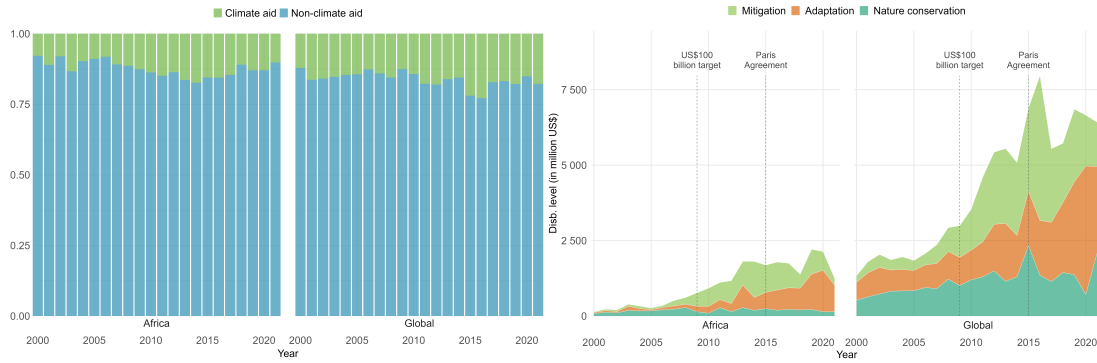
classification analysis. One could be worried about the overrepresentation of forest conservation projects. In Section A.2 of the Appendix, we discuss the effect of including REDD+ projects in our sample, which account for 0.4% of global climate aid and 0.2% of climate aid in Africa.

Table 1: Descriptive statistics on global and African climate aid projects

	Global			Africa		
	#	Mean	SD	#	Mean	SD
Number of projects	121,384			34,879		
Commitments	79,217	1.96	29.57	31,365	2.30	43.50
Disbursements	106,679	0.88	8.44	25,798	0.74	5.40
World Bank projects	89,174	1.06	9.85	18,800	0.85	6.22
OECD-DAC projects	17,505	0.47	3.52	6,997	0.55	3.53

Notes: Aid projects are sourced from the GODAD dataset between 1989 and 2021 (Bomprezzi et al., 2024). Climate classification is obtained by using the procedure described in Toetzke et al. (2022). The levels of commitment and disbursement are expressed in million constant 2014 USD.

Figure 1: Flows of geocoded climate aid



Notes: The left figure illustrates the percentage of geocoded aid projects from the GODAD database (Bomprezzi et al., 2024) that are classified as targeting climate objectives by region. The right figure displays the disbursement levels of geocoded climate aid projects, measured in million 2014 USD, also organized by region. These climate aid projects are categorized according to their objectives, including mitigation, adaptation, and nature conservation (Toetzke et al., 2022). Important climate negotiation events are indicated at the top of the figures.

Table 1 provides descriptive statistics on climate aid projects at both African and global scales. Figure 1 plots the slightly increasing share of climate-dedicated aid projects within geocoded aid at the global and regional scales (left), and the upward trend in disbursements over time (right).

3.2.3 Selection bias

A key limitation of the GODAD dataset is that only a subset of ODA projects can be geocoded, so our analysis considers only a portion of total donor-funded projects. This restriction may reduce the robustness and generalizability of the results, as the geocoded subset may not fully represent the overall distribution of aid. Potential bias arises if geocoded projects systematically differ from non-geocoded ones, particularly for initiatives related to deforestation. For example, subnational programs targeting deforestation may be less likely to be geolocated, which could lead to overestimation of the effect of climate aid. Selection bias could therefore result in either over- or underestimation and may also influence the causal pathways through which aid affects deforestation outcomes.

Table 2: Balance table for climate aid OECD CRS data: geocoded vs. non-geocoded

	Type	Non-geocoded climate aid		Geocoded climate aid		Mean diff.	Variance ratio
		Mean	SD	Mean	SD		
Disb. level (in log)	Contin.	11.258	2.152	11.252	1.866	-0.003	0.752
Year	Contin.	2012.788	5.377	2013.830	4.910	0.202	0.834
Donor: United States	Binary	0.153		0.125		-0.028	
Donor: Austria	Binary	0.018		0.018		-0.001	
Donor: Belgium	Binary	0.025		0.027		0.002	
Donor: Denmark	Binary	0.022		0.013		-0.009	
Donor: Finland	Binary	0.021		0.047		0.026	
Donor: France	Binary	0.098		0.038		-0.059	
Donor: Germany	Binary	0.249		0.313		0.064	
Donor: Greece	Binary	0.004		0.001		-0.003	
Donor: Iceland	Binary	0.001		0.001		0.000	
Donor: Ireland	Binary	0.006		0.006		0.000	
Donor: Italy	Binary	0.031		0.063		0.032	
Donor: Luxembourg	Binary	0.007		0.004		-0.003	
Donor: Netherlands	Binary	0.022		0.014		-0.008	
Donor: Norway	Binary	0.070		0.065		-0.005	
Donor: Portugal	Binary	0.005		0.005		0.001	
Donor: Spain	Binary	0.072		0.117		0.045	
Donor: Sweden	Binary	0.055		0.018		-0.038	
Donor: Switzerland	Binary	0.047		0.040		-0.007	
Donor: United Kingdom	Binary	0.095		0.087		-0.008	
Flow type: ODA grants	Binary	0.970		0.974		0.003	
Flow type: ODA loans	Binary	0.022		0.024		0.002	
Flow type: Other	Binary	0.008		0.003		-0.005	
Sector: Economic infrastructure and services	Binary	0.171		0.127		-0.044	
Sector: Emergency	Binary	0.053		0.047		-0.007	
Sector: Multisector	Binary	0.089		0.093		0.005	
Sector: Production	Binary	0.523		0.539		0.016	
Sector: Social infrastructure and services	Binary	0.164		0.194		0.030	
Continent: Africa	Binary	0.370		0.335		-0.036	
Continent: Americas	Binary	0.253		0.328		0.074	
Continent: Asia	Binary	0.332		0.311		-0.020	
Continent: Europe	Binary	0.035		0.024		-0.012	
Continent: Oceania	Binary	0.010		0.003		-0.007	
Climate sector: Adaptation	Binary	0.207		0.214		0.007	
Climate sector: Mitigation	Binary	0.236		0.188		-0.047	
Climate sector: Nature conservation	Binary	0.558		0.598		0.040	

Notes: Projects displayed here are from the OECD CRS from the period between 1989 and 2020, and have been classified as climate aid by using the procedure described in [Toetzke et al. \(2022\)](#). Geocoded climate aid is provided by the GODAD dataset, and sectors are categorized according to [Bomprezzi et al.'s \(2024\)](#) one. The third and fifth columns represent means for continuous variables and proportions for categorical variables.

To explore potential selection bias, we compare geocoded and non-geocoded climate aid projects. Table 2 presents a balance table comparing project characteristics, reporting means and standard deviations for continuous variables, proportions for categorical variables, and mean differences with variance ratios. Appendix Figure A.1 visualizes these differences. Overall, (log) disbursement levels and flow types show minimal differences, though geocoded projects have lower variance. However, other characteristics reveal notable discrepancies. First, sectoral classification is unbalanced: projects related to economic infrastructure and services are underrepresented, while those related to social infrastructure and services are overrepresented. Since economic infrastructure may drive deforestation, this bias could underestimate the effect of geocoded climate aid on deforestation. Second, African projects are underrepresented among geocoded projects, leading to the potential omission of projects that influence deforestation outcomes. Third, climate-classified projects targeting mitigation, and especially large-scale energy projects, are underrepresented, which may lead to either under- or overestimation of deforestation impacts. Conversely, projects promoting nature conservation are overrepresented, reflecting the bias toward agricultural and sustainable land-use projects. These patterns in geocoding practices suggest that selection bias should be taken into account in subsequent analyses.

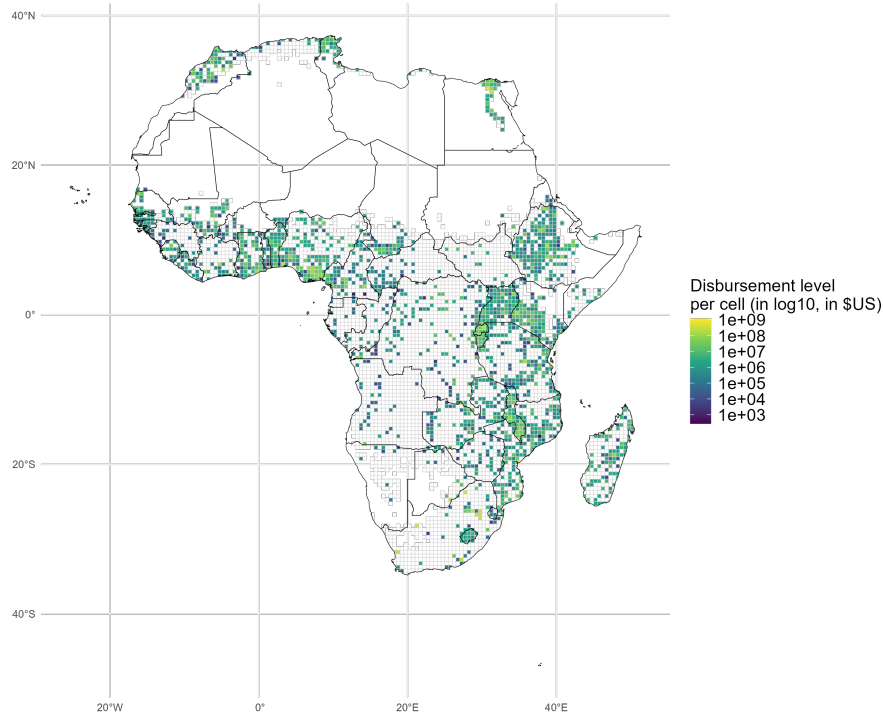
Our framework addresses potential selection bias in several ways. First, including year $\times$ location fixed effects at the ADMIN1 level absorbs regional, non-geocoded projects, with results remaining robust (Column 5, Section 5.1). Second, the IV approach reduces measurement error arising from differences in geocoding (Section 4.3). Third, using a binary treatment indicator instead of the intensive margin—which may be mismeasured due to geocoding bias—produces consistent results (Section 5.4.1). If non-geocoded projects were assigned to already-included cells, their intensive effects are inherently excluded by the binary measure. These robustness checks provide confidence in our findings, though selection bias remains a key limitation of this work. Fourth, this selection bias is a concern only for projects from the OECD CRS database—and not for World Bank projects, which account for a bit less than 75% of the included projects. Therefore, results should be interpreted in the context of the geocoded projects and not generalized to all aid or climate aid from all donors.

3.2.4 Independent variable

The independent variable measures climate aid intensity as the total positive disbursements (in constant 2014 USD) allocated per grid cell, capturing the spatial distribution of aid. When a project spans multiple locations, its disbursement is evenly divided across all identified sites. Figure 2 maps the disbursement levels per cell, while Figure A.3 in the Appendix presents four maps illustrating climate aid projects disbursement by climate objective. These visualizations

highlight spatial heterogeneity, which supports our finer-scale strategy: the Sahel region in West Africa has many adaptation projects but few mitigation projects, whereas coastal West Africa and the central area of the Democratic Republic of Congo receive numerous nature conservation projects but relatively fewer adaptation initiatives.

Figure 2: Disbursement level of climate aid projects per cell between 2001 and 2021



Notes: The data, expressed in constant 2014 USD, is taken from GODAD database (Bomprezzi et al., 2024). A common logarithm scale is used for this figure.

3.3 Deforestation

3.3.1 Forest cover data

The Global Forest Change (GFC) dataset provides a time-series of forest extent and change from 2001 to 2023, using 2000 as the baseline (Hansen et al., 2013, 2022). Trees are defined as vegetation taller than 5 meters in 1 arc-second pixels (around 30×30 m). Key variables include (i) forest loss, a binary annual indicator of pixel-level change from forest to non-forest, and (ii) tree cover, representing canopy closure in 2000.

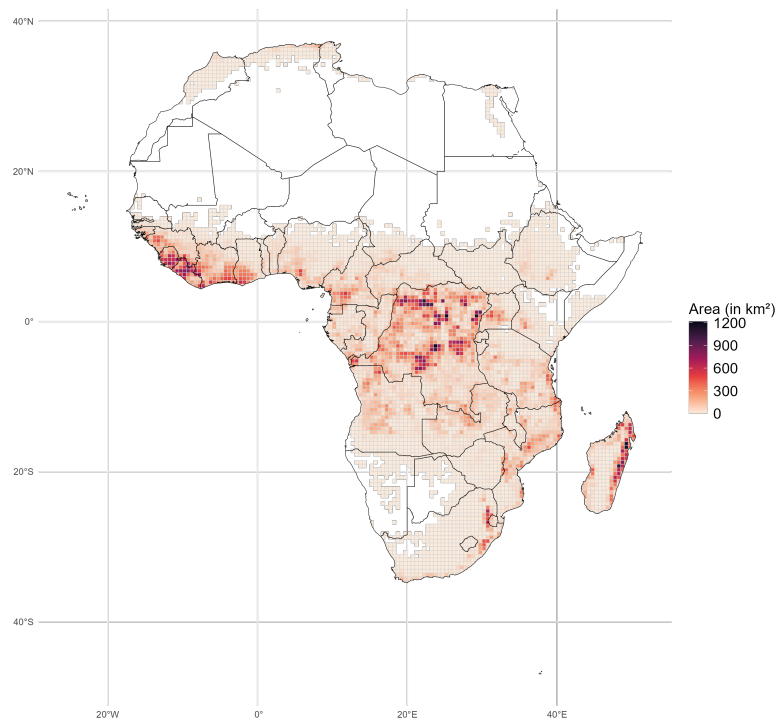
GFC underestimates forest loss compared with other tropical forest datasets (Vancutsem et al., 2021); for example, 138.9 million hectares of disturbances between 2001 and 2019 were not detected, with African forest loss underestimated by 39.4% (2000–2012). These discrepancies

mainly reflect difficulty detecting gradual processes, including degradation, regrowth, and post-degradation deforestation. Although [Vancutsem et al. \(2021\)](#) provide a finer classification of disturbance types, agreement in Africa is low (38%), partly due to changes in GFC processing and inclusion of burned areas (especially 2015–2016).

Despite these limitations, GFC remains suitable for African analysis. It allows continent-wide coverage, whereas alternative datasets focus on tropical regions. Other datasets such as [Vancutsem et al. \(2021\)](#) also struggle to capture African forest dynamics, reporting low degradation (22.3%) and limited regrowth (7.9%). GFC’s global consistency and long-term coverage make it a practical tool for studying deforestation in Africa, despite known biases.

3.3.2 Dependent variable

Figure 3: Cumulative deforested area per cell between 2001 and 2021



Note: The data, expressed in square kilometers, is taken from GFC database ([Hansen et al., 2013](#)).

The total deforested area is computed by summing the area of pixels classified as forest loss above 25% initial tree cover, where each pixel’s area is calculated as the product of the 2000 forest cover share and the cell’s surface in square kilometers. Values are aggregated to the grid cell level defined above. Figure 3 maps cumulative deforested area per cell between 2001 and

2021, showing that tropical regions experience the highest deforestation. Aggregating data helps mitigate non-classical measurement errors and panel estimation bias (Alix-García and Millimet, 2023; Garcia and Heilmayr, 2024). Following several empirical studies (e.g., see Berman et al., 2023; Girard et al., 2022; Groom et al., 2022), we set the threshold at 25% forest cover in the baseline year. This choice reflects the data’s ability to detect tall woody vegetation (Hansen et al., 2010). In addition, we explore alternative thresholds of 50% and 75% in Section 5.4 (Figure D.9).

3.4 Descriptive statistics

Table 3: Descriptive statistics

Deforestation statistics					
	# of cells		Mean	SD	Median
Deforested area (in km²)					
Unconditional	5,532		129.88	13.67	67.41
No climate project	3,622		121.22	12.51	62.59
At least one climate project	1,910		144.48	16.61	76.54
Climate projects statistics					
	# of cells	# of projects	Mean	SD	Median
Level of disbursement (in constant million 2014 USD)					
Unconditional	1,953	27,085	3.70	30.85	0
With no deforestation	49	676	1.92	12.77	0
At least one square meter deforested	1,904	26,409	3.77	31.36	0
Cells percentage statistics					
	Unconditionally	With no climate project	With at least one climate project		
Percentage of cells with deforested area (in %)	96.11	95.39	97.5		
	Unconditionally	With no deforestation	With at least one square meter deforested		
Percentage of cells with climate projects (in %)	34.03	21.88	34.53		

Notes: All statistics are displayed for the period 2001-2021 and are the author’s computations. Deforestation statistics display the number of cells where at least one square meter has been deforested, combined with the mean, standard deviation, and median area value, unconditionally (row 1), and conditionally that the cell does not receive any climate projects disbursement (row 2) or at least one USD of disbursement (row 3). The climate projects statistic table displays the number of cells where at least one USD of climate aid has been disbursed, the number of projects where at least one USD of climate aid has been disbursed, combined with the mean, standard deviation, and median value of the level of disbursement per cell, unconditionally (row 1), or conditionally that the cells is never deforested (row 2) or has at least one square meter deforested (row 3). Cell percentage statistics display the percentage of cells with deforested area, unconditionally (column 1), and conditionally that the cell does not receive any climate projects disbursement (column 2) or at least one USD of disbursement (column 3); and the percentage of cells with climate projects, unconditionally (column 1), and conditionally that the cell is not deforested (column 2) or at least one square meter is deforested (column 3).

Table 3 presents descriptive statistics for both the independent and dependent variables. Approximately 96% of grid cells in our sample exhibit at least one square meter of deforestation, with an average deforested area of 130 km² over 2001–2021 in cells where deforestation occurs. Only 1,910 deforested cells contain at least one climate aid project, reflecting the spatial concentration

of projects, which are mainly allocated in urban or less-forested areas. Among cells with both deforestation and at least one climate project, the median and mean deforested areas are higher than in cells without projects.

Restricting to cells with at least one climate aid project (1,953 cells) increases the share of deforested cells to 97.5%, compared to 95.4% in cells without projects (3,622 cells). Most climate aid projects occur in deforested cells: 35% of deforested cells contain climate projects, versus 22% of non-deforested cells (224 cells). The 27,085 climate aid projects included in the sample correspond to an average disbursement of 3.7 million USD per cell (median 0 USD).⁵

4 Empirical strategy

4.1 General specification

To estimate the impact of climate aid on deforestation, we regress the following general model:

$$\text{Deforestation}_{ict} = \beta \text{ClimateAid}_{ict} + \Gamma \mathbf{X}_{ict} + \lambda_{ct} + \lambda_i + \varepsilon_{ict} \quad (1)$$

where subscripts i , c , and t denote the cell, country, and year, respectively. The dependent variable is the amount of deforestation per cell-year, as defined in Section 3.3. The main variable of interest, ClimateAid_{ict} , captures the amount of climate aid received by the cell-year. The coefficient of interest is β . We include country-year (λ_{ct}) and cell (λ_i) fixed effects. The inclusion of the former accounts for any time-variant country characteristics, such as macroeconomic shocks or policy changes (gross domestic product, institution and political qualities, etc.), while the latter allows us to integrate any time-invariant cell-specific characteristics, such as local geography, topography, or soil characteristics. These fixed effects ensure that the identifying variation comes from within-cell changes over time. The error term, ε_{ict} , is allowed to be correlated within cells, and we cluster standard deviations at the cell level, unless otherwise specified.

4.2 Controls

We include a set of control variables, $\mathbf{X}_{ict}$, to account for other determinants of deforestation. This set includes weather shocks, population density, conflict incidence, and other economic activities.

To account for weather shocks, we include control variables capturing mean precipitation levels, mean Standardized Precipitation-Evapotranspiration Index (SPEI), mean temperature, and

⁵The discrepancy with Table 1 arises because some projects occur in islands or cells without tree cover at baseline, which are excluded from our sample.

two binary indicators for extreme temperature events. Precipitation data are sourced from the CHIRPS dataset, which provides rainfall estimates at a 0.05° resolution (Funk et al., 2015). We aggregated precipitation levels based on our grid, taking the mean value per cell. While aggregating precipitation data at the grid-cell level results in some loss of information, given that precipitation patterns are highly localized and extreme events may be underestimated, it remains useful as a control for spatial trends (Funk et al., 2015). SPEI data are obtained from the Copernicus ESSD database, and more specifically from the 12-month time scale Global SPEI dataset covering 1981–2022 (Gebrechorkos et al., 2023). We used the raster data for the December months to represent the cumulative annual SPEI, and we aggregated them from the original 0.05° resolution to our grid size by averaging all pixels. Temperature data are derived from the Copernicus ERA5 dataset, which provides monthly land surface temperature estimates from 1950 onward at a 0.1° resolution (Muñoz-Sabater et al., 2021). The primary variable of interest is the 2-meter air temperature, for which we computed the mean temperature per grid cell. Additionally, two binary extreme temperature indicators had been created: (i) an indicator of extreme temperature based on an excess of two standard deviations above the historical mean, and (ii) an indicator of extreme temperature based on the hottest 10% of years during the 2000–2021 period. These variables help capture the influence of temperature anomalies on the observed outcomes and are complementary to the averaged variables, the former being more conservative than the latter.

To account for potential other confounding factors, we include control variables related to population density, conflict incidence, and other economic activities. Population estimates are derived from the LandScan Global dataset developed by the Oak Ridge National Laboratory. This dataset provides gridded population estimates at a 30 arc-second resolution, based on the ambient location of individuals over a 24-hour period. Unlike traditional census data, LandScan captures the full potential activity space of individuals rather than just their residential locations. To match our grid resolution, we aggregated the population data by summing the total number of people within each grid cell for each year within the study period. Conflict data are obtained from the Armed Conflict Location & Event Data (ACLED) project, which provides georeferenced, event-based records of political violence and protests (Raleigh et al., 2023). Events are categorized based on the type of disorder, including political violence, demonstrations, and strategic developments. We construct a conflict intensity measure by counting the total number of events occurring within each grid cell over time. This variable captures potential disruptions that could impact forested areas and economic activity. Additionally, we include one-year lag total disbursements per cell and year from non-climate ODA projects from the GODAD dataset as a further proxy for economic activity, allowing us to control for broader development interventions that may influence land use and deforestation patterns (Bomprezzi et al., 2024). Table 4 displays summary statistics

on the dependent and independent variables, as well as control variables, and variables used to perform the mechanism analysis (see Section 5.3).

Table 4: Summary statistics

Variable	Mean	SD	N
Area deforested (km ²)	3.08	7.95	120,876
Disbursement level (million 2014 USD)	0.16	2.67	120,876
Treated (cell hosting at least one climate project, binary)	0.11	0.31	120,876
Mean temperature (°C)	23.43	3.51	120,834
Mean precipitation (mm)	1,098.07	566.02	120,876
Mean SPEI (z-values)	-0.13	0.94	114,366
Extreme temperature: > 2 SD of the historical mean	0.01	0.10	120,834
Extreme temperature: 10% hottest year	0.14	0.35	120,834
Population (thousand)	161.19	464.78	120,786
Conflicts (number)	0.85	10.59	120,876
Lag disbursement level (no climate aid), (million 2014 USD)	1.22	12.13	120,876
Tree cover in 2000 (km ²)	719.75	923.24	120,876
Nightlight intensity (nW cm ⁻² sr ⁻¹)	0.10	0.76	120,876
Crop price index in the period (base 2000 USD, log)	4.78	0.20	116,435
Market access (log)	1.82	4.85	87,342

4.3 Endogeneity issues

The OLS estimates of β could be biased because of endogeneity. In our case, endogeneity may arise for two main reasons.

First, climate aid is not randomly allocated across space: donors strategically distribute aid based on political, economic, or recipient characteristics, and aid may target areas where forests are most threatened.⁶ It may also correlate with underlying economic activity, itself linked to deforestation, potentially biasing estimates toward zero. Second, measurement error arises because aid is often multi-year, spans multiple locations, or may be misclassified between general ODA and climate aid (Toetzke et al., 2022). Selection bias is another concern, as only a subset of projects is geocoded, which may not fully represent the spatial distribution of climate aid.

To address endogeneity, we implement a two-stage least squares (2SLS) instrumental variable (IV) strategy. The ideal instrument captures exogenous variation in climate aid that affects deforestation only through aid allocation. By leveraging shifts in the determinants of climate aid allocation that are independent of local deforestation dynamics, we aim to isolate the causal effect of aid. Following Nunn and Qian (2014), we adopt a shift-share design: exogenous time-varying shifts are combined with cell-level shares.

⁶For recent evidence on climate aid allocation, see Halimanjaya (2015); Weiler and Sanubi (2019); Weiler et al. (2018); Jain and Bardhan (2023); Bugden and Brazil (2024); Liu et al. (2024); Bayramoglu et al. (2023).

The main intuition behind our excluded instrument is that donor-specific climate aid disbursement *out of* Africa is a good predictor of donor-specific climate aid disbursement *in* Africa. To do so, we disaggregate climate aid disbursements at the donor level and exploit how OECD countries and the World Bank allocate climate aid across countries and sectors.⁷ Budgets in both systems are fungible, i.e., fixed annually and dispatched across projects. We find a positive and statistically significant correlation between them,⁸ which aligns with our expectations on donor-year relationships between the number of projects outside Africa and in Africa. Hence, we use as an exogenous shift variable this annual change in the number of climate aid projects implemented outside Africa for each donor, which affects the level of disbursements in Africa but is *a priori* uncorrelated with African deforestation or other local cell-level economic shocks. Figure 4 illustrates this last idea: it plots, at a global scale, the number of geocoded climate aid projects to Africa and outside Africa, each normalised by the region-specific total over the period. The accompanying bars show the difference between these fractions at the global scale and reveal no clear time trend or shock that could invalidate the exclusion restriction. In the Appendix, Figure B.5 presents the same evidence disaggregated by donor. Last, to capture spatial heterogeneity, we use for each cell the frequency of exposure to climate aid projects. With this specification, we compare cells that are frequent versus rare recipients of climate aid in a continuous fashion, and this across donors.

Formally, the excluded instrument is constructed as follows, where $\mathcal{D}$ represents the set of donor countries:

$$\text{PredictedClimateAid}_{ict} = \sum_{d \in \mathcal{D}} \text{FrequencyClimateAid}_{ic}^d \frac{\text{ClimateAidProjects}_t^{d, \text{outside Africa}}}{\text{TotalClimateAidProjects}_{\text{outside Africa}}} \quad (2)$$

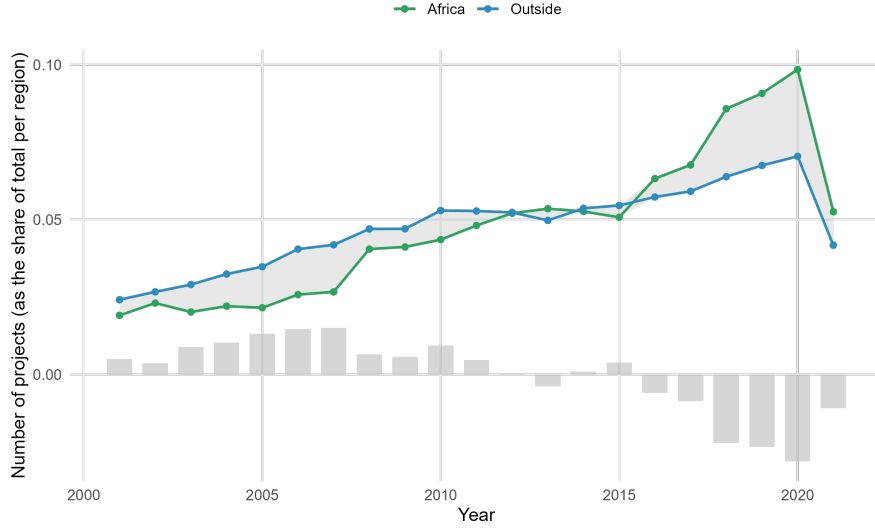
On the one hand, the shift measures exogenous annual changes in each donor's global climate aid allocation outside Africa, capturing fluctuations in donor capacity that are plausibly unrelated to local deforestation. Here, $\frac{\text{ClimateAidProjects}_t^{d, \text{outside Africa}}}{\text{TotalClimateAidProjects}_{\text{outside Africa}}}$ captures exogenous temporal variation in donor d 's global climate aid supply outside Africa, which is plausibly unrelated to deforestation in any given cell. On the other hand, the share captures each cell's historical exposure to climate aid from a given donor, measured as the fraction of years a cell received aid during the 2001-2021 period.⁹ Formally, $\text{FrequencyClimateAid}_{ic}^d$ measures the fraction of years (2001–2021) that cell i

⁷For the World Bank, country offices annually designate priority countries and determine allocations across ten broad lending sectors. For OECD donors, the process is country-specific but typically involves parliamentary approval of multi-year ODA targets. The relevant ministry then assigns envelopes to national development agencies, which allocate funds across bilateral and multilateral programs (or special initiatives) and across countries and sectors. Most projects require approval prior to funding, and for most agencies, the climate dimension is embedded as a transversal pillar guiding allocations *via* grants and loans.

⁸Pearson's product-moment coefficient correlation equals 0.16 ($p = 0.002$) and Spearman's ρ 0.13 ($p = 0.013$).

⁹We use this sample period because pre-period data on climate aid shares are very scarce, resulting in numerous zero weights in

Figure 4: Number of geocoded climate aid projects, per region and year, as a share of total projects per region



Notes: The solid lines show the number of geocoded climate aid projects implemented in Africa (in green) and outside Africa (in blue), normalized by the total number of projects of each region. The grey area is reported as bar plots, which indicate the annual difference between these two shares.

in country c received climate aid from donor d , i.e., $\text{FrequencyClimateAid}_{ic}^d = \frac{1}{21} \sum_{t=2001}^{2021} T_{ict}^d$, where T_{ict}^d equals 1 if cell i received aid from donor d in year t . By combining these terms, the instrument leverages exogenous variations in the supply of climate aid that are unlikely to be directly correlated with local deforestation outcomes with endogenous spatial exposure to treatment. This allows us to isolate the causal effect of climate aid on deforestation while minimizing the risk of endogeneity biases due to reverse causality or unobserved confounders. Descriptive statistics of the shift-share instrument are displayed in Table B.2.

4.4 IV-2SLS estimation

Armed with the excluded instrument, we estimate a two-stage model. In the first stage, we regress climate aid on the predicted climate aid, along with a set of control variables $\mathbf{X}_{ict}$, country-year fixed effects λ_{ct} , and cell fixed effects λ_i . The first-stage equation is given by:

$$\text{ClimateAid}_{ict} = \delta \text{PredictedClimateAid}_{ict} + \eta \mathbf{X}_{ict} + \lambda_{ct} + \lambda_i + \varepsilon_{ict}^{\text{first-stage}} \quad (3)$$

In the second stage, we use the predicted climate aid from the first stage, $\widehat{\text{ClimateAid}}_{ict}$, to estimate the impact of climate aid on deforestation:

the instrument, leading to a significant loss of statistical power for the instrument.

$$\text{Deforestation}_{ict} = \beta \widehat{\text{ClimateAid}}_{ict} + \Gamma \mathbf{X}_{ict} + \lambda_{ct} + \lambda_i + \varepsilon_{ict}^{\text{second-stage}} \quad (4)$$

4.5 Validity of the excluded instrument

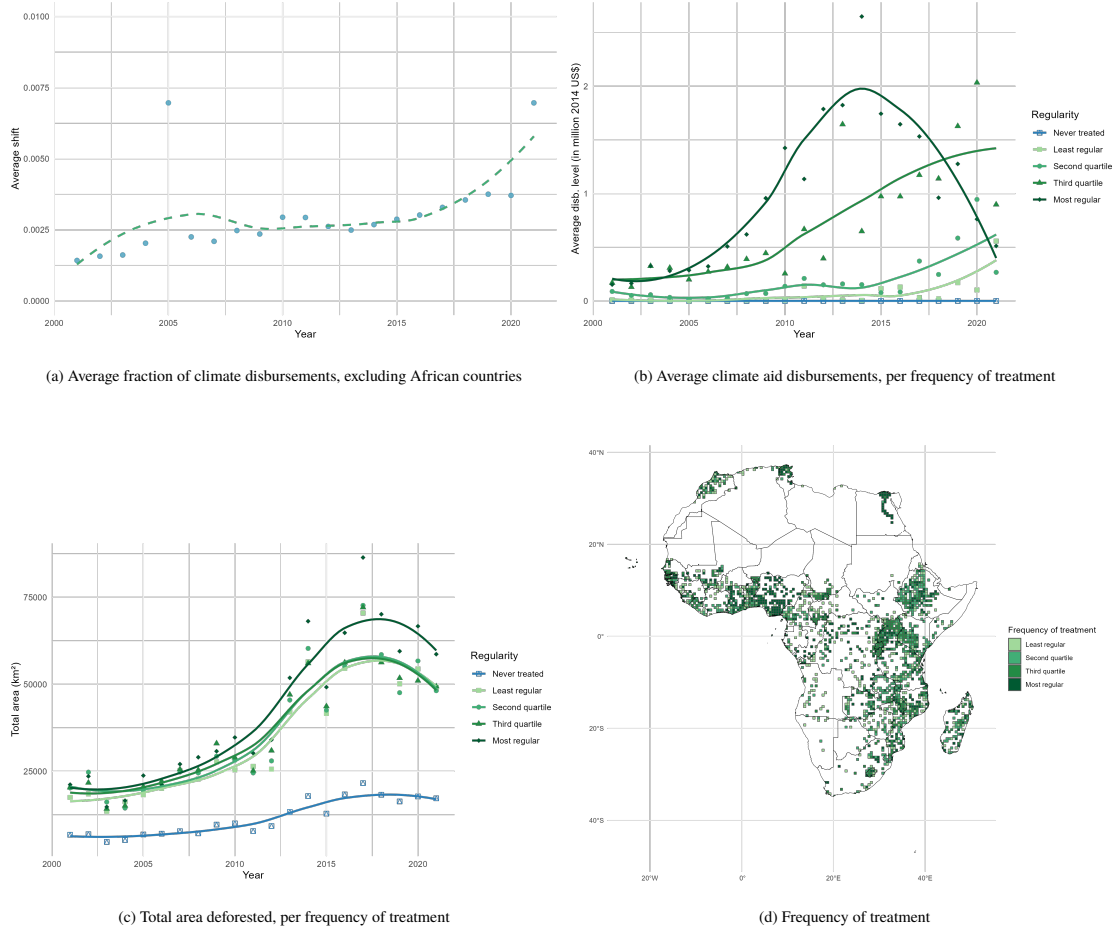
The validity of our IV strategy rests on several general ideas. First, the excluded instrument, $\widehat{\text{PredictedClimateAid}}_{ict}$, should be a good predictor of observed (endogenous) climate aid in the first stage, as reflected in equation 3. This is what the first-stage results check (see Table C.15). We also report the first-stage F-statistics (and their p-values) in all resulting tables: all Kleibergen-Paap Wald-statistics are above the usual thresholds for our benchmark specification, supporting the relevance of the excluded instrument.

Second, while the exclusion restriction cannot be directly tested, we check the correlations of the excluded instrument with several observable characteristics at the cell-year level. Although these correlations with control variables do not fully demonstrate the exogeneity of the instrument or the relevance of the controls, they can indicate the validity of these covariates while controlling for potential bad controls. As shown in Figure B.6, the weather controls are either insignificant or yield very low estimates. However, we should exercise caution regarding more structural variables, such as the lagged disbursement values of non-climate aid or population density.

Third, to fully consider all endogeneity concerns that could arise from our excluded instrument, we follow the checklist established by [Borusyak et al. \(2025\)](#). To correctly integrate potential confounders, we include determinants of climate aid that could be linked to deforestation, such as conflict events or population share. Additionally, we include the one-year lag non-climate aid level of disbursement, and we interact the averaged weather controls with the frequency of exposure of the cells. In our setting, the incomplete share control outlined by [Borusyak et al. \(2025\)](#) is simply the share of the instrument for each cell i , and therefore is already included in cell fixed-effects. As discussed above, it is difficult to introduce lagged shares in our setting, as the spatial distribution of pre-period treatment is very sparse, resulting in a majority of zero shares that consequently decrease the power of the instrument. Alternatively, we use shares that are defined on the total GODAD dataset, i.e., encompassing all types of projects and not specifically climate-related ones. As a result, the first stage regressions are either weakly significant or not significant, which do not allow us to conclude on the validity of our instrument combined with these shares. We include in the Appendix, in Section B.4, replications of benchmark results using these pre-period shares (before 2001) and also sub-period shares (before 2011). In addition, we observe very low Kleibergen-Paap Wald statistics for the non-significant first stage estimates, which could indicate a weak instrument. As suggested by [Borusyak et al. \(2025\)](#), to overstep potential spurious regressions, we reproduce our benchmark specification using as a shift the

extracted unpredictable component of our time-series shift (see Section B.5 in the Appendix). As a standard pre-trend test, we also compute our benchmark specification, introducing the lagged deforestation, to capture the inherent persistence of forest cover change (see Section B.6 in the Appendix). Last, we change the clustering at the level of identifying variation, i.e. by year (see Section B.7 in the Appendix).

Figure 5: Time trends in shift, independent and dependent variables; map of the frequency of treatment



Notes: Figure (a) shows average time variations of the shift instrument over our period of interest. Figures (b) and (c) display time series for, respectively, the average independent variable and the total dependent variable, over our period of interest, and differentiating per frequency of treatment: cells that are the most regularly treated, the third quartile, the second quartile, cells that are the less regularly treated, and cells that are never treated. Figure (d) illustrates this frequency of treatment over a map.

Fourth, we seriously take into account [Christian and Barrett \(2024\)](#) concerns about serial correlation and spurious regression. Figure 5 displays average time-series variations of our shift, i.e. the average fraction of climate aid disbursement outside Africa per donor; gathered with time-series variations of our average independent variable, average climate aid disbursements in

Africa, and of our sum dependent variable, total deforested area. We find no evidence that the parallel trends assumption is violated in our setting. Looking at the shift variable, we observe a slightly increasing trend over time, though the trajectory is not clearly defined.¹⁰ In terms of outcomes, we compare trends in average climate aid disbursements and total deforested area across treatment groups. The results show a clear divergence in climate aid disbursements: areas receiving higher levels of aid exhibit visibly different trends compared to those with low or no aid. In contrast, trends in deforestation appear broadly parallel across treatment groups, suggesting that pre-treatment dynamics in the outcome variable do not differ systematically.

5 Results

5.1 Benchmark results

Table 5: Climate aid and deforestation: OLS and IV estimates

	OLS	Deforested area 2SLS			
	(1)	(2)	(3)	(4)	(5)
Disb. level	0.005 (0.004)	1.02*** (0.214)	0.881*** (0.206)	0.944*** (0.337)	0.833*** (0.307)
Controls: weather shocks			✓	✓	✓
Controls: weather $\times$ freq. of exposure			✓	✓	✓
Controls: non-climate aid (lag)				✓	✓
Controls: conflicts, population				✓	✓
Observations	120,876	120,876	114,366	114,280	114,366
Kleibergen-Paap Wald stat, Disb. level		54.315	44.654	20.051	28.949
Cragg-Donald F-test stat, Disb. level		381.11	386.82	160.38	180.43
Dependent variable mean	3.0849	3.0849	3.2007	3.2031	3.2007
ADMIN1 $\times$ year FE					✓
Country $\times$ year FE	✓	✓	✓	✓	
Cell FE	✓	✓	✓	✓	✓

Notes: Column (1) displays an OLS regression, and columns (2-5) 2SLS regressions. First-stage regressions of the columns (2-5) are displayed in Table C.15. Columns (1-5) dependent variable is the deforested area, in million square meters. The independent variable is the level of disbursement in million constant 2014 USD of climate aid projects. ***, **, and * reveal significance at the 1%, 5% and 10% level, respectively. Cell and country $\times$ year fixed-effects are used in columns (2-4). Cell and ADMIN1 $\times$ year fixed-effects are used in column (5). Weather shock controls, included in columns (3-5), denote average precipitation, temperature, and SPEI, as well as two dummies of extreme temperature. Weather $\times$ frequency of exposure, included in columns (4-5), denotes the interaction of the average weather controls with the share of the instrument. Non-climate aid (lag), included in columns (4-5), denotes the one-year lag level of disbursement of non-climate aid. Conflicts and population, included in columns (4-5), denote the number of conflicts and of inhabitants. Standard errors are clustered at the cell level. Kleibergen-Paap Wald statistic and Cragg-Donald F-test statistic are reported for columns (2-5).

¹⁰Notably, two years stand out as outliers: 2005 and 2021. These anomalies can be attributed to global events that significantly influenced international ODA flows. In 2005, the Indian Ocean tsunami and the Kashmir earthquake triggered a substantial increase in global aid disbursements, particularly to affected regions. Similarly, in 2021, the COVID-19 pandemic led to a sharp rise in ODA as donor countries responded to the global crisis.

Table 5 presents the benchmark OLS and IV results, providing estimates of the effect of climate aid on deforestation. The OLS results in column (1) indicate a small, negative, and non-significant correlation between climate aid and deforestation. This pattern suggests endogeneity may be at work, biasing the coefficient in either direction. For example, if donors target aid to areas already experiencing forest loss (reverse causality), the estimate will be biased upward. In contrast, if aid flows disproportionately to better-governed countries (where deforestation levels are lower), the estimate will be biased downward. The IV results in columns (2-5) reveal a positive and significant effect of climate aid on deforestation. The results remain robust even after including weather shock controls, and additional local activity measures (population, conflicts) that could influence deforestation dynamics. Non-climate aid disbursement and share-interacted averaged weather measures are introduced as additional controls. These findings suggest that addressing endogeneity is crucial to identifying the true effect of climate aid on forest loss.

To evaluate the economic significance of these estimates, we consider the impact of a one-standard-deviation increase in climate aid on deforestation. When climate aid increases by constant 2014 2.7 million USD (1 SD), deforestation increases by 2.5 square kilometers, which is about a third of the typical variation in deforestation (0.32 SD). This effect is large relative to the typical variation in deforestation, indicating that changes in climate aid allocation can drive significant shifts in forest loss. The results highlight the unintended environmental consequences of climate aid, raising concerns about its potential role in accelerating deforestation rather than participating in mitigating environmental degradation.

5.2 Heterogeneity

Given the continental scale of our analysis, aggregate benchmark results may mask substantial heterogeneity. This subsection explores several potential sources of heterogeneity: (i) initial level of forest cover, (ii) climate-related objectives of climate aid, (iii) sectoral classification and land occupation of climate aid. In terms of methods, we study heterogeneity by either interacting our independent variable with a spatially-heterogeneous variable, or by dividing our independent variable according to this heterogeneity. Because the independent variable is endogenous, the interaction or division is also endogenous; accordingly, we instrument by interacting with the instruments, or constructing appropriate and separate shares for the instrument, respectively. This interacted or modified IV strategy can suffer from multicollinearity among instruments and weak identification of the interaction term.

Heterogeneity by initial level of forest cover. Table 6 presents results from the 2SLS regressions specified in Equations 3 and 4, in which the main independent variable is interacted with

quintiles of initial forest cover at the baseline year, i.e., in 2000. The spatial distribution of these quintiles is illustrated in Figure C.7.

Table 6: Climate aid, deforestation and initial forest cover: IV estimates

	Deforested area 2SLS			
	(1)	(2)	(3)	(4)
Disb. level $\times$ Forest cover[Q1]	-0.516** (0.247)	-0.536* (0.323)	-0.826* (0.430)	-0.541 (0.373)
Disb. level $\times$ Forest cover[Q2]	-0.330*** (0.118)	-0.410** (0.176)	-1.11*** (0.397)	-0.638** (0.270)
Disb. level $\times$ Forest cover[Q3]	-0.249 (0.161)	-0.190 (0.182)	-1.14*** (0.372)	-1.37*** (0.484)
Disb. level $\times$ Forest cover[Q4]	3.69*** (1.10)	3.46*** (1.08)	2.62*** (0.921)	1.31* (0.794)
Disb. level $\times$ Forest cover[Q5]	14.6*** (3.69)	13.8*** (3.66)	13.1*** (3.55)	8.74*** (2.94)
Controls: weather shocks		✓	✓	✓
Controls: weather $\times$ freq. of exposure		✓	✓	✓
Controls: non-climate aid (lag)			✓	✓
Controls: conflicts, population			✓	✓
Observations	120,876	114,366	114,280	114,280
Kleibergen-Paap Wald stat, Quintile	1.5783	1.9493	2.1478	1.2608
Kleibergen-Paap Wald stat, Quintile	2.7149	2.8687	3.7961	4.9454
Kleibergen-Paap Wald stat, Quintile	8.3294	7.4009	9.7668	10.480
Kleibergen-Paap Wald stat, Quintile	6.0391	6.0026	5.5231	3.6925
Kleibergen-Paap Wald stat, Quintile	4.1520	5.0051	4.8197	6.3119
Dependent variable mean	3.0849	3.2007	3.2031	3.2031
ADMIN1 $\times$ year FE				✓
Country $\times$ year FE	✓	✓	✓	
Cell FE	✓	✓	✓	✓

Notes: Columns (1-4) are 2SLS regressions. Columns (1-4) dependent variable is the deforested area, in million square meters. The independent variable is the level of disbursement in million constant 2014 USD of climate aid projects, interacted with quintiles of initial forest cover area in 2000. ***, **, and * reveal significance at the 1%, 5% and 10% level, respectively. Cell and country $\times$ year fixed-effects are used in columns (1-3). Cell and ADMIN1 $\times$ year fixed-effects are used in column (4). Weather shock controls, included in columns (2-4), denote average precipitation, temperature, and SPEI, as well as two dummies of extreme temperature. Weather $\times$ frequency of exposure, included in columns (3-4), denotes the interaction of the average weather controls with the share of the instrument. Non-climate aid (lag), included in columns (3-4), denotes the one-year lag level of disbursement of non-climate aid. Conflicts and population, included in columns (3-4), denote the number of conflicts and of inhabitants. Standard errors are clustered at the cell level. Kleibergen-Paap Wald statistics are reported for all columns.

The results from Table 6 reveal considerable variation in the effects of climate aid on deforestation across different levels of initial forest cover. One will observe that the Kleibergen-Paap statistics values are below the threshold value of 10, indicating weak instruments when interacting with quintiles of initial forest cover. As a result, the following findings should be interpreted with caution. In the lowest quintiles, the estimated effect is negative and significant. For the fourth and fifth quintiles, the effect becomes positive and strongly significant. These patterns remain robust when including control variables.

These findings indicate that the effect of climate aid on deforestation is conditional on initial forest

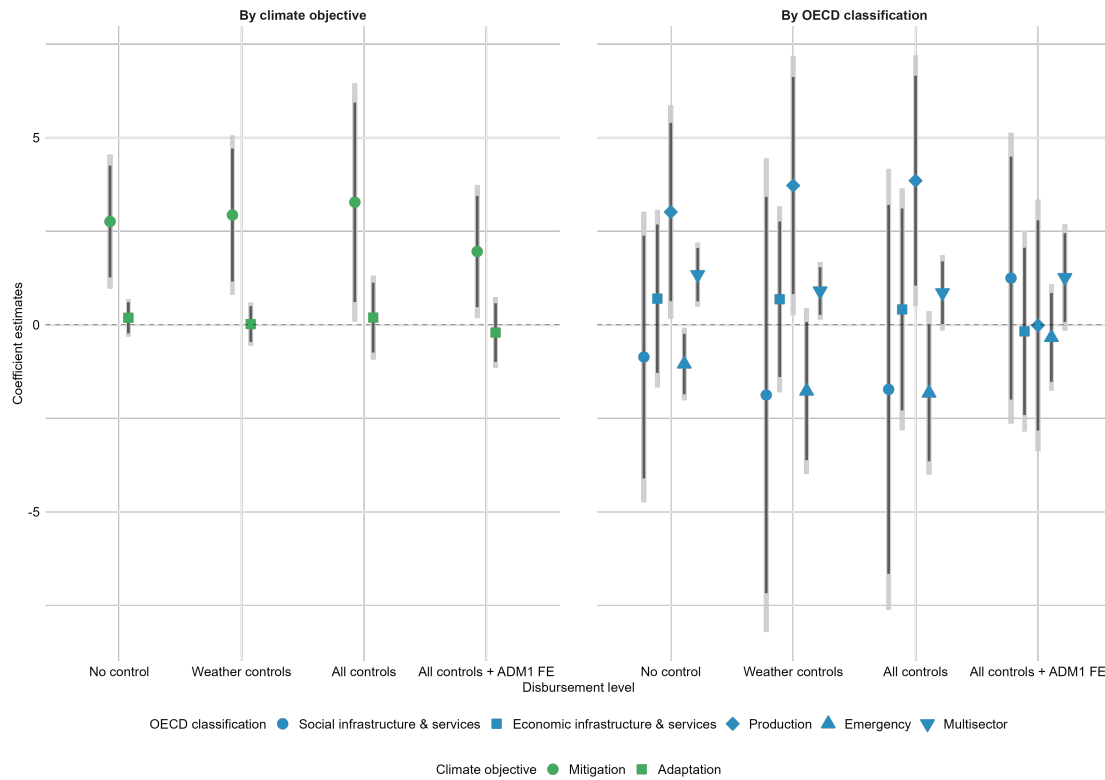
cover: areas with relatively low forest cover in 2000 tend to experience reduced deforestation following climate aid, whereas areas with higher initial forest cover show increased deforestation. Two mechanisms may help explain this pattern. First, because our main outcome is an absolute level (annual area of tree cover lost), densely forested cells can disproportionately influence level-based estimates. As a robustness check, we therefore use the percentage of tree cover loss, as defined by [Desbureaux et al. \(2025\)](#), as a relative outcome variable. Normalizing by forest stock, Table C.18 in the Appendix shows that the previously negative estimates in the lower quintiles dissipate, while strong positive effects emerge in the third to fifth quintiles. Second, our empirical strategy does not model underlying structural mechanisms. Yet Table 6 suggests heterogeneity across forest cover quintiles that could reflect such forces, with an ambiguous net effect. A proper assessment would require a structural framework (e.g., integrating explicit land-use and price responses), which lies beyond the scope of this paper.

Heterogeneity by climate-related objectives. Figure A.3 in the Appendix shows a general map with the level of disbursement for all types of projects, gathered with three different maps showing the same variable but classified according to the climate-related objective of the projects. Projects fall into distinct categories: mitigation, adaptation, and nature conservation, obtained following the procedure detailed in [Toetzke et al. \(2022\)](#). The maps highlight the spatial heterogeneity of climate aid, revealing regional differences in project focus and the overlap of multiple objectives, as already discussed in Section 3. To address our concerns regarding multicollinearity from using multiple instruments, we decided to combine the (small) nature conservation category with the categories for mitigation and adaptation. This includes projects labeled as sustainable land use under adaptation, as well as those labeled as nature conservation, biodiversity, and other under mitigation.

Figure 6, on the left subfigure, shows simultaneous 2SLS regression estimates across levels of disbursement differentiated according to climate objectives, for four specifications, from parsimonious to conservative. In the Appendix, Table C.13 displays all statistics of these regressions. We observe that estimates for mitigation-linked disbursements are positive and significant, while adaptation-linked disbursements are rather positive but insignificant. Different factors could explain this result. Mitigation projects may involve large infrastructure or land-expanding investments (e.g., hydropower dams, new irrigation systems for farmers). These can raise pressure on nearby forests and, consequently, increase deforestation. When we move to more conservative specifications, the confidence intervals widen, indicating greater uncertainty and suggesting heterogeneous (or mixed) impacts across settings. Results regarding adaptation are consistent with the fact that adaptation projects are typically smaller-scale and less land-intensive. However, we observe that some Kleibergen-Paap statistics are below the usual threshold, meaning that our in-

strument is weak (see Table C.13). In particular, it suggests that the issue of multicollinearity is particularly prominent here.

Figure 6: Climate aid by climate objective/OECD classification and deforestation: IV estimates



Notes: The estimates of marginal effects obtained by 2SLS regressions for disbursement levels according to (i) climate objective (on the left), or (ii) OECD classification (on the right) are represented by a different green or blue form, respectively. 90% confidence interval is displayed in light grey and 95% confidence interval in dark grey.

Heterogeneity by sectoral classification and land occupation. To explore whether the impact of climate aid on deforestation varies by economic sector, we categorize aid projects based on their OECD purpose codes. Following the classification proposed by [Bomprezzi et al. \(2024\)](#), we define five sectoral groups: (a) social infrastructure and services, including the Education, Health, and Government, Society and Budget purpose codes; economic infrastructure and services including Transport and Storage, Communications, Energy, and Finance, Business and Services purpose codes; production sector including Agriculture, Forestry, Other Industries, and Environment purpose codes; emergency assistance including Emergency purpose code; and multisector including Multisector and Others purpose codes. This classification allows us to investigate whether disbursement levels and their effects on forests differ by sector, and whether these

differences can be interpreted in terms of land use intensity.

On the right side of Figure 6, the results of simultaneous regressions for the five sector-specific OECD disbursement sectors are reported. Table C.14 shows associated statistics in the Appendix. Two sectors stand out. Production disbursements are consistently associated with significant increases in deforestation across most specifications. Multisectoral disbursements also show positive associations, but the evidence is weaker and less robust. In the case of production climate aid, this result may be interpreted as follows. Projects targeting agriculture, industries, and related sectors are likely to directly or indirectly stimulate land expansion, thereby increasing deforestation. The multisectoral category is more ambiguous, as it is very large and includes a wide range of projects with potentially conflicting objectives. One possible explanation is that overlapping goals (e.g., economic development and environmental protection) may lead to trade-offs or inconsistencies in implementation, thereby intensifying pressure on land. Although taking these results with caution, as the threat of multicollinearities is particularly prominent as the number of simultaneous variables is high, it appears that not all climate aid projects affect forests in the same fashion and that land-based projects are those actively participating in deforestation.

5.3 Mechanisms

The impact of climate aid on deforestation may be mediated by several, potentially competing, theoretical mechanisms, as outlined in Section 2. We provide suggestive evidence on potential channels through which climate aid influences deforestation outcomes.

5.3.1 Economic activity

Climate aid may affect deforestation by stimulating local economic activity (see Section 2 for detailed discussion). To test this mechanism, we use nighttime light emissions as a proxy for economic development, following the corresponding standard literature (Henderson et al., 2012).¹¹ More specifically, we employ the NPP-VIIRS-like dataset to calculate the average nightlight intensity per grid cell and year (Chen et al., 2021).

Our identification strategy proceeds in two steps. First, we examine whether climate aid influences local economic activity, proxied by nightlight intensity. We use the same shift-share instrument, as the variation leveraged by our shift-share strategy is *a priori* also exogenous to nightlight intensity at the cell level. As shown in the first row of Table 7, climate aid is associated with higher nightlight intensity only in parsimonious specifications. Nevertheless, once

¹¹Henderson et al. (2012) show that nightlight intensity captures variation in economic activity and could serve as a reliable indicator of local economic activity across multiple spatial and institutional scales, including households, firms, and governments.

we control for a broader set of covariates or include ADMIN1-level fixed effects, the effect becomes statistically insignificant. This suggests that climate aid has little or no effect on nightlight intensity, which already partly undermines this channel as a mediator of deforestation. Next, we interact climate aid with quintiles of initial forest cover (rows 2–6) to examine whether heterogeneity analysis allows this mediator to emerge more clearly. These interaction terms are significant under simpler specifications but lose significance as controls are added. Notably, in columns (2) and (4), the fourth quintile, i.e. where most climate aid-related deforestation occurs according to Table 6, shows a positive and significant relationship with nightlight intensity. However, this effect vanishes in more stringent specifications (columns 6 and 8).

Table 7: Climate aid, nightlight intensity and initial forest cover: IV estimates

	Nightlight intensity 2SLS							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Disb. level	0.141*** (0.035)		0.142*** (0.033)		0.053 (0.036)		0.013 (0.017)	
Disb. level $\times$ Forest cover[Q1]		-0.113 (0.161)		-0.102 (0.123)		-0.127 (0.122)		-0.005 (0.039)
Disb. level $\times$ Forest cover[Q2]		0.180** (0.071)		0.146* (0.079)		0.110 (0.082)		-0.013 (0.021)
Disb. level $\times$ Forest cover[Q3]		0.209*** (0.056)		0.227*** (0.061)		0.133* (0.077)		0.048 (0.044)
Disb. level $\times$ Forest cover[Q4]		0.152*** (0.053)		0.159*** (0.058)		0.073 (0.057)		0.057 (0.035)
Disb. level $\times$ Forest cover[Q5]		0.033* (0.019)		0.008 (0.037)		-0.064 (0.055)		-0.029 (0.027)
Controls: weather shocks			✓	✓	✓	✓	✓	✓
Controls: weather $\times$ freq. of exposure			✓	✓	✓	✓	✓	✓
Controls: non-climate aid (lag)					✓	✓	✓	✓
Controls: conflicts, population					✓	✓	✓	✓
Observations	120,876	120,876	114,366	114,366	114,280	114,280	114,280	114,280
Kleibergen-Paap Wald stat, Disb. level	54.315		44.654		20.051		19.546	
Kleibergen-Paap Wald stat, quintile		1.5783		1.9493		2.1478		1.2608
Kleibergen-Paap Wald stat, quintile		2.7149		2.8687		3.7961		4.9454
Kleibergen-Paap Wald stat, quintile		8.3294		7.4009		9.7668		10.480
Kleibergen-Paap Wald stat, quintile		6.0391		6.0026		5.5231		3.6925
Kleibergen-Paap Wald stat, quintile		4.1520		5.0051		4.8197		6.3119
Dependent variable mean	0.10432	0.10432	0.07996	0.07996	0.08002	0.08002	0.08002	0.08002
ADMIN1 $\times$ year FE							✓	✓
Country $\times$ year FE	✓	✓	✓	✓	✓	✓		
Cell FE	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Columns (1-8) are 2SLS regressions. Columns (1-4) dependent variable is the average nightlight intensity, in $\text{nW cm}^{-2} \text{sr}^{-1}$. The independent variable is the level of disbursement in million constant 2014 USD of climate aid projects, or the level of disbursement interacted with quintiles of initial forest cover area in 2000. ***, **, and * reveal significance at the 1%, 5% and 10% level, respectively. Cell and country $\times$ year fixed-effects are used in columns (1-6). Cell and ADMIN1 $\times$ year fixed-effects are used in columns (7-8). Weather shock controls, included in columns (2-8), denote average precipitation, temperature, and SPEI, as well as two dummies of extreme temperature. Weather $\times$ frequency of exposure, included in columns (2-8), denotes the interaction of the average weather controls with the share of the instrument. Non-climate aid (lag), included in columns (5-8), denotes the one-year lag level of disbursement of non-climate aid. Conflicts and population, included in columns (5-8), denote the number of conflicts and of inhabitants. Standard errors are clustered at the cell level. Kleibergen-Paap Wald statistics are reported for all columns.

Overall, these results suggest that climate aid does not consistently increase economic activity at

the local level, and therefore likely is not the primary mediator driving deforestation. While not being a causal claim, the evidence points to economic activity being an unlikely mechanism for the observed deforestation effects of climate aid.

5.3.2 Agricultural expansion

Another mechanism outlined in Section 2 concerns the improvement of local production techniques, particularly enhancements in land productivity within the agricultural sector. An increase in yield could lead to either a reduction or an intensification of deforestation, depending on the theoretical lens adopted: the Borlaug hypothesis suggests that higher yields reduce pressure on forests, while the Jevons paradox posits that increased productivity can ultimately expand land use due to higher returns. Given the tight coupling of land-use dynamics and the lack of disaggregated panel data regarding agricultural area in Africa, identifying the direction and magnitude of this channel is empirically challenging.

To investigate this possible channel through which climate aid might influence deforestation and overcome this obstacle, we follow the approach developed by [Berman et al. \(2023\)](#), who construct a spatially explicit crop price index. This index combines cell-level agricultural suitability for 15 key crops, interacted with yearly international crop price indices. Specifically, it reflects each grid cell's relative suitability, based on the GAEZ V4 dataset ([FAO, 2012](#)), weighted by the corresponding annual global price index drawn from the World Bank historical commodity database.¹² This index captures spatial heterogeneity in exposure to international agricultural price changes, or in other words, the influence of global crop markets. Since it has been shown to affect cropland expansion even in sub-Saharan Africa ([Berman et al., 2023](#)), we use it here as a proxy for agricultural expansion pressures at the cell level.

Using the same instrumental variable strategy for the same reasons as for the nightlight intensity, we estimate the effect of climate aid on the logarithm of this crop price index. We also interact climate aid disbursements with initial forest cover to assess whether the effect varies by baseline year forest cover. Table 8 shows that climate aid has a positive and statistically significant effect on the crop price index (row 1). This effect remains significant even when disaggregated by forest cover quintiles (rows 2-6). More specifically, the fourth and fifth quintiles, i.e. areas with higher initial tree cover and where climate aid-induced deforestation is most pronounced, exhibit significant impacts. This parallel pattern with the deforestation pattern suggests that climate aid may exacerbate deforestation through a mechanism linked to agricultural expansion, as proxied here by crop price index. We consider this our preferred theoretical mechanism explanation.

¹²Crops include banana, barley, cocoa, coconuts, coffee, cotton, maize, palm oil, rice, sorghum, soybeans, sugar, tea, tobacco, and wheat. See [Berman et al. \(2023\)](#) for detailed construction.

Table 8: Climate aid, crop price index and initial forest cover: IV estimates

	Crop price index (log) 2SLS							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Disb. level	0.005*** (0.002)		0.004** (0.002)		0.006** (0.003)		-0.001 (0.002)	
Disb. level $\times$ Forest cover[Q1]		-0.031*** (0.012)		-0.032** (0.013)		-0.030** (0.012)		-0.011* (0.006)
Disb. level $\times$ Forest cover[Q2]		-0.002 (0.002)		-0.005* (0.003)		-0.003 (0.004)		-0.007** (0.003)
Disb. level $\times$ Forest cover[Q3]		0.012*** (0.002)		0.011*** (0.003)		0.014*** (0.004)		0.006* (0.003)
Disb. level $\times$ Forest cover[Q4]		0.024*** (0.007)		0.025*** (0.008)		0.028*** (0.009)		0.006** (0.003)
Disb. level $\times$ Forest cover[Q5]		0.041*** (0.012)		0.039*** (0.012)		0.042*** (0.013)		0.008* (0.004)
Controls: weather shocks			✓	✓	✓	✓	✓	✓
Controls: weather $\times$ freq. of exposure			✓	✓	✓	✓	✓	✓
Controls: non-climate aid (lag)					✓	✓	✓	✓
Controls: conflicts, population					✓	✓	✓	✓
Observations	116,435	116,435	110,325	110,325	110,322	110,322	110,322	110,322
Kleibergen-Paap Wald stat, Disb. level	54.288		49.303		26.348		21.777	
Kleibergen-Paap Wald stat, quintile		1.7285		1.5807		1.7537		1.4340
Kleibergen-Paap Wald stat, quintile		2.6071		2.9440		3.6139		5.0366
Kleibergen-Paap Wald stat, quintile		8.8103		7.8679		9.9680		10.903
Kleibergen-Paap Wald stat, quintile		6.0302		5.9459		5.1321		3.6813
Kleibergen-Paap Wald stat, quintile		4.1470		5.1036		4.8653		6.4238
Dependent variable mean	4.7809	4.7809	4.7782	4.7782	4.7782	4.7782	4.7782	4.7782
ADMIN1 $\times$ year FE							✓	✓
Country $\times$ year FE	✓	✓	✓	✓	✓	✓		
Cell FE	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Columns (1-8) are 2SLS regressions. Columns (1-4) dependent variable is the logarithm of the crop price index, as constructed by [Berman et al. \(2023\)](#). The independent variable is the level of disbursement in million constant 2014 USD of climate aid projects or the level of disbursement interacted with quintiles of initial forest cover area in 2000. ***, **, and * reveal significance at the 1%, 5% and 10% level, respectively. Cell and country $\times$ year fixed-effects are used in columns (1-6). Cell and ADMIN1 $\times$ year fixed-effects are used in column (7-8). Weather shock controls, included in columns (2-8), denote average precipitation, temperature, and SPEI, as well as two dummies of extreme temperature. Weather $\times$ frequency of exposure, included in columns (2-8), denotes the interaction of the average weather controls with the share of the instrument. Non-climate aid (lag), included in columns (5-8), denotes the one-year lag level of disbursement of non-climate aid. Conflicts and population, included in columns (5-8), denote the number of conflicts and of inhabitants. Standard errors are clustered at the cell level. Kleibergen-Paap Wald statistics are reported for all columns.

5.3.3 Infrastructure development

Another potential mechanism through which climate aid could influence deforestation is *via* local demand shocks associated with infrastructure development. Improved infrastructure can enhance access to markets, thereby increasing economic activity and potentially exerting pressure on forested areas. This result has been put forward at the national scale, for example, by [Abman and Lundberg \(2024\)](#) for the oil palm commodity market in Ghana. However, the reverse effect could also be at stake: the economic isolation of locations could also be a driver of deforestation, as adaptation strategies to local shocks could be reduced ([Alix-Garcia et al., 2013](#); [Heß et al., 2021](#)).

To account for this channel, we control for changes in market access using a variable constructed by [Müller-Crepon \(2023\)](#). This variable proxies access to economic markets by leveraging time-

varying road networks, as well as the location and population of major African cities.¹³ It is computed using a standard gravity-based formulation, where trade elasticity is calibrated following the estimate from [Eaton and Kortum \(2002\)](#). Nevertheless, as displayed in Table 9, our benchmark coefficients remain stable while incorporating this proxy for market access.¹⁴ In other words, it means that market access does not seem to be a main channel for climate aid-induced deforestation.

Table 9: Role of market access: IV estimates

	Deforested area 2SLS			
	(1)	(2)	(3)	(4)
Disb. level	0.553*** (0.140)	0.492*** (0.143)	0.472** (0.228)	0.223 (0.178)
Market access (log)	0.029 (0.057)	0.007 (0.056)	0.007 (0.056)	-0.093* (0.052)
Controls: weather shocks		✓	✓	✓
Controls: weather $\times$ freq. of exposure		✓	✓	✓
Controls: non-climate aid (lag)			✓	✓
Controls: conflicts, population			✓	✓
Observations	87,342	83,866	83,833	83,833
Kleibergen-Paap Wald stat, Disb. level	46.031	37.645	14.409	19.544
Dependent variable mean	2.4422	2.5147	2.5157	2.5157
ADMIN1 $\times$ year FE				✓
Country $\times$ year FE	✓	✓	✓	
Cell FE	✓	✓	✓	✓

Notes: The columns (1-4) display 2SLS regressions. First-stage regressions of the columns (1-4) are displayed in Table C.17. The columns (1-4) dependent variable is the deforested area, in square meters. The independent variable is the level of disbursement of climate aid. The variable market access is computed using time-variant road networks and the location and population of cities. ***, **, and * reveal significance at the 1%, 5% and 10% level, respectively. Cell and country $\times$ year fixed-effects are used in the columns (1-3). Cell and ADMIN1 $\times$ year fixed-effects are used in column (4). Weather shock controls, included in columns (2-4), denote average precipitation, temperature, and SPEI, as well as two dummies of extreme temperature. Weather $\times$ frequency of exposure, included in columns (2-4), denotes the interaction of the average weather controls with the share of the instrument. Non-climate aid (lag), included in columns (3-4), denotes the one-year lag level of disbursement of non-climate aid. Conflicts and population, included in columns (3-4), denote the number of conflicts and inhabitants. Standard errors are clustered at the cell level. Kleibergen-Paap Wald statistic is reported for all columns.

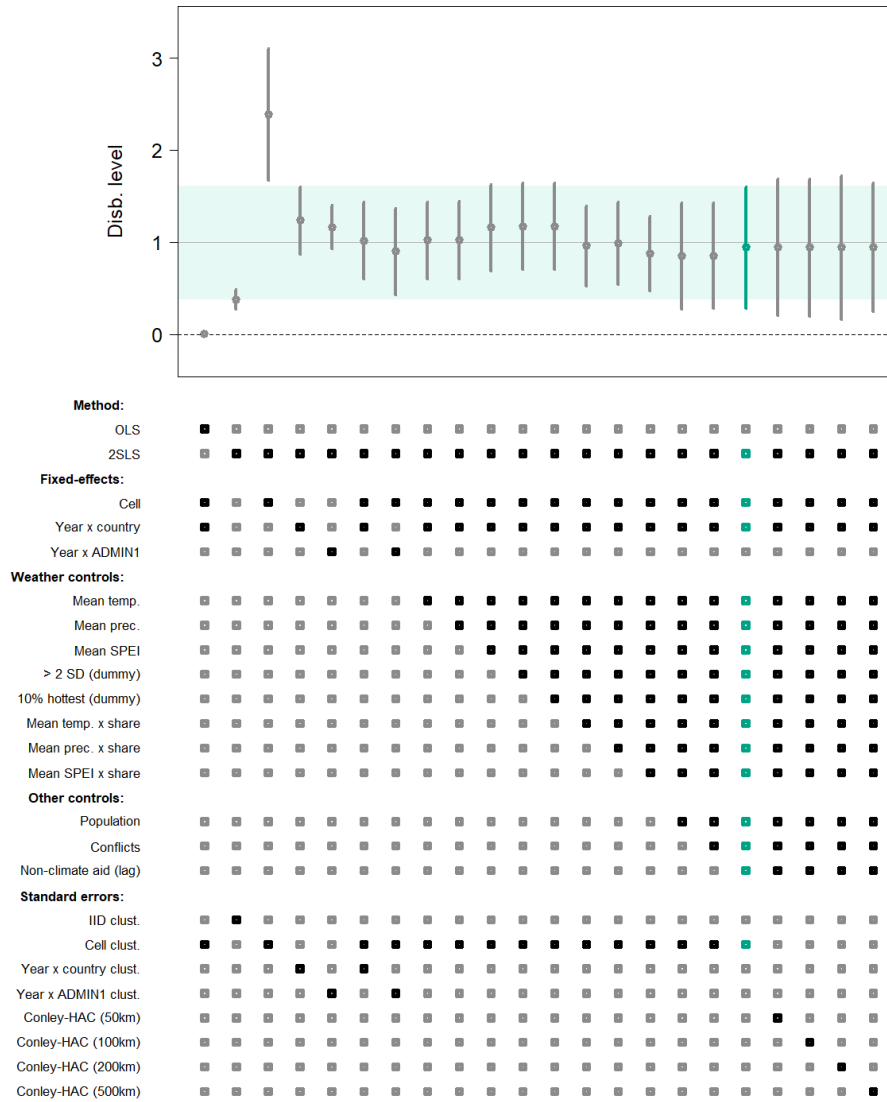
5.4 Sensitivity and robustness analyses

Our results and conclusions are robust to various specification changes. Figure 7 summarizes the effect of these choices on the main estimate.

¹³The number of observations in the regressions is lower when taking this variable into account, as this variable is only defined for inland Africa, and not for African islands (Madagascar, Cabo Verde, São Tomé and Príncipe, etc.). In addition, we choose to take the log-transformation of the market access variable because it is skewed.

¹⁴See Table C.19 in the Appendix, which displays the benchmark coefficients for the exact same set of observations.

Figure 7: Sensitivity of estimation to various specifications



Notes: Estimates are grouped according to the dimension tested: (i) the estimation method, (ii) the fixed-effects included, (iii) the weather controls, (iv) the other controls, (v) the standard error estimator. Confidence interval at 95%. The grey horizontal line indicates the mean of the estimates, and the turquoise rectangle shows the +/- 1.5 deviation from the mean. Preferred specification in turquoise.

5.4.1 Dealing with zeros: are outliers driving the results?

A potential concern in our analysis is that both the dependent variable, the deforested area in each cell, and the independent variable, the amount of USD disbursed for climate aid in each cell, contain a large share of zero values. If the dependent has a large proportion of zero values, the log-transformation significantly reduces observations. However, including a dependent

variable without log-transformation effectively assigns equal weights to all values, and potentially to outliers. The standard methodology has been to use a “log-like” transformation. Recent methodological research highlights the risks of using “log-like” transformation when the dependent variable is measured in units, as is the case here, with the deforested area expressed in square kilometers (Chen and Roth, 2024). To investigate whether our results are driven by outliers, we conduct two alternative analyses based on various definitions of the variables. The first one is based on the extensive margin of the treatment, using a binary variable to indicate if a cell is treated or not. The second one uses a log-transformation of the dependent variable, getting rid of the zero mass. Results are stable, suggesting a weak bias of the zeros in our analysis: the marginal effects are still positive and significant. Both of these analyses can be found in the Appendix, in Section D.1.

5.4.2 Alternative deforestation metrics

The measure of deforestation used in the analysis to compute the benchmark results is the absolute area of forest loss per cell and year, defined in levels (in million square kilometers). As a robustness check, we follow Desbureaux et al. (2025) and use an alternative metric: the percentage of tree cover loss, defined as the deforested area divided by the total tree cover area per cell and year. This alternative definition allows us to test whether the results are robust to using a relative, rather than an absolute, measure of deforestation intensity. Results using this alternative specification are presented in the Appendix, Section D.3. Under this specification, a 2.7 million USD (1 SD) increase in climate aid is associated with a 0.07 percentage point increase in tree cover loss, equivalent to approximately 47% of the standard deviation of forest loss in the sample. While the two specifications are not strictly comparable since they rely on different definitions of deforestation and assumptions about the relationship between variables, the magnitude of the estimated effect remains broadly consistent with the benchmark results.

5.4.3 Stricter definition of forested pixels

The main specification uses a broad definition of forested pixels, prior to aggregation at the 50 km $\times$ 50 km level, including all pixels with at least 25% tree cover in the year 2000. As a robustness check, we apply stricter thresholds for defining forested areas, considering only pixels with baseline tree cover greater than or equal to 50%, and 75% to be categorized as forested pixels, following, for example, Berman et al. (2023). Results from this robustness analysis are presented in Table D.25, in the Appendix. The positive relationship between climate aid and deforestation holds under these more conservative definitions, with only slight changes in statistical significance. However, the magnitude of the estimated effect decreases as the threshold for defining

forested pixels becomes more stringent.

5.4.4 Spatial auto-correlation

To account for spatial autocorrelation, we cluster standard errors using a Conley-HAC (Heteroskedasticity and Autocorrelation Consistent) estimator. We choose to take the most conservative approach by computing Conley standard errors, which are robust to the spatial structure; HAC standard errors, which are robust to the time structure; and computing the standard error by combining both of them, and taking the maximum of these three standard errors. We implement Conley-HAC clustering using various distance cutoffs (radii) to assess robustness: 50, 100, 200, and 500 km. The results are presented in the Appendix, in Table E.26. The main findings remain robust when accounting for spatially correlated standard errors. As displayed in Table E.26, the standard error increases up to the buffer of 200 km, with a peak reached between 100 km and 200 km. Afterwards, the standard error decreases.

5.4.5 Bias in the two-way-fixed-effect estimates

Recent developments in the difference-in-differences literature have highlighted that two-way fixed effects estimates may be biased in the presence of treatment effect heterogeneity (de Chaisemartin and D’Haultfoeuille, 2024). To assess the potential for such bias in our setting, we re-estimate our benchmark model while sequentially excluding one year or one country at a time. The results are presented in Figures E.10 and E.11 in the Appendix. When dropping individual years, we observe limited heterogeneity overall. When excluding individual countries, estimates are relatively stable for most. However, we find a downward bias when dropping the Democratic Republic of Congo, and to a lesser extent Liberia and Madagascar, which are countries with high levels of deforestation, and an upward bias when excluding Ethiopia, Morocco, and South Africa, where forest cover is limited.

5.4.6 First difference

Building on the recommendation of Christian and Barrett (2024) to reduce the spurious regression bias, we transform our specification into a stationary one, using first differences of our outcome and control variables. To instrument this novel specification, we chose to differentiate the shift of our Bartik instrument, keeping the share constant. As first differencing makes the cells’ fixed effects disappear, the first and second stage specifications are as follows:

$$\Delta \text{ClimateAid}_{ict} = \delta^{fd} \Delta \text{PredictedClimateAid}_{ict} + \eta^{fd} \Delta \mathbf{X}_{ict} + \lambda_{ct} + \Delta \varepsilon_{ict}^{first-stage, fd} \quad (5)$$

$$\Delta \text{Deforestation}_{ict} = \beta^{fd} \widehat{\Delta \text{ClimateAid}}_{ict} + \Gamma^{fd} \Delta \mathbf{X}_{ict} + \lambda_{ct} + \Delta \varepsilon_{ict}^{\text{second-stage}, fd} \quad (6)$$

Table E.27 in the Appendix displays the corresponding above regressions. Estimates are positive and significant for all specifications, with strong first stages (see Table E.28). These reassuring results allow us to suggest the robustness of our results to the serial correlation issue.

6 Carbon cost of climate aid

This section provides a back-of-the-envelope exercise by measuring the estimated environmental costs tied to the deforestation effect of climate aid projects. Given data and methodological constraints, the figures presented should be interpreted as illustrative, providing orders of magnitude rather than precise values.

CO₂ emissions conversion. We follow the procedure of [Jayachandran et al. \(2017\)](#) and [Abman and Carney \(2020\)](#) to translate our benchmark estimates of deforested area into CO₂ emissions. Our calculation focuses on greenhouse gas emissions from tree biomass and is therefore conservative, excluding emissions from land-conversion practices and soil organic carbon.

To approximate aboveground biomass (AGB), we rely on the Africa AGB map from the National Centre for Earth Observation ([University of Leicester, 2021](#)), combined with forest cover data from [Hansen et al. \(2013\)](#). Using two aggregation strategies, we obtain an average AGB of 52 MgC/ha (unweighted mean) and 157 MgC/ha (weighted mean). Following [Cairns et al. \(1997\)](#), we approximate belowground biomass (BGB) as 24% of AGB. Biomass is converted to carbon using a standard factor of 0.5, and carbon to CO₂-equivalent using 3.67.

Applying these values to our benchmark regression results (Table 5), we find that a 1 million USD increase in climate aid disbursement leads to 94 hectares of additional deforestation per cell and year. This corresponds to 11.1 ktCO₂-eq (unweighted) to 33.7 ktCO₂-eq (weighted). Aggregating over time and space, climate aid-induced emissions amount to 1.34–4.08 GtCO₂-eq in total, or 0.06–0.19 GtCO₂-eq annually. For comparison, the Congo River basin emits roughly 0.53 GtCO₂-eq per year from forest loss ([Harris et al., 2021](#)).

Valuing CO₂ emissions. We monetize these emissions using the Social Cost of Carbon (SCC), as displayed in Table 10. Interpolating values reported by the US EPA ([EPA, 2023](#)) and consistent with recent academic estimates ([Rennert et al., 2022](#)), the SCC in 2021 ranges from 112 to 315 USD/tCO₂-eq for discount rates of 2.5% to 1.5%. Converting to 2014 USD, this implies that the hidden environmental costs of climate aid-induced deforestation exceed the average disbursement

Table 10: Valuing carbon emissions

	Near-term discount rate	Social cost of carbon (in USD/tCO ₂ -eq)	Mean				Weighted mean			
			ABG	BGC	SOC	Total carbon	ABG	BGC	SOC	Total carbon
Carbon emissions (in ktCO ₂ -eq)			8.93	2.14		11.08	27.20	6.53		33.73
Net cost of carbon (in million USD)	2.5%	111.59	1.00	0.24		1.24	3.04	0.73		3.76
	2%	177.45	1.59	0.38		1.97	4.83	1.16		5.99
	1.5%	314.66	2.81	0.67		3.49	8.56	2.05		10.61

Notes: AGB, BGB, and SOC stand for aboveground, belowground, and soil organic carbon, respectively. Values are expressed in ktCO₂-eq and 2014 million USD.

per cell and year by roughly an order of magnitude. For the medium case (2% discount rate), costs are about twelve times higher than disbursements (see Table 4).

Taken together, these estimates suggest that the climate externalities of aid disbursements are large and negative: the induced deforestation generates social costs that substantially outweigh the direct financial resources provided. However, these estimates must be balanced against the potential benefits of climate aid, which include emissions reductions, adaptation to climate shocks, and development co-benefits not captured in our framework. It is also worth noting that our analysis does not assume a direct opportunity cost of climate aid. If such disbursements had not been made, the funds may not have been reallocated to equally beneficial or environmentally neutral uses. Our estimates should therefore be interpreted as highlighting unintended costs of existing programs, rather than implying that the absence of climate aid would necessarily generate a superior outcome.

7 Conclusion

This study aims to provide new insights into the potential unintended environmental consequences of geocoded climate aid. It builds on the analysis of the impact of climate projects on deforestation in Africa from 2001 to 2021. Using a novel geocoded dataset, we find evidence that climate aid is associated with increased forest loss. Based on the estimates obtained from the empirical analysis, we value at an average of 18,353 square kilometers the extent of deforestation that can be attributed to climate aid projects, representing about 5% of total deforestation over the period. With back-of-the-envelope computations, we estimate that the amount of emissions released linked to climate aid projects is roughly equal to 64 MtCO₂-eq per year. These findings highlight the need for more rigorous design and monitoring of climate aid policies to ensure they do not inadvertently exacerbate land-use change and that they take into account potential

channels driving deforestation.

Climate aid is needed to allow all economies to cope with climate change impacts while enhancing climate change mitigation. However, this study highlights a critical but often overlooked issue: some climate aid projects have unintended negative effects on forests. Forests are vital for storing carbon, providing essential ecosystem services, and preserving biodiversity; harming them undermines the very goals climate aid seeks to achieve. As a result, the central policy implication is that climate aid, and more broadly, climate finance, must be designed with safeguards that ensure its alignment with forest conservation. Evidence from REDD+ programs demonstrates the availability of cost-effective approaches to curb deforestation and degradation while sustaining local livelihoods ([Roopsind et al., 2019](#); [Groom et al., 2022](#); [West et al., 2023](#)). Scaling up such interventions will require increased international investment and the use of innovative financing mechanisms that account for net benefits in carbon storage, biodiversity, and other environmental outcomes. In parallel, expanding the deployment of robust monitoring, reporting, and verification (MRV) systems will be essential to track and validate the environmental impacts of funded projects.

We acknowledge several limitations of our work. First, we focus on project-based ODA and are therefore exposed to selection bias concerns of geocoded aid data. By concentrating on this segment of climate finance, we omit policy-based and budget-support operations ([World Bank, 2020](#)). Incorporating these instruments would allow us to study broader, economy-wide structural transformation that could indirectly promote forest preservation. Second, by relying on the Global Forest Change dataset ([Hansen et al., 2013](#)), we measure tree cover loss but not gain. Positive impacts of climate aid through reforestation or afforestation may thus be undercounted and are not explicitly analyzed here. Third, our estimates are essentially contemporaneous and do not model dynamics. Future work could exploit project time stamps to estimate dynamic treatment effects, test for anticipation and persistence, and compare short-, medium-, and long-run effects. Lastly, an extension may be made to other areas with high forest pressure, allowing for the comparison of the potential heterogeneous effects of climate aid worldwide.

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Appendix

A Data

A.1 Climate aid projects: additional figures

A.1.1 Climate aid: descriptive statistics

Table A.1: Descriptive statistics on global and African climate aid projects

	Global			Africa		
	#	Mean	SD	#	Mean	SD
Adaptation	26,868	0.86	8.08	6,014	0.63	5.95
Mitigation	38,253	1.69	13.64	11,062	1.37	8.03
Nature conservation	41,557	0.62	5.93	8,721	0.50	3.01
Adaptation	26,868	0.86	8.08	6,014	0.63	5.95
Biodiversity	1,164	0.27	0.69	384	0.27	0.67
Biofuel-energy	457	0.32	1.06	82	0.16	0.72
Energy-efficiency	9,146	1.89	22.18	1,756	1.14	9.07
Geothermal-energy	652	2.45	6.46	234	3.08	6.24
Hydro-energy	6,252	2.15	7.32	1,287	1.93	4.82
Marine-energy	2	0.12	0.12	1	0.16	0.10
Nature conservation	3,703	0.48	1.22	998	0.41	1.03
Other-environment-protection-projects	22,410	0.91	9.10	2,873	0.58	2.97
Other-mitigation-projects	10,467	3.38	18.57	3,527	3.87	11.90
Renewables-multiple	7,368	1.00	7.39	1,931	0.70	6.73
Solar-energy	2,633	1.12	8.01	1,317	1.01	8.13
Sustainable-land-use	14,279	0.46	3.27	4,464	0.52	3.60
Wind-energy	1,272	2.94	8.65	923	3.35	9.59
Agriculture	3,470	0.29	0.98	1,041	0.25	0.75
Communications	1	0.12	0.17	0	0.33	0.34
Education	149	0.19	0.45	61	0.20	0.42
Emergency	3,916	1.03	5.02	1,315	1.40	9.04
Energy	13,691	1.75	7.01	4,455	2.10	10.53
Environment	4,225	0.42	3.35	863	0.31	0.85
Finance, Business and Services	528	0.69	3.29	42	0.20	0.39
Forestry	1,671	0.47	1.61	136	0.22	0.38
Government, Society and Budget	692	0.16	0.58	180	0.19	0.65
Health	5,673	0.81	3.17	1,262	0.59	3.75
Multisector and Others	66,558	1.00	10.76	15,397	0.78	5.76
Other Industries	731	0.44	1.34	258	0.38	1.10
Transport and Storage	5,369	1.80	8.50	783	1.94	5.03
HIC	4,031	0.76	9.09	124	0.92	4.26
INX	95	0.25	0.34			
LIC	9,294	0.51	2.84	8,787	0.50	2.89
LMC	43,557	0.80	5.57	12,774	0.78	6.36
UMC	49,700	1.17	12.22	4,111	4.77	14.84

Notes: Aid projects are sourced from the GODAD dataset between 1989 and 2021 (Bomprezzi et al., 2024). Climate classification is obtained by using the procedure described in Toetzke et al. (2022), climate categories being exposed in the second subtable. The third subtable is based on the OECD sector classification. The fourth subtable uses the World Bank classification of countries per income groups. All values are expressed in levels of disbursement, in million constant 2014 USD.

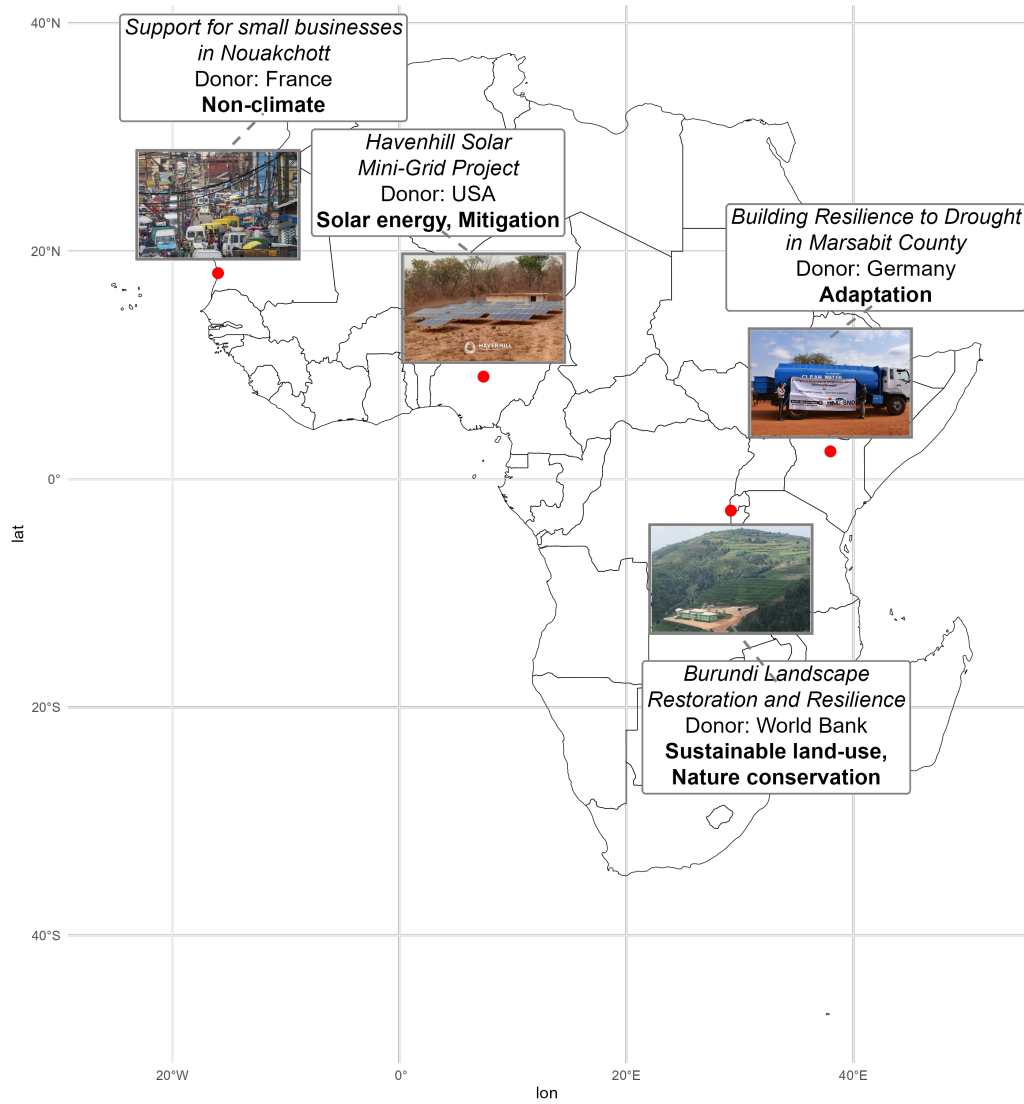
A.1.2 Mean differences between geocoded and non-geocoded climate aid

Figure A.1: Mean differences for different project characteristics between geocoded and non-geocoded climate aid from the OECD CRS



A.1.3 Examples of climate-classification of GODAD projects

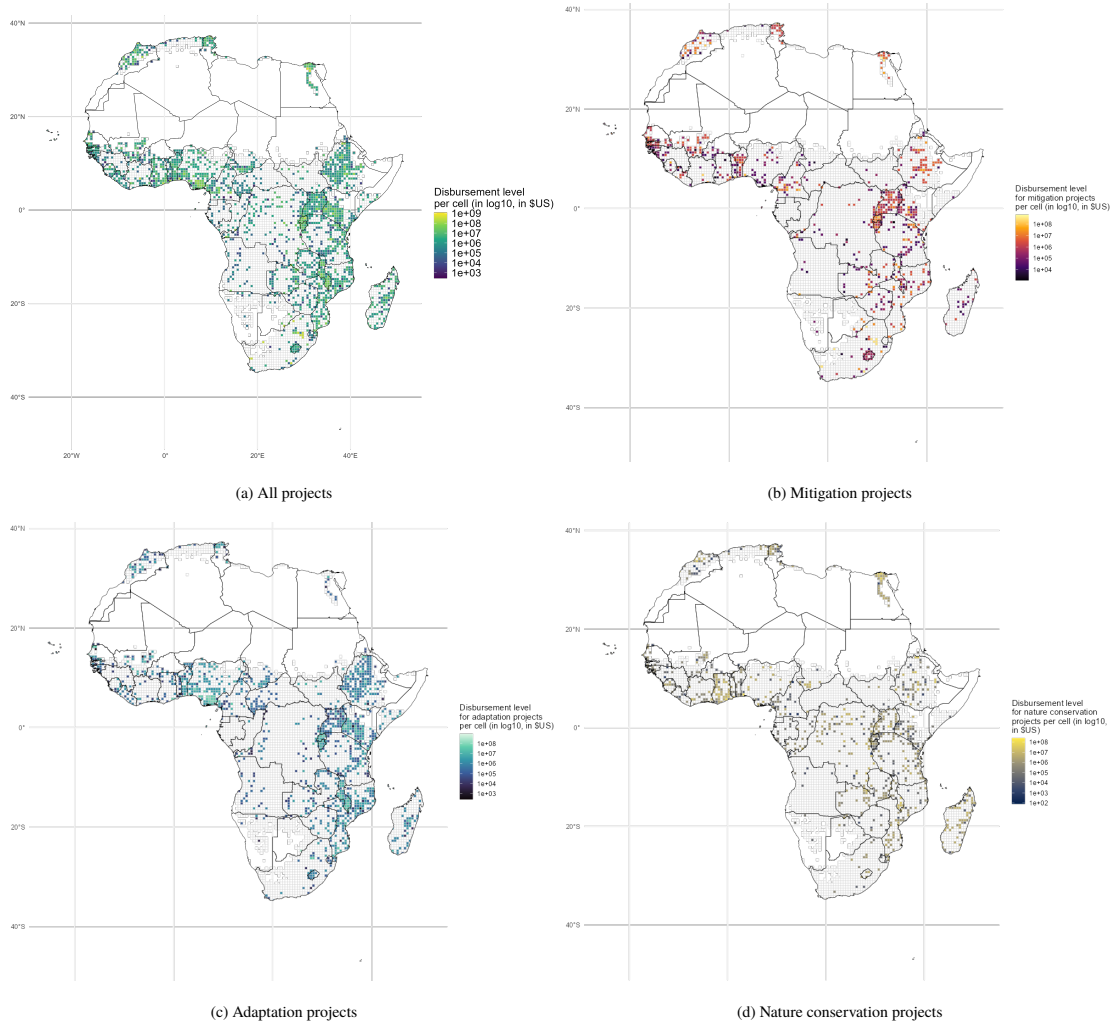
Figure A.2: Four examples of geocoded GODAD projects classified into climate aid (in bold)



Note: GODAD database provides these examples of projects (Bomprezzi et al., 2024), that are then classified through the dedicated replication process described by Toetke et al. (2022).

A.1.4 Heterogeneous mapping of projects

Figure A.3: (a-b-c-d) Disbursement levels for all climate aid projects, and climate aid projects assigned as aiming mitigation, adaptation, or nature conservation objectives per cell between 2021 and 2021.



Note: The data, expressed in constant 2014 USD, is taken from GODAD database

A.2 REDD+ projects

One initiative at the intersection of climate aid and forest preservation is the REDD+ program (Reducing Emissions from Deforestation and Forest Degradation). Since its establishment in 2007, REDD+ has integrated developing countries' forests into international climate negotiations. The program aims at providing financial incentives to local smallholders and communities to reduce deforestation and forest degradation, and to promote afforestation and reforestation.

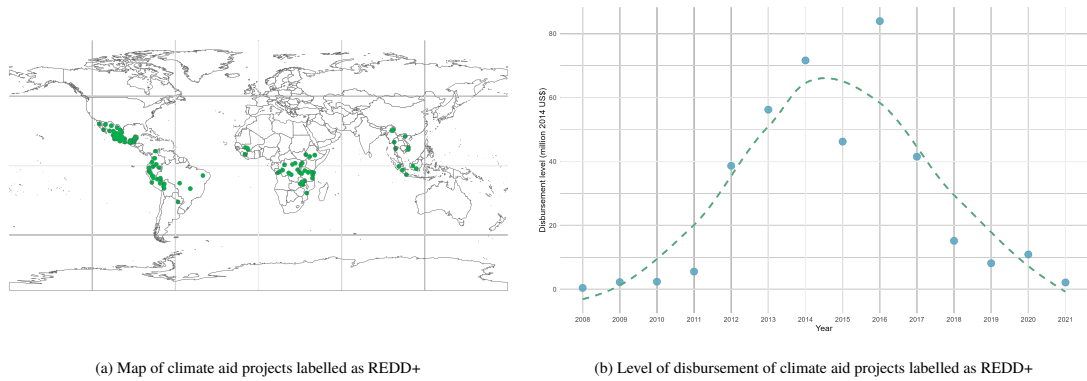
These programs are structured around results-based payments, linking funding to measurable environmental outcomes (Angelsen, 2017). In addition to reducing carbon emissions, REDD+ also targets to generate non-carbon benefits, including improved livelihoods, biodiversity conservation, climate adaptation, or the protection of indigenous rights. REDD+ initiatives can take various policy forms, including command-and-control regulations and community-based forest management (Angelsen, 2017). A growing body of literature has evaluated the impact of REDD+ in South America, Southeast Asia, or Africa (Jayachandran et al., 2017; Roopsind et al., 2019; Demarchi et al., 2021; Groom et al., 2022; West et al., 2023). These studies generally find positive effects in deforestation reduction and quantify these effects in terms of avoided CO₂ emissions. Overall, REDD+ appears to be a relatively cost-effective climate mitigation strategy. However, the scale of REDD+ programs remains limited due to insufficient funding (Groom et al., 2022).

Initially, REDD+ was envisioned to be financed through carbon markets, where countries or firms could pay for verified emission reductions. However, the failure to reach an international consensus on binding national emission caps and the establishment of a global carbon market prevented this approach from materializing (Angelsen et al., 2017). Instead, REDD+ has been largely financed through development aid budgets, leading to what some refer to as the “aidification” of REDD+ by its absorption into existing development and conservation frameworks (Angelsen, 2017; Duchelle et al., 2018). This approach offers advantages for donor countries, as it allows them to leverage existing development expertise, channel funds through established aid mechanisms, and align REDD+ financing with broader international aid targets.

As a result, a portion of ODA classified as climate aid includes REDD+ projects. Through a keyword search in our climate aid database, we identified 565 projects referencing REDD+, of which 171 are located in Africa, spanning 120 global locations and 36 African locations (see Figure A.4a). As illustrated in Figure A.4b, the total disbursement for REDD+-related projects between 2001 and 2021 amounted to approximately 385 million USD (in 2014 dollars) globally and 51 million USD in Africa. These figures represent roughly 0.4% of total global climate aid disbursements and only 0.2% of climate aid disbursements in Africa. The World Bank emerges as the largest REDD+ donor in our climate aid database, followed by Norway and the USA, while the main recipient countries are Mexico, Brazil, and Zambia. However, these statistics do not fully align with REDD+ program data reported by Atmadja et al. (2022). This suggests that, although our dataset captures a subset of REDD+ projects, the majority of REDD+ initiatives are likely not included. As highlighted by Duchelle et al. (2018), REDD+ programs generally target small-scale actors and are not designed to address the broader, structural drivers of deforestation that are the focus of our analysis. Consequently, our findings should not be interpreted as an evaluation of REDD+ programs, which remain relatively limited in scope and scale within our

dataset and thus play a minor role in our empirical results.

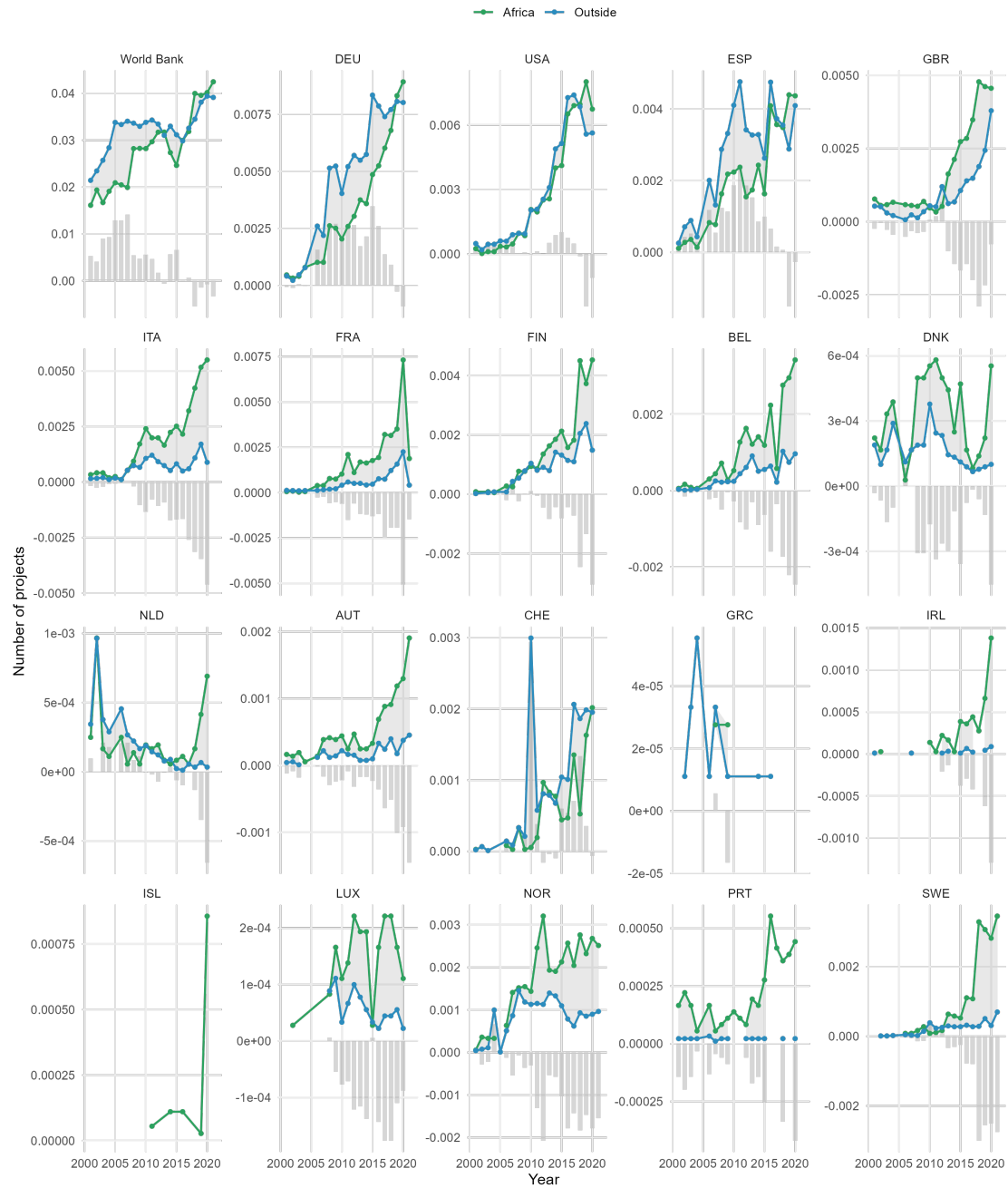
Figure A.4: Geocoded climate aid projects labelled as REDD+



B Instrumental variable

B.1 Shift variable: representation at the donor level

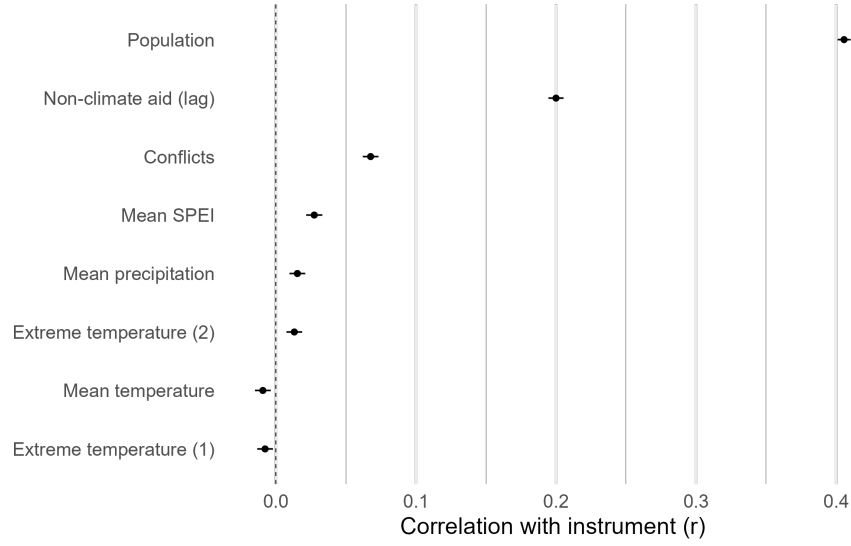
Figure B.5: Number of geocoded projects, per region, year, and donor countries, as a share of total projects per region



Notes: The solid lines show the number of geocoded climate aid projects implemented in Africa (in green) and outside Africa (in blue), normalized by the total number of projects of each region, and divided across donor countries. The grey area is reported as bar plots, which indicate the annual difference between these two shares.

B.2 Controls correlations

Figure B.6: Instrument and control variables correlations



Notes: This figure displays correlations between the instrument and each control variable. 95% confidence intervals are displayed.

B.3 Instrument: descriptive statistics

Table B.2: Instrument: descriptive statistics

	Mean	SD	Median	# of instrument	# of shift	# of share
Instrument (PredictedCA _{ict})	2.48	5.53	0	14,133		
Annual proportion of climate aid outside Africa (shift _t)	2.67e-03	1.26e-03	2.36e-03		21	
Frequency of exposure (share _{ic})	0.077	0.148	0			2,019

Notes: Definitions of the instruments and their shifts and shares are described in Section 4.3.

B.4 Differing share periods

B.4.1 Pre-period shares on total ODA

Table B.3: Climate aid and deforestation, pre-period shares: OLS and IV estimates

	Deforested area 2SLS			
	(1)	(2)	(3)	(4)
Disb. level	0.818** (0.369)	0.719** (0.348)	0.625 (0.956)	0.468 (0.787)
Controls: weather shocks		✓	✓	✓
Controls: weather $\times$ freq. of exposure		✓	✓	✓
Controls: non-climate aid (lag)			✓	✓
Controls: conflicts, population			✓	✓
Observations	120,876	114,366	114,280	114,366
Kleibergen-Paap Wald stat, Disb. level	14.199	15.781	2.3986	6.5541
Cragg-Donald F-test stat, Disb. level	76.142	93.261	12.361	19.101
Dependent variable mean	3.0849	3.2007	3.2031	3.2007
ADMIN1 $\times$ year FE				✓
Country $\times$ year FE	✓	✓	✓	
Cell FE	✓	✓	✓	✓

Notes: All columns display 2SLS regressions. First-stage regressions of all columns are displayed in Table B.4. Columns (1-3) dependent variable is the deforested area, in million square meters. The independent variable is the level of disbursement in million constant 2014 USD of climate aid projects. ***, **, and * reveal significance at the 1%, 5% and 10% level, respectively. Cell and country $\times$ year fixed-effects are used in columns (1-3). Weather shock controls, included in columns (2-3), denote average precipitation, temperature, and SPEI, as well as two dummies of extreme temperature. Weather $\times$ frequency of exposure, included in column (3), denotes the interaction of the average weather controls with the share of the instrument. Non-climate aid (lag), included in column (3), denotes the one-year lag level of disbursement of non-climate aid. Conflicts and population, included in column (3), denote the number of conflicts and of inhabitants. Standard errors are clustered at the cell level. Kleibergen-Paap Wald statistic and Cragg-Donald F-test statistic are reported for columns (1-3).

Table B.4: Climate aid and deforestation, pre-period shares: first stage

	Disb. level 2SLS			
	(1)	(2)	(3)	(4)
Instrument	0.1183*** (0.0314)	0.1139*** (0.0287)	0.0420 (0.0271)	0.0522** (0.0204)
Controls: weather shocks		✓	✓	✓
Controls: weather $\times$ freq. of exposure		✓	✓	✓
Controls: non-climate aid (lag)			✓	✓
Controls: conflicts, population			✓	✓
Observations	120,876	114,366	114,280	114,366
Kleibergen-Paap Wald stat (1st stage)	14.199	15.781	2.3986	6.5541
Kleibergen-Paap Wald p-value (1st stage)	0.00016	7.12×10^{-5}	0.12145	0.01047
Cragg-Donald F-test stat (1st stage)	76.142	93.261	12.361	19.101
Cragg-Donald F-test p-value (1st stage)	2.67×10^{-18}	4.67×10^{-22}	0.00044	1.24×10^{-5}
ADMIN1 $\times$ year FE				✓
Country $\times$ year FE	✓	✓	✓	
Cell FE	✓	✓	✓	✓

Notes: All columns display the first stages of the 2SLS regressions of Table B.3. Columns (1-3)'s dependent variable is the level of disbursement of climate aid. The independent variable is the instrument. ***, **, and * reveal significance at the 1%, 5% and 10% level, respectively. Cell and country $\times$ year fixed-effects are used in all columns. Weather shock controls, included in columns (1-3), denote average precipitation, temperature, and SPEI, as well as two dummies of extreme temperature. Weather $\times$ frequency of exposure, included in columns (2-3), denotes the interaction of the average weather controls with the share of the instrument. Non-climate aid (lag), included in column (3), denotes the interaction of the level of disbursement of non-climate aid with years. Conflicts and population, included in column (3), denote the number of conflicts and of inhabitants. Standard errors are clustered at the cell level. Kleibergen-Paap Wald statistic and Cragg-Donald F-test statistic are reported for all columns.

B.4.2 Sub-period shares on total ODA

Table B.5: Climate aid and deforestation, sub-period shares: OLS and IV estimates

	Deforested area			
	2SLS			
	(1)	(2)	(3)	(4)
Disb. level	1.41*** (0.387)	0.979*** (0.316)	1.18 (0.749)	0.860 (0.627)
Controls: weather shocks		✓	✓	✓
Controls: weather $\times$ freq. of exposure		✓	✓	✓
Controls: non-climate aid (lag)			✓	✓
Controls: conflicts, population			✓	✓
Observations	120,876	114,366	114,280	114,366
Kleibergen-Paap Wald stat, Disb. level	28.230	29.609	5.9542	11.323
Cragg-Donald F-test stat, Disb. level	158.68	228.37	48.547	61.263
Dependent variable mean	3.0849	3.2007	3.2031	3.2007
ADMIN1 $\times$ year FE				✓
Country $\times$ year FE	✓	✓	✓	
Cell FE	✓	✓	✓	✓

Notes: All columns display 2SLS regressions. First-stage regressions of all columns are displayed in Table B.6. Columns (1-3) dependent variable is the deforested area, in million square meters. The independent variable is the level of disbursement in million constant 2014 USD of climate aid projects. ***, **, and * reveal significance at the 1%, 5% and 10% level, respectively. Cell and country $\times$ year fixed-effects are used in columns (1-3). Weather shock controls, included in columns (2-3), denote average precipitation, temperature, and SPEI, as well as two dummies of extreme temperature. Weather $\times$ frequency of exposure, included in column (3), denotes the interaction of the average weather controls with the share of the instrument. Non-climate aid (lag), included in column (3), denotes the one-year lag level of disbursement of non-climate aid. Conflicts and population, included in column (3), denote the number of conflicts and of inhabitants. Standard errors are clustered at the cell level. Kleibergen-Paap Wald statistic and Cragg-Donald F-test statistic are reported for columns (1-3).

Table B.6: Climate aid and deforestation, sub-period shares: first stage

	Disb. level 2SLS			
	(1)	(2)	(3)	(4)
Instrument	0.0967*** (0.0182)	0.1000*** (0.0184)	0.0478** (0.0196)	0.0518*** (0.0154)
Controls: weather shocks		✓	✓	✓
Controls: weather $\times$ freq. of exposure		✓	✓	✓
Controls: non-climate aid (lag)			✓	✓
Controls: conflicts, population			✓	✓
Observations	120,876	114,366	114,280	114,366
Kleibergen-Paap Wald stat (1st stage)	28.230	29.609	5.9542	11.323
Kleibergen-Paap Wald p-value (1st stage)	1.08×10^{-7}	5.3×10^{-8}	0.01468	0.00077
Cragg-Donald F-test stat (1st stage)	158.68	228.37	48.547	61.263
Cragg-Donald F-test p-value (1st stage)	2.32×10^{-36}	1.52×10^{-51}	3.24×10^{-12}	5.04×10^{-15}
ADMIN1 $\times$ year FE				✓
Country $\times$ year FE	✓	✓	✓	
Cell FE	✓	✓	✓	✓

Notes: All columns display the first stages of the 2SLS regressions of Table B.5. Columns (1-3)'s dependent variable is the level of disbursement of climate aid. The independent variable is the instrument. ***, **, and * reveal significance at the 1%, 5% and 10% level, respectively. Cell and country $\times$ year fixed-effects are used in all columns. Weather shock controls, included in columns (1-3), denote average precipitation, temperature, and SPEI, as well as two dummies of extreme temperature. Weather $\times$ frequency of exposure, included in columns (2-3), denotes the interaction of the average weather controls with the share of the instrument. Non-climate aid (lag), included in column (3), denotes the interaction of the level of disbursement of non-climate aid with years. Conflicts and population, included in column (3), denote the number of conflicts and of inhabitants. Standard errors are clustered at the cell level. Kleibergen-Paap Wald statistic and Cragg-Donald F-test statistic are reported for all columns.

B.5 Unpredictable component

Table B.7: Climate aid and deforestation, unpredictable component: OLS and IV estimates

	Deforested area 2SLS			
	(1)	(2)	(3)	(4)
Disb. level	1.28*** (0.263)	1.11*** (0.259)	1.27*** (0.449)	1.13*** (0.419)
Controls: weather shocks		✓	✓	✓
Controls: weather $\times$ freq. of exposure		✓	✓	✓
Controls: non-climate aid (lag)			✓	✓
Controls: conflicts, population			✓	✓
Observations	120,876	114,366	114,280	114,366
Kleibergen-Paap Wald stat, Disb. level	53.898	43.991	16.670	23.837
Cragg-Donald F-test stat, Disb. level	195.29	190.76	78.484	79.017
Dependent variable mean	3.0849	3.2007	3.2031	3.2007
ADMIN1 $\times$ year FE				✓
Country $\times$ year FE	✓	✓	✓	
Cell FE	✓	✓	✓	✓

Notes: All columns display 2SLS regressions. First-stage regressions of all columns are displayed in Table B.8. Columns (1-4) dependent variable is the deforested area, in million square meters. The independent variable is the level of disbursement in million constant 2014 USD of climate aid projects. ***, **, and * reveal significance at the 1%, 5% and 10% level, respectively. Cell and country $\times$ year fixed-effects are used in columns (1-3). Cell and ADMIN1 $\times$ year fixed-effects are used in column (4). Weather shock controls, included in columns (2-4), denote average precipitation, temperature, and SPEI, as well as two dummies of extreme temperature. Weather $\times$ frequency of exposure, included in columns (3-4), denotes the interaction of the average weather controls with the share of the instrument. Non-climate aid (lag), included in columns (3-4), denotes the one-year lag level of disbursement of non-climate aid. Conflicts and population, included in columns (3-4), denote the number of conflicts and of inhabitants. Standard errors are clustered at the cell level. Kleibergen-Paap Wald statistic and Cragg-Donald F-test statistic are reported for columns (1-4).

Table B.8: Climate aid and deforestation, unpredictable component: first stage

	Disb. level 2SLS			
	(1)	(2)	(3)	(4)
Instrument - unpredictable component	0.1517*** (0.0202)	0.1161*** (0.0192)	0.0878*** (0.0208)	0.0647*** (0.0227)
Controls: weather shocks		✓	✓	✓
Controls: weather $\times$ freq. of exposure		✓	✓	✓
Controls: non-climate aid (lag)			✓	✓
Controls: conflicts, population			✓	✓
Observations	120,876	114,366	114,280	114,280
Kleibergen-Paap Wald stat (1st stage)	56.469	36.702	17.883	8.1377
Kleibergen-Paap Wald p-value (1st stage)	5.75×10^{-14}	1.38×10^{-9}	2.35×10^{-5}	0.00434
Cragg-Donald F-test stat (1st stage)	142.07	114.48	65.361	34.709
Cragg-Donald F-test p-value (1st stage)	9.8×10^{-33}	1.05×10^{-26}	6.3×10^{-16}	3.84×10^{-9}
ADMIN1 $\times$ year FE				✓
Country $\times$ year FE	✓	✓	✓	
Cell FE	✓	✓	✓	✓

Notes: All columns display the first stages of the 2SLS regressions of Table B.7. Columns (1-4)'s dependent variable is the level of disbursement of climate aid. The independent variable is the instrument. ***, **, and * reveal significance at the 1%, 5% and 10% level, respectively. Cell and country $\times$ year fixed-effects are used in all columns. Cell and ADMIN1 $\times$ year fixed-effects are used in column (4). Weather shock controls, included in columns (2-4), denote average precipitation, temperature, and SPEI, as well as two dummies of extreme temperature. Weather $\times$ frequency of exposure, included in columns (3-4), denotes the interaction of the average weather controls with the share of the instrument. Non-climate aid (lag), included in columns (3-4), denotes the one-year lag level of disbursement of non-climate aid. Conflicts and population, included in columns (3-4), denote the number of conflicts and of inhabitants. Standard errors are clustered at the cell level. Kleibergen-Paap Wald statistic and Cragg-Donald F-test statistic are reported for all columns.

B.6 Pre-trend test: lagged deforestation

Table B.9: Climate aid and deforestation, lagged deforestation: OLS and IV estimates

	Deforested area					
	OLS			2SLS		
	(1)	(2)	(3)	(4)	(5)	(6)
Disb. level	0.004 (0.002)	0.005 (0.004)	0.002 (0.004)	0.633*** (0.147)	0.640*** (0.163)	0.739** (0.302)
Deforested area (lag)	0.415*** (0.018)	0.402*** (0.019)	0.402*** (0.019)	0.414*** (0.018)	0.402*** (0.019)	0.402*** (0.019)
Controls: weather shocks		✓	✓		✓	✓
Controls: weather $\times$ freq. of exposure		✓	✓		✓	✓
Controls: non-climate aid (lag)			✓			✓
Controls: conflicts, population			✓			✓
Observations	115,120	108,920	108,839	115,120	108,920	108,839
Kleibergen-Paap Wald stat, Disb. level				37.460	30.444	12.076
Cragg-Donald F-test stat, Disb. level				267.36	281.92	102.26
Dependent variable mean	3.1503	3.2684	3.2708	3.1503	3.2684	3.2708
Cell FE	✓	✓	✓	✓	✓	✓
country-year fixed effects	✓	✓	✓	✓	✓	✓

Notes: Columns (1-3) display OLS regressions and columns (4-6) display 2SLS regressions. First-stage regressions of columns (4-6) are displayed in Table B.10. Columns (1-6) dependent variable is the deforested area, in million square meters. The independent variable is the level of disbursement in million constant 2014 USD of climate aid projects. Lagged deforested area is also included as a control. ***, **, and * reveal significance at the 1%, 5% and 10% level, respectively. Standard errors are clustered at the cell level. Kleibergen-Paap Wald statistic and Cragg-Donald F-test statistic are reported for columns (4-6).

Table B.10: Climate aid and deforestation, lagged deforestation: first stage

	Disb. level 2SLS		
	(1)	(2)	(3)
Instrument	0.1835*** (0.0300)	0.1595*** (0.0289)	0.0985*** (0.0283)
Deforested area (lag)	0.0004 (0.0008)	0.0002 (0.0008)	-0.0004 (0.0009)
Controls: weather shocks		✓	✓
Controls: weather $\times$ freq. of exposure		✓	✓
Controls: non-climate aid (lag)			✓
Controls: conflicts, population			✓
Observations	115,120	108,920	108,839
Kleibergen-Paap Wald stat (1st stage)	37.460	30.444	12.076
Kleibergen-Paap Wald p-value (1st stage)	9.36×10^{-10}	3.44×10^{-8}	0.00051
Cragg-Donald F-test stat (1st stage)	267.36	281.92	102.26
Cragg-Donald F-test p-value (1st stage)	5.01×10^{-60}	3.44×10^{-63}	4.98×10^{-24}
Cell FE	✓	✓	✓
country-year fixed effects	✓	✓	✓

Notes: All columns display the first stages of the 2SLS regressions of Table B.9. Columns (1-3)'s dependent variable is the level of disbursement of climate aid. The independent variable is the instrument. Lagged deforested area is also included as a control. ***, **, and * reveal significance at the 1%, 5% and 10% level, respectively. Cell and country $\times$ year fixed-effects are used in all columns. Weather shock controls, included in columns (1-3), denote average precipitation, temperature, and SPEI, as well as two dummies of extreme temperature. Weather $\times$ frequency of exposure, included in columns (2-3), denotes the interaction of the average weather controls with the share of the instrument. Non-climate aid (lag), included in column (3), denotes the interaction of the level of disbursement of non-climate aid with years. Conflicts and population, included in column (3), denote the number of conflicts and of inhabitants. Standard errors are clustered at the cell level. Kleibergen-Paap Wald statistic and Cragg-Donald F-test statistic are reported for all columns.

B.7 Year-based clustering

Table B.11: Climate aid and deforestation, year clustering: OLS and IV estimates

	Deforested area				
	OLS	2SLS			
	(1)	(2)	(3)	(4)	(5)
Disb. level	0.005*	1.02***	0.881***	0.944**	0.833**
	(0.003)	(0.175)	(0.218)	(0.340)	(0.296)
Controls: weather shocks			✓	✓	✓
Controls: weather $\times$ freq. of exposure			✓	✓	✓
Controls: non-climate aid (lag)				✓	✓
Controls: conflicts, population				✓	✓
Observations	120,876	120,876	114,366	114,280	114,366
Kleibergen-Paap Wald stat, Disb. level		38.562	21.474	10.361	9.6137
Cragg-Donald F-test stat, Disb. level		366.27	371.88	154.18	193.08
Dependent variable mean	3.0849	3.0849	3.2007	3.2031	3.2007
ADMIN1 $\times$ year FE					✓
Country $\times$ year FE	✓	✓	✓	✓	
Cell FE	✓	✓	✓	✓	✓

Notes: First column displays an OLS regression, and columns (2-5) display 2SLS regressions. First-stage regressions of all columns are displayed in Table B.12. Columns (1-5) dependent variable is the deforested area, in million square meters. The independent variable is the level of disbursement in million constant 2014 USD of climate aid projects. ***, **, and * reveal significance at the 1%, 5% and 10% level, respectively. Cell and country $\times$ year fixed-effects are used in columns (1-4). Cell and ADMIN1 $\times$ year fixed-effects are used in column (5). Weather shock controls, included in columns (3-5), denote average precipitation, temperature, and SPEI, as well as two dummies of extreme temperature. Weather $\times$ frequency of exposure, included in columns (3-5), denotes the interaction of the average weather controls with the share of the instrument. Non-climate aid (lag), included in columns (4-5), denotes the one-year lag level of disbursement of non-climate aid. Conflicts and population, included in columns (4-5), denote the number of conflicts and of inhabitants. Standard errors are clustered at the year level. Kleibergen-Paap Wald statistic and Cragg-Donald F-test statistic are reported for columns (2-5).

Table B.12: Climate aid and deforestation, year clustering: first stage

	Disb. level 2SLS			
	(1)	(2)	(3)	(4)
Instrument	0.1831*** (0.0295)	0.1592*** (0.0344)	0.1051*** (0.0326)	0.1100*** (0.0355)
Controls: weather shocks		✓	✓	✓
Controls: weather $\times$ freq. of exposure		✓	✓	✓
Controls: non-climate aid (lag)			✓	✓
Controls: conflicts, population			✓	✓
Observations	120,876	114,366	114,280	114,366
Kleibergen-Paap Wald stat (1st stage)	38.562	21.474	10.361	9.6137
Kleibergen-Paap Wald p-value (1st stage)	5.32×10^{-10}	3.59×10^{-6}	0.00129	0.00193
Cragg-Donald F-test stat (1st stage)	366.27	371.88	154.18	193.08
Cragg-Donald F-test p-value (1st stage)	1.63×10^{-81}	1×10^{-82}	2.23×10^{-35}	7.39×10^{-44}
ADMIN1 $\times$ year FE				✓
Country $\times$ year FE	✓	✓	✓	
Cell FE	✓	✓	✓	✓

Notes: All columns display the first stages of the 2SLS regressions of Table B.11. Columns (1-4)'s dependent variable is the level of disbursement of climate aid. The independent variable is the instrument. ***, **, and * reveal significance at the 1%, 5% and 10% level, respectively. Cell and country $\times$ year fixed-effects are used in all columns. Cell and ADMIN1 $\times$ year fixed-effects are used in column (4). Weather shock controls, included in columns (2-4), denote average precipitation, temperature, and SPEI, as well as two dummies of extreme temperature. Weather $\times$ frequency of exposure, included in columns (3-4), denotes the interaction of the average weather controls with the share of the instrument. Non-climate aid (lag), included in columns (3-4), denotes the one-year lag level of disbursement of non-climate aid. Conflicts and population, included in columns (3-4), denote the number of conflicts and of inhabitants. Standard errors are clustered at the year level. Kleibergen-Paap Wald statistic and Cragg-Donald F-test statistic are reported for all columns.

C Additional results

C.1 Heterogeneity: tables

C.1.1 Climate-related objectives

Table C.13: Climate aid by type and deforestation: IV estimates

	Deforested area 2SLS			
	(1)	(2)	(3)	(4)
Disb. level for mitigation	2.76*** (0.912)	2.93*** (1.08)	3.27** (1.62)	1.96** (0.907)
Disb. level for adaptation	0.184 (0.255)	0.017 (0.291)	0.189 (0.570)	-0.211 (0.478)
Controls: weather shocks		✓	✓	✓
Controls: weather $\times$ freq. of exposure		✓	✓	✓
Controls: non-climate aid (lag)			✓	✓
Controls: conflicts, population			✓	✓
Observations	120,876	114,366	114,280	114,280
Kleibergen-Paap Wald stat (1st stage), Disb. level for mitigation	13.1	6.65	4.87	9.30
Kleibergen-Paap Wald stat (1st stage), Disb. level for adaptation	18.4	27.2	20.7	15.8
Dependent variable mean	3.08	3.20	3.20	3.20
ADMIN1 $\times$ year FE				✓
Country $\times$ year FE	✓	✓	✓	
Cell FE	✓	✓	✓	✓

Notes: Columns (1-4) are 2SLS regressions. First-stage regressions of the columns (2-5) are displayed in Table C.16. Columns (1-4) dependent variable is the deforested area, in million square meters. The independent variable is the level of disbursement in million constant 2014 USD of climate aid projects; the total level is restricted to mitigation projects in the first row, and the total level is restricted to adaptation projects in the second row. ***, **, and * reveal significance at the 1%, 5% and 10% level, respectively. Cell and country $\times$ year fixed-effects are used in columns (1-3). Cell and ADMIN1 $\times$ year fixed-effects are used in column (4). Weather shock controls, included in columns (1-4), denote average precipitation, temperature, and SPEI, as well as two dummies of extreme temperature. Weather $\times$ frequency of exposure, included in columns (1-4), denotes the interaction of the average weather controls with the share of the instrument. Non-climate aid (lag), included in columns (1-4), denotes the one-year lag level of disbursement of non-climate aid. Conflicts and population, included in columns (1-4), denote the number of conflicts and of inhabitants. Standard errors are clustered at the cell level. Kleibergen-Paap Wald statistics are reported for all columns.

C.1.2 Sectoral classification and land occupation

Table C.14: Climate aid by OECD classification and deforestation: IV estimates

	Deforested area 2SLS			
	(1)	(2)	(3)	(4)
Disb. level for social infrastructure & services	-0.864 (1.98)	-1.88 (3.23)	-1.73 (3.01)	1.25 (1.98)
Disb. level for economic infrastructure & services	0.696 (1.21)	0.681 (1.27)	0.408 (1.65)	-0.178 (1.36)
Disb. level for production	3.01** (1.45)	3.72** (1.77)	3.85** (1.71)	-0.020 (1.71)
Disb. level for emergency	-1.05** (0.493)	-1.77 (1.13)	-1.83 (1.11)	-0.342 (0.723)
Disb. level for multisector	1.34*** (0.435)	0.899** (0.389)	0.854* (0.511)	1.26* (0.724)
Controls: weather shocks		✓	✓	✓
Controls: weather × freq. of exposure		✓	✓	✓
Controls: non-climate aid (lag)			✓	✓
Controls: conflicts, population			✓	✓
Observations	120,876	114,366	114,280	114,280
Kleibergen-Paap Wald stat, Disb. level for social infrastructure & services	3.8348	3.9407	3.3717	4.9521
Kleibergen-Paap Wald stat, Disb. level for economic infrastructure & services	3.4895	2.4049	1.9128	2.9733
Kleibergen-Paap Wald stat, Disb. level for production	9.6477	8.6201	8.3107	11.643
Kleibergen-Paap Wald stat, Disb. level for emergency	1.8673	4.1163	4.0418	4.2148
Kleibergen-Paap Wald stat, Disb. level for multisector	7.7294	5.5295	6.1622	4.1064
Dependent variable mean	3.0849	3.2007	3.2031	3.2031
ADMIN1 × year FE				✓
Country × year FE	✓	✓	✓	
Cell FE	✓	✓	✓	✓

Notes: Columns (1-4) are 2SLS regressions. Columns (1-4) dependent variable is the deforested area, in million square meters. The independent variable is the level of disbursement in million constant 2014 USD of climate aid projects; based on sectoral classification made by [Bomprezzi et al. \(2024\)](#). ***, **, and * reveal significance at the 1%, 5% and 10% level, respectively. Cell and country × year fixed-effects are used in columns (1-3). Cell and ADMIN1 × year fixed-effects are used in column (4). Weather shock controls, included in columns (1-4), denote average precipitation, temperature, and SPEI, as well as two dummies of extreme temperature. Weather × frequency of exposure, included in columns (1-4), denotes the interaction of the average weather controls with the share of the instrument. Non-climate aid (lag), included in columns (1-4), denotes the one-year lag level of disbursement of non-climate aid. Conflicts and population, included in columns (1-4), denote the number of conflicts and of inhabitants. Standard errors are clustered at the cell level. Kleibergen-Paap Wald statistics are reported for all columns.

C.2 First stage regressions

C.2.1 Benchmark results

Table C.15: Climate aid and deforestation: first stage

	Disb. level 2SLS			
	(1)	(2)	(3)	(4)
Instrument	0.1831*** (0.0248)	0.1592*** (0.0238)	0.1051*** (0.0235)	0.1100*** (0.0204)
Controls: weather shocks		✓	✓	✓
Controls: weather $\times$ freq. of exposure		✓	✓	✓
Controls: non-climate aid (lag)			✓	✓
Controls: conflicts, population			✓	✓
Observations	120,876	114,366	114,280	114,366
Kleibergen-Paap Wald stat (1st stage)	54.315	44.654	20.051	28.949
Kleibergen-Paap Wald p-value (1st stage)	1.72×10^{-13}	2.36×10^{-11}	7.55×10^{-6}	7.45×10^{-8}
Cragg-Donald F-test stat (1st stage)	381.11	386.82	160.38	180.43
Cragg-Donald F-test p-value (1st stage)	9.66×10^{-85}	5.66×10^{-86}	9.88×10^{-37}	4.23×10^{-41}
ADMIN1 $\times$ year FE				✓
Country $\times$ year FE	✓	✓	✓	
Cell FE	✓	✓	✓	✓

Notes: All columns display the first stages of the 2SLS regressions of Table 5. Columns (1-4)'s dependent variable is the level of disbursement of climate aid. The independent variable is the instrument. ***, **, and * reveal significance at the 1%, 5% and 10% level, respectively. Cell and country $\times$ year fixed-effects are used in all columns. Cell and ADMIN1 $\times$ year fixed-effects are used in column (5). Weather shock controls, included in columns (2-4), denote average precipitation, temperature, and SPEI, as well as two dummies of extreme temperature. Weather $\times$ frequency of exposure, included in columns (3-4), denotes the interaction of the average weather controls with the share of the instrument. Non-climate aid (lag), included in columns (3-4), denotes the interaction of the level of disbursement of non-climate aid with years. Conflicts and population, included in columns (3-4), denote the number of conflicts and of inhabitants. Standard errors are clustered at the cell level. Kleibergen-Paap Wald statistic is reported for all columns.

C.2.2 Heterogeneity

Table C.16: Climate aid by type and deforestation: first stage

	Disb. level for mitigation	Disb. level for adaptation		Disb. level for mitigation	Disb. level for adaptation
	2SLS			2SLS	
	No control			Weather controls	
	(1)	(2)		(1)	(2)
Instrument for mitigation	0.0766*** (0.0166)	0.0384* (0.0216)	Instrument for mitigation	0.0666*** (0.0185)	0.0337 (0.0248)
Instrument for adaptation	0.0158 (0.0103)	0.2254*** (0.0379)	Instrument for adaptation	0.0065 (0.0109)	0.1909*** (0.0262)
Controls: weather shocks			Controls: weather shocks	✓	✓
Controls: weather × freq. of exposure			Controls: weather × freq. of exposure	✓	✓
Controls: non-climate aid (lag)			Controls: non-climate aid (lag)		
Controls: conflicts, population			Controls: conflicts, population		
Observations	120,876	120,876	Observations	114,366	114,366
Wald (1st stage), stat.	13.080	18.397	Wald (1st stage), stat.	6.6507	27.171
Kleibergen-Paap Wald p-value (1st stage)	2.09×10^{-6}	1.03×10^{-8}	Kleibergen-Paap Wald p-value (1st stage)	0.00129	1.59×10^{-12}
Cragg-Donald F-test stat (1st stage)	42.636	327.27	Cragg-Donald F-test stat (1st stage)	27.776	552.03
Cragg-Donald F-test p-value (1st stage)	3.09×10^{-19}	1.8×10^{-142}	Cragg-Donald F-test p-value (1st stage)	8.71×10^{-13}	2.62×10^{-239}
Country × year FE	✓	✓	Country × year FE	✓	✓
Cell FE	✓	✓	Cell FE	✓	✓

	Disb. level for mitigation	Disb. level for adaptation		Disb. level for mitigation	Disb. level for adaptation
	2SLS			2SLS	
	All controls, country × year FE			All controls, ADMIN1 × year FE	
	(1)	(2)		(1)	(2)
Instrument for mitigation	0.0488** (0.0204)	0.0009 (0.0147)	Instrument for mitigation	0.0634*** (0.0163)	-0.0062 (0.0117)
Instrument for adaptation	-0.0164 (0.0202)	0.1639*** (0.0255)	Instrument for adaptation	-0.0198 (0.0193)	0.1370*** (0.0278)
Controls: weather shocks	✓	✓	Controls: weather shocks	✓	✓
Controls: weather × freq. of exposure	✓	✓	Controls: weather × freq. of exposure	✓	✓
Controls: non-climate aid (lag)	✓	✓	Controls: non-climate aid (lag)	✓	✓
Controls: conflicts, population	✓	✓	Controls: conflicts, population	✓	✓
Observations	114,280	114,280	Observations	114,280	114,280
Wald (1st stage), stat.	4.8743	20.688	Wald (1st stage), stat.	9.2976	15.804
Kleibergen-Paap Wald p-value (1st stage)	0.00764	1.04×10^{-9}	Kleibergen-Paap Wald p-value (1st stage)	9.17×10^{-5}	1.37×10^{-7}
Cragg-Donald F-test stat (1st stage)	13.949	366.29	Cragg-Donald F-test stat (1st stage)	24.591	221.68
Cragg-Donald F-test p-value (1st stage)	8.76×10^{-7}	2.72×10^{-159}	Cragg-Donald F-test p-value (1st stage)	2.1×10^{-11}	8.62×10^{-97}
Country × year FE	✓	✓	ADMIN1 × year FE	✓	✓
Cell FE	✓	✓	Cell FE	✓	✓

Notes: All columns display the first stages of the 2SLS regressions of Table C.13. Each table corresponds to the specification denoted in the header. ***, **, and * reveal significance at the 1%, 5% and 10% level, respectively. Standard errors are clustered at the cell level. Kleibergen-Paap Wald statistic and Cragg-Donald F-test statistic are reported for all columns.

C.2.3 Mechanisms

Table C.17: Climate aid, deforestation, and market access: first stage

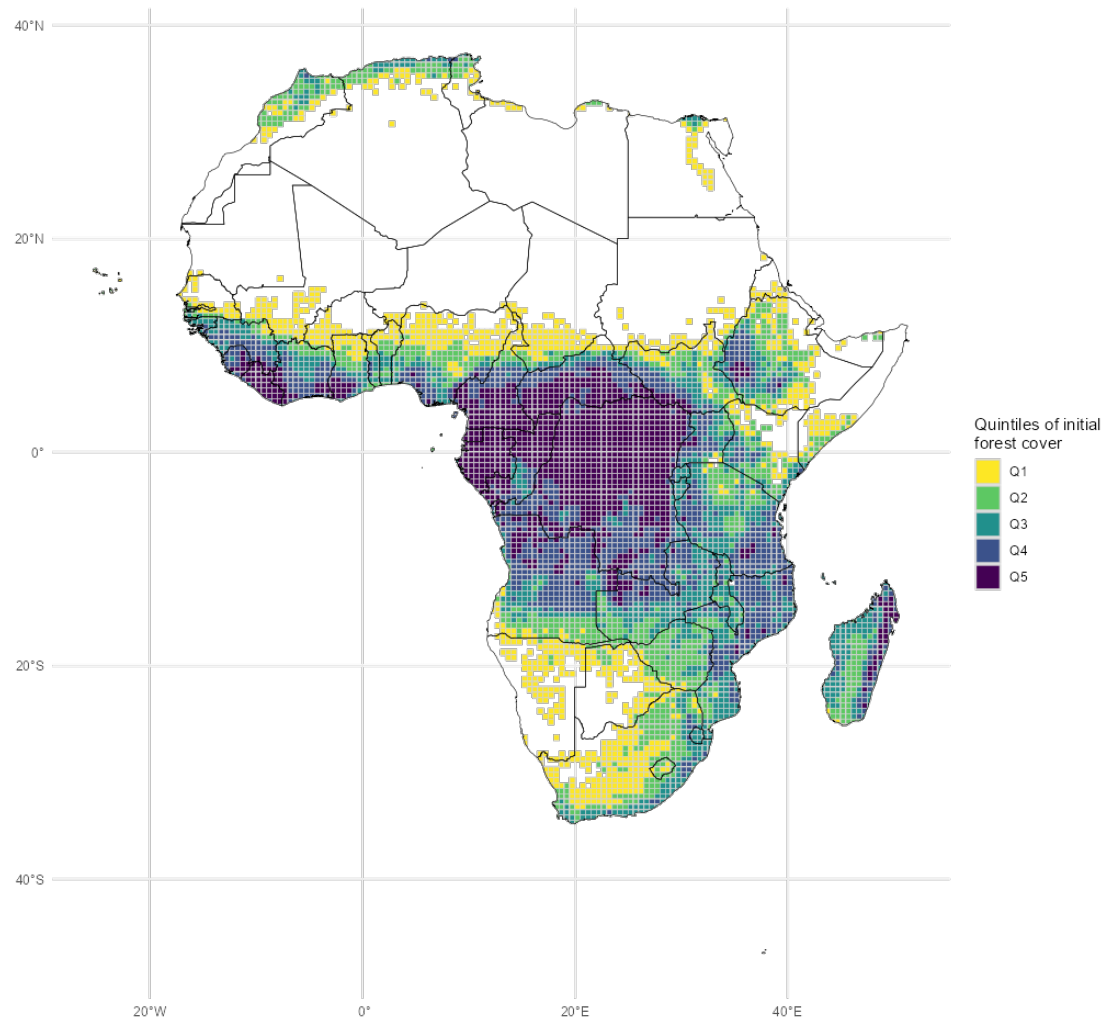
	Disb. level 2SLS			
	(1)	(2)	(3)	(4)
Instrument	0.1987*** (0.0293)	0.1753*** (0.0286)	0.1278*** (0.0337)	0.1474*** (0.0333)
Market access (log)	-0.0353 (0.0501)	-0.0313 (0.0456)	-0.0337 (0.0455)	0.0254 (0.0221)
Controls: weather shocks		✓	✓	✓
Controls: weather $\times$ freq. of exposure		✓	✓	✓
Controls: non-climate aid (lag)			✓	✓
Controls: conflicts, population			✓	✓
Observations	87,342	83,866	83,833	83,833
Kleibergen-Paap Wald p-value (1st stage)	1.17×10^{-11}	8.53×10^{-10}	0.00015	9.84×10^{-6}
Cragg-Donald F-test stat (1st stage)	297.00	396.69	202.77	234.19
ADMIN1 $\times$ year FE				✓
Country $\times$ year FE	✓	✓	✓	
Cell FE	✓	✓	✓	✓

Notes: All columns display the first stages of the 2SLS regressions of Table 9. The columns (1-4) dependent variable is the level of disbursement of climate aid. The independent variable is the instrument. ***, **, and * reveal significance at the 1%, 5% and 10% level, respectively. Cell and country $\times$ year fixed-effects are used in all columns. Cell and ADMIN1 $\times$ year fixed-effects are used in all columns. Weather shock controls, included in columns (2-4), denote average precipitation, temperature, and SPEI, as well as two dummies of extreme temperature. Weather $\times$ frequency of exposure, included in columns (3-4), denotes the interaction of the average weather controls with the share of the instrument. Non-climate aid (lag), included in columns (3-4), denotes the interaction of the level of disbursement of non-climate aid with years. Conflicts and population, included in columns (3-4), denote the number of conflicts and of inhabitants. Standard errors are clustered at the cell level. Kleibergen-Paap Wald statistic and Cragg-Donald F-test statistic are reported for all columns.

C.3 Mechanisms and heterogeneity maps

C.3.1 Quintiles of initial forest cover

Figure C.7: Quintiles of forest cover in 2000



Note: Data are sourced from the GFC database ([Hansen et al., 2013](#)), which gives baseline tree cover values that have been aggregated at the cell level and then classified into quintiles.

C.3.2 Heterogeneity on quintiles with outcome in relative terms

Table C.18: Climate aid, percentage of tree cover loss, and initial forest cover: IV estimates

	Percentage of tree cover loss			
	2SLS			
	(1)	(2)	(3)	(4)
Disb. level $\times$ Forest cover[Q1]	-0.0001 (8.83×10^{-5})	-0.0001 (9.73×10^{-5})	-0.0001 (9.87×10^{-5})	4.58×10^{-5} (9.96×10^{-5})
Disb. level $\times$ Forest cover[Q2]	$5.48 \times 10^{-5***}$ (1.99×10^{-5})	$6.74 \times 10^{-5***}$ (2.57×10^{-5})	$9.69 \times 10^{-5**}$ (3.81×10^{-5})	$4.26 \times 10^{-5**}$ (2×10^{-5})
Disb. level $\times$ Forest cover[Q3]	$7.04 \times 10^{-5***}$ (1.44×10^{-5})	$7.45 \times 10^{-5***}$ (1.77×10^{-5})	$9.49 \times 10^{-5***}$ (3.26×10^{-5})	$5.11 \times 10^{-5***}$ (1.98×10^{-5})
Disb. level $\times$ Forest cover[Q4]	$0.0001***$ (3.36×10^{-5})	$0.0001***$ (3.69×10^{-5})	$0.0001***$ (4.78×10^{-5})	$5 \times 10^{-5**}$ (1.99×10^{-5})
Disb. level $\times$ Forest cover[Q5]	$0.0001***$ (2.82×10^{-5})	$9.27 \times 10^{-5**}$ (3.72×10^{-5})	$0.0001**$ (4.61×10^{-5})	$6.29 \times 10^{-5**}$ (2.91×10^{-5})
Controls: weather shocks		✓	✓	✓
Controls: weather $\times$ freq. of exposure		✓	✓	✓
Controls: non-climate aid (lag)			✓	✓
Controls: conflicts, population			✓	✓
Observations	120,876	114,366	114,280	114,280
Kleibergen-Paap Wald stat, Quintile	1.5783	1.9493	2.1478	1.2608
Kleibergen-Paap Wald stat, Quintile	2.7149	2.8687	3.7961	4.9454
Kleibergen-Paap Wald stat, Quintile	8.3294	7.4009	9.7668	10.480
Kleibergen-Paap Wald stat, Quintile	6.0391	6.0026	5.5231	3.6925
Kleibergen-Paap Wald stat, Quintile	4.1520	5.0051	4.8197	6.3119
Dependent variable mean	7.87×10^{-5}	7.9×10^{-5}	7.9×10^{-5}	7.9×10^{-5}
ADMIN1 $\times$ year FE				✓
Country $\times$ year FE	✓	✓	✓	
Cell FE	✓	✓	✓	✓

Notes: Columns (1-4) are 2SLS regressions. Columns (1-4) dependent variable is the percentage of tree cover loss. The independent variable is the level of disbursement in million constant 2014 USD of climate aid projects, interacted with quintiles of initial forest cover area in 2000. ***, **, and * reveal significance at the 1%, 5% and 10% level, respectively. Cell and country $\times$ year fixed-effects are used in columns (1-3). Cell and ADMIN1 $\times$ year fixed-effects are used in column (4). Weather shock controls, included in columns (2-4), denote average precipitation, temperature, and SPEI, as well as two dummies of extreme temperature. Weather $\times$ frequency of exposure, included in columns (3-4), denotes the interaction of the average weather controls with the share of the instrument. Non-climate aid (lag), included in columns (3-4), denotes the one-year lag level of disbursement of non-climate aid. Conflicts and population, included in columns (3-4), denote the number of conflicts and of inhabitants. Standard errors are clustered at the cell level. Kleibergen-Paap Wald statistics are reported for all columns.

C.3.3 Benchmark results with similar sample

Table C.19: Climate aid and deforestation: OLS and IV estimates (subsample)

	Deforested area 2SLS			
	(1)	(2)	(3)	(4)
Disb. level	0.554*** (0.140)	0.494*** (0.143)	0.475** (0.228)	0.222 (0.178)
Controls: weather shocks		✓	✓	✓
Controls: weather $\times$ freq. of exposure		✓	✓	✓
Controls: non-climate aid (lag)			✓	✓
Controls: conflicts, population			✓	✓
Observations	87,312	83,856	83,823	83,823
Kleibergen-Paap Wald stat, Disb. level	45.999	37.524	14.359	19.546
Dependent variable mean	2.4426	2.5147	2.5157	2.5157
ADMIN1 $\times$ year FE				✓
Country $\times$ year FE	✓	✓	✓	
Cell FE	✓	✓	✓	✓

Notes: Columns (1-4) 2SLS regressions. Columns (1-4) dependent variable is the deforested area, in million square meters. The independent variable is the level of disbursement in million constant 2014 USD of climate aid projects. ***, **, and * reveal significance at the 1%, 5% and 10% level, respectively. Cell and country $\times$ year fixed-effects are used in columns (1-3). Cell and ADMIN1 $\times$ year fixed-effects are used in column (4). Weather shock controls, included in columns (2-4), denote average precipitation, temperature, and SPEI, as well as two dummies of extreme temperature. Weather $\times$ frequency of exposure, included in columns (3-4), denotes the interaction of the average weather controls with the share of the instrument. Non-climate aid (lag), included in columns (3-4), denotes the one-year lag level of disbursement of non-climate aid. Conflicts and population, included in columns (3-4), denote the number of conflicts and of inhabitants. Standard errors are clustered at the cell level. Kleibergen-Paap Wald statistic is reported for all columns.

D Sensitivity

D.1 Dealing with zeros: are outliers driving the results?

Binary treatment of climate aid. Climate aid could affect forests through several channels: *via* the intensive margin (e.g. the level of USD disbursed in each cell for climate-related aid projects), or *via* the extensive margin (e.g. whether a climate-related aid project is implemented in a specific cell). In this subsection, we focus on the latter definition of climate aid. We redefine our treatment as a dummy variable that takes the value of 1 if a positive disbursement of climate aid is allocated to cell i in the country c at time t . Using this definition of climate aid helps address the large share of zero values in the independent variable definition.

Table D.20: Binary treatment of climate aid and deforestation: OLS and IV estimates

	OLS	Deforested area 2SLS			
	(1)	(2)	(3)	(4)	(5)
Treatment	0.824*** (0.212)	4.48*** (0.726)	3.37*** (0.620)	2.47*** (0.629)	1.45** (0.675)
Controls: weather shocks			✓	✓	✓
Controls: weather $\times$ freq. of exposure			✓	✓	✓
Controls: non-climate aid (lag)				✓	✓
Controls: conflicts, population				✓	✓
Observations	120,876	120,876	114,366	114,280	114,280
Kleibergen-Paap Wald stat, Treatment		290.44	272.60	246.39	213.95
Dependent variable mean	3.0849	3.0849	3.2007	3.2031	3.2031
ADMIN1 $\times$ year FE					✓
Country $\times$ year FE		✓	✓	✓	
Cell FE		✓	✓	✓	✓

Notes: Column (1) displays an OLS regression, and columns (2-5) 2SLS regressions. First-stage regressions of the columns (2-5) are displayed in Table D.21. Columns (1-5) dependent variable is the deforested area, in square meters. The independent variable is a dummy variable equal to 1 if the cell is treated. ***, **, and * reveal significance at the 1%, 5% and 10% level, respectively. Cell and country $\times$ year fixed-effects are used in columns (2-4). Cell and ADMIN1 $\times$ year fixed-effects are used in columns (5). Weather shock controls, included in columns (3-5), denote average precipitation, temperature, and SPEI, as well as two dummies of extreme temperature. Weather $\times$ frequency of exposure, included in columns (4-4), denotes the interaction of the average weather controls with the share of the instrument. Non-climate aid (lag), included in columns (4-5), denotes the one-year lag level of disbursement of non-climate aid. Conflicts and population, included in columns (4-5), denote the number of conflicts and of inhabitants. Standard errors are clustered at the cell level. Kleibergen-Paap Wald statistic is reported for all columns.

Table D.20 presents the OLS and IV results using this definition of climate aid. The marginal coefficients for the effect of the treatment on deforested areas are all positive and statistically significant. The Kleibergen-Paap statistics for the treatment variable exceed the conventional threshold, suggesting that the instrument is strong and relevant for this new definition of the treatment variable. Nevertheless, the binary expression of the treatment results in a lower estimated deforestation effect of climate aid projects. When climate aid is allocated to a cell of a country at a certain time (1 SD), deforestation increases by around 0.76 square kilometers, which is equivalent to one-tenth of the typical variation in deforestation (0.1 SD, in square kilometers). The effect of the binary treatment is smaller than that of the level of disbursement, which includes a large share of zeros. This outcome suggests that the potential bias arising from this large share of zeros that inflates the estimated effect may exist, but does not influence either the sign or the significance of the results.

Log transformation of deforestation. We try to replicate our results in enabling the transformation of the deforested area into a logarithmic form (see histogram D.8). We acknowledge that

Table D.21: Binary treatment of climate aid and deforestation: first stage

	Treatment 2SLS			
	(1)	(2)	(3)	(4)
Instrument	0.258*** (0.015)	0.258*** (0.016)	0.249*** (0.016)	0.266*** (0.018)
Controls: weather shocks		✓	✓	✓
Controls: weather $\times$ freq. of exposure		✓	✓	✓
Controls: non-climate aid (lag)			✓	✓
Controls: conflicts, population			✓	✓
Observations	120,876	114,366	114,280	114,280
Kleibergen-Paap Wald p-value (1st stage)	4.76×10^{-65}	3.63×10^{-61}	1.82×10^{-55}	2.12×10^{-48}
Cragg-Donald F-test stat (1st stage)	2,415.2	2,044.1	1,797.9	1,773.2
ADMIN1 $\times$ year FE				✓
Country $\times$ year FE	✓	✓	✓	
Cell FE	✓	✓	✓	✓

Notes: All columns display the first stages of the 2SLS regressions of Table D.20. All columns' dependent variable is the dummy variable of the treatment of each cell. The independent variable is the instrument. ***, **, and * reveal significance at the 1%, 5% and 10% level, respectively. Cell and country $\times$ year fixed-effects are used in columns (1-3). Cell and ADMIN1 $\times$ year fixed-effects are used in columns (4). Weather shock controls, included in columns (2-4), denote average precipitation, temperature, and SPEI, as well as two dummies of extreme temperature. Weather $\times$ frequency of exposure, included in columns (2-4), denotes the interaction of the average weather controls with the share of the instrument. Non-climate aid (lag), included in columns (3-4), denotes the interaction of the level of disbursement of non-climate aid with years. Conflicts and population, included in columns (3-4), denote the number of conflicts and of inhabitants. Standard errors are clustered at the cell level. Kleibergen-Paap Wald statistic and Cragg-Donald F-test statistic are reported for all columns.

this restriction substantially alters the composition of our analytical sample, making the results incomparable to those obtained from the full dataset in Section 5.1. However, this approach allows us to test our specification on a distinct subset of observations while eliminating the impact of potential outliers.

The results presented in Table D.22 compare OLS and 2SLS estimates of the effect of the level of disbursement of climate aid on deforestation, where the dependent variable is expressed in logarithmic form. Columns (2-5) present the 2SLS estimates, with specifications that sequentially include additional controls. Marginal coefficients are positive and significant for columns (2-3). On average, a 1-unit increase in climate aid disbursement is associated with about 29% increase in the deforested area, holding all else constant. These results are comparable to the benchmark

results displayed in 5.1. However, a critical concern arises for columns (5), with coefficients still positive but insignificant. This issue likely stems from the reduced number of observations available in the 2SLS specifications, but also from the assumptions made on the relationship between the dependent variable and the controls. The results underscore a positive relationship between climate aid and deforestation, but the latter concerns suggest caution in interpreting these estimates.

Table D.22: Climate aid and (log) deforestation: OLS and IV estimates

	OLS	Deforested area (in log)			
		2SLS			
	(1)	(2)	(3)	(4)	(5)
Disb. level	-0.011*	0.318***	0.271**	0.290**	0.170
	(0.006)	(0.098)	(0.108)	(0.130)	(0.159)
Controls: weather shocks			✓	✓	✓
Controls: weather $\times$ freq. of exposure			✓	✓	✓
Controls: non-climate aid (lag)				✓	✓
Controls: conflicts, population				✓	✓
Observations	98,873	98,873	93,786	93,728	93,728
Kleibergen-Paap Wald stat, Disb. level		51.217	46.631	39.944	29.396
Dependent variable mean	-0.94304	-0.94304	-0.88596	-0.88341	-0.88341
ADMIN1 $\times$ year FE					✓
Country $\times$ year FE		✓	✓	✓	
Cell FE		✓	✓	✓	✓

Notes: Column (1) displays an OLS regression, and columns (2-5) 2SLS regressions. First-stage regressions of the columns (2-5) are displayed in Table D.23. Columns (1-5) dependent variable is the log transformation of the deforested area, in million square meters. The independent variable is the level of disbursement of climate aid by cell. ***, **, and * reveal significance at the 1%, 5%, and 10% level, respectively. Cell and country $\times$ year fixed-effects are used in columns (2-4). Cell and ADMIN1 $\times$ year fixed-effects are used in columns (5). Weather shock controls, included in columns (3-5), denote average precipitation, temperature, and SPEI, as well as two dummies of extreme temperature. Weather $\times$ frequency of exposure, included in columns (4-4), denotes the interaction of the average weather controls with the share of the instrument. Non-climate aid (lag), included in columns (4-5), denotes the one-year lag level of disbursement of non-climate aid. Conflicts and population, included in columns (4-5), denote the number of conflicts and of inhabitants. Standard errors are clustered at the cell level. Kleibergen-Paap Wald statistic is reported for all columns.

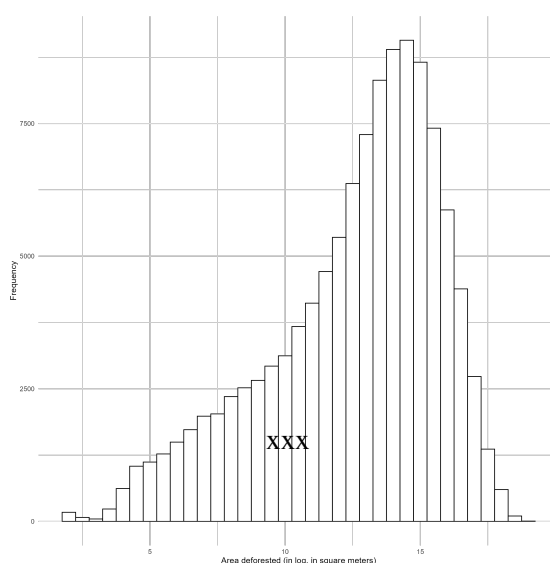
Table D.23: Climate aid and (log) deforestation: first stage

	Disb. level 2SLS			
	(1)	(2)	(3)	(4)
Instrument	0.4721*** (0.0660)	0.4119*** (0.0603)	0.3390*** (0.0536)	0.2835*** (0.0523)
Controls: weather shocks		✓	✓	✓
Controls: weather $\times$ freq. of exposure		✓	✓	✓
Controls: non-climate aid (lag)			✓	✓
Controls: conflicts, population			✓	✓
Observations	98,873	93,786	93,728	93,728
Kleibergen-Paap Wald p-value (1st stage)	8.33×10^{-13}	8.62×10^{-12}	2.63×10^{-10}	5.92×10^{-8}
Cragg-Donald F-test stat (1st stage)	346.00	379.03	255.23	233.65
ADMIN1 $\times$ year FE				✓
Country $\times$ year FE	✓	✓	✓	
Cell FE	✓	✓	✓	✓

Notes: All columns display the first stages of the 2SLS regressions of Table D.22. All columns' dependent variable is the level of disbursement of climate aid. The independent variable is the instrument. ***, **, and * reveal significance at the 1%, 5% and 10% level, respectively. Cell and country $\times$ year fixed-effects are used in columns (1-3). Cell and ADMIN1 $\times$ year fixed-effects are used in columns (4). Weather shock controls, included in columns (2-4), denote average precipitation, temperature, and SPEI, as well as two dummies of extreme temperature. Weather $\times$ frequency of exposure, included in columns (2-4), denotes the interaction of the average weather controls with the share of the instrument. Non-climate aid (lag), included in columns (3-4), denotes the interaction of the level of disbursement of non-climate aid with years. Conflicts and population, included in columns (3-4), denote the number of conflicts and of inhabitants. Standard errors are clustered at the cell level. Kleibergen-Paap Wald statistic and Cragg-Donald F-test statistic are reported for all columns.

D.2 Histogram of deforested areas

Figure D.8: Histogram of the deforested areas, in log



D.3 Alternative deforestation metrics

Table D.24: Climate aid and percentage of tree cover loss: OLS and IV estimates

	OLS	Percentage of tree cover loss		
		2SLS		
	(1)	(2)	(3)	(4)
Disb. level	0.0003 (0.0002)	0.047*** (0.013)	0.055*** (0.017)	0.069** (0.029)
Controls: weather shocks			✓	✓
Controls: weather $\times$ freq. of exposure			✓	✓
Controls: non-climate aid (lag)				✓
Controls: conflicts, population				✓
Observations	120,876	120,876	114,366	114,280
Kleibergen-Paap Wald stat, Disb. level		54.315	44.654	20.051
Dependent variable mean	0.07873	0.07873	0.07898	0.07904
Country $\times$ year FE	✓	✓	✓	✓
Cell FE	✓	✓	✓	✓

Notes: Column (1) displays an OLS regression, and columns (2-4) 2SLS regressions. Columns (1-4) dependent variable is the percentage of tree cover loss. The independent variable is the level of disbursement of climate aid by cell. ***, **, and * reveal significance at the 1%, 5%, and 10% level, respectively. Cell and country $\times$ year fixed-effects are used in columns (2-4). Weather shock controls, included in columns (3-4), denote average precipitation, temperature, and SPEI, as well as two dummies of extreme temperature. Weather $\times$ frequency of exposure, included in column (4), denotes the interaction of the average weather controls with the share of the instrument. Non-climate aid (lag), included in column (4), denotes the one-year lag level of disbursement of non-climate aid. Conflicts and population, included in column (4), denote the number of conflicts and of inhabitants. Standard errors are clustered at the cell level. Kleibergen-Paap Wald statistic is reported for all columns.

D.4 Stricter definition of forested pixels

Figure D.9: Forest cover area in 2000 with different pixel-level thresholds of forest definition

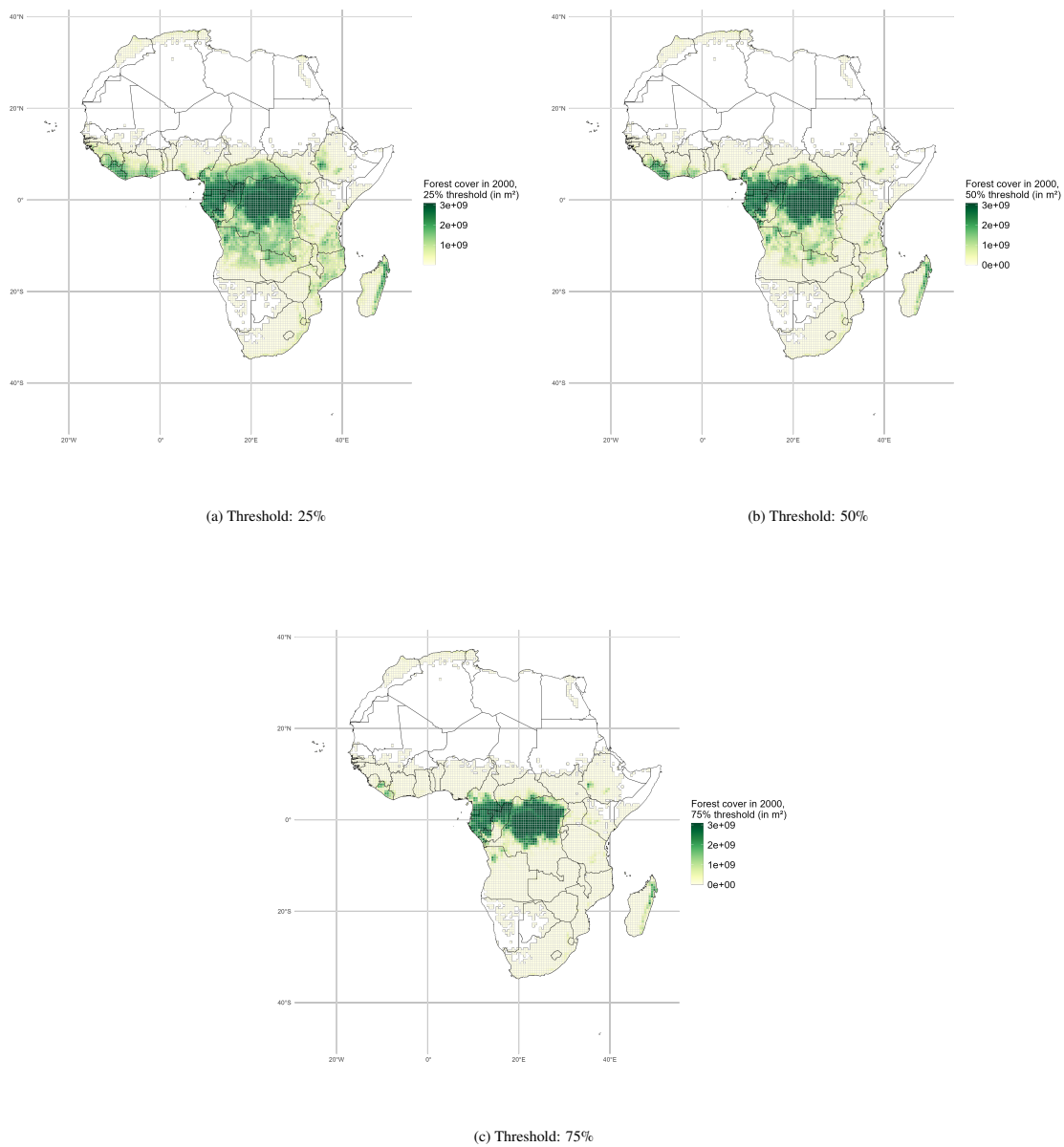


Table D.25: Climate aid and deforested area: IV estimates for different thresholds of baseline tree cover

	Threshold: 25%	Threshold: 50% 2SLS	Threshold: 75%
	Deforested area		
	(1)	(2)	(3)
Disb. level	0.944*** (0.337)	0.875*** (0.303)	0.365** (0.168)
Controls: weather shocks	✓	✓	✓
Controls: weather × freq. of exposure	✓	✓	✓
Controls: non-climate aid (lag)	✓	✓	✓
Controls: conflicts, population	✓	✓	✓
Observations	114,280	114,280	114,280
Kleibergen-Paap Wald stat, Disb. level	20.051	20.051	20.051
Dependent variable mean	3.2031	2.5795	1.5224
Country × year FE	✓	✓	✓
Cell FE	✓	✓	✓

Notes: Columns (1-4) display 2SLS regressions. Columns (1-4) dependent variable is the deforested area, with the forested area being defined according to different percentage thresholds of initial tree cover. The independent variable is the level of disbursement of climate aid by cell. ***, **, and * reveal significance at the 1%, 5%, and 10% level, respectively. Cell and country × year fixed-effects are used in columns (1-4). Weather shock controls, included in columns (1-4), denote average precipitation, temperature, and SPEI, as well as two dummies of extreme temperature. Weather × frequency of exposure, included in columns (1-4), denotes the interaction of the average weather controls with the share of the instrument. Non-climate aid (lag), included in columns (1-4), denotes the interaction of the level of disbursement of non-climate aid with years. Conflicts and population, included in columns (1-4), denote the number of conflicts and of inhabitants. Standard errors are clustered at the cell level. Kleibergen-Paap Wald statistic is reported for all columns.

E Robustness

E.1 Spatial auto-correlation

Table E.26: Climate aid and deforested area: IV estimates with Conley-HAC standard error

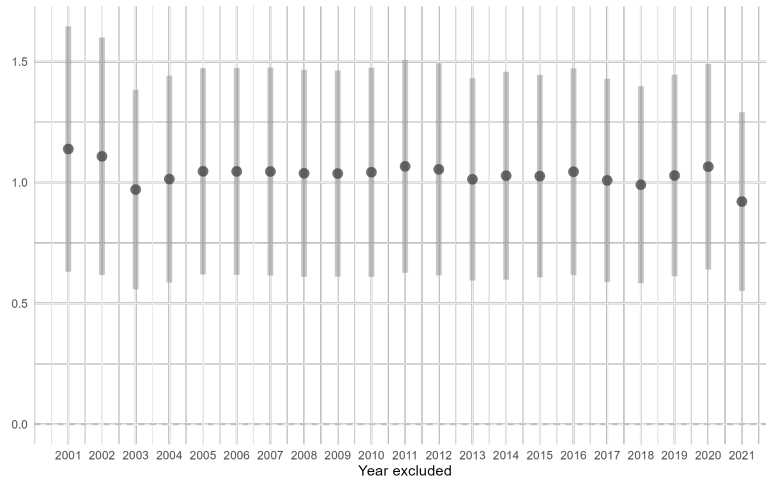
Radius	Deforested area 2SLS			
	50km	100km	200km	500km
	(1)	(2)	(3)	(4)
Disb. level	1.22*** (0.448)	1.22** (0.476)	1.22** (0.475)	1.22*** (0.463)
Controls: weather shocks	✓	✓	✓	✓
Controls: weather $\times$ freq. of exposure	✓	✓	✓	✓
Controls: non-climate aid (lag)	✓	✓	✓	✓
Controls: conflicts, population	✓	✓	✓	✓
Observations	114,280	114,280	114,280	114,280
Kleibergen-Paap Wald stat, Disb. level	21.264	21.264	21.264	21.264
Dependent variable mean	3.2031	3.2031	3.2031	3.2031
Country $\times$ year FE	✓	✓	✓	✓
Cell FE	✓	✓	✓	✓

Notes: Columns (1-4) display 2SLS regressions. Columns (1-4) dependent variable is the deforested area, with forested area being defined according to different percentage thresholds of initial tree cover. The independent variable is the level of disbursement of climate aid by cell. ***, **, and * reveal significance at the 1%, 5%, and 10% level, respectively. Cell and country $\times$ year fixed-effects are used in columns (1-4). Weather shock controls, included in all columns, denote average precipitation, temperature, and SPEI, as well as two dummies of extreme temperature. Weather $\times$ frequency of exposure, included in all columns, denotes the interaction of the average weather controls with the share of the instrument. Non-climate aid (lag), included in all columns, denotes the interaction of the level of disbursement of non-climate aid with years. Conflicts and population, included in all columns, denote the number of conflicts and of inhabitants. We compute [Conley \(1999\)](#) standard errors allowing for spatial autocorrelation at different buffers. We also compute HAC standard errors. Conley-HAC standard errors stand for taking the more conservative option. Conley-HAC standard errors are reported between parentheses. Kleibergen-Paap Wald statistic is reported for all columns.

E.2 Bias in the two-way-fixed-effect estimates

E.2.1 Year bias

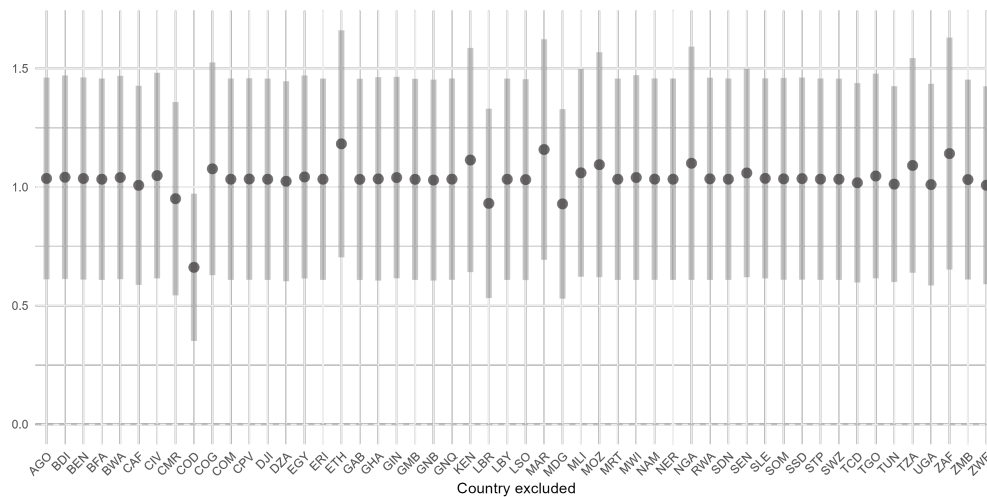
Figure E.10: Dropping years, one by one



Note: Each point estimate and confidence interval (at the 95% level) come from a regression from the benchmark specification, with all controls included, except one year that has been excluded and is displayed on the x-axis.

E.2.2 Country bias

Figure E.11: Dropping countries, one by one



Note: Each point estimate and confidence interval (at the 95% level) come from a regression from the benchmark specification, with all controls included, except one country that has been excluded and is displayed on the x-axis.

E.3 First difference

Table E.27: First difference for climate aid and deforestation: OLS and IV estimates

	OLS	Δ Deforested area			
		2SLS			
	(1)	(2)	(3)	(4)	(5)
Δ Disb. level	-0.0003 (0.002)	1.50*** (0.463)	1.57*** (0.481)	1.67*** (0.582)	1.60*** (0.514)
Controls: Δ weather shocks			✓	✓	✓
Controls: Δ weather $\times$ freq. of exposure			✓	✓	✓
Controls: Δ non-climate aid (lag)				✓	✓
Controls: Δ conflicts, Δ population				✓	✓
Observations	115,120	115,120	108,920	108,833	108,833
Kleibergen-Paap Wald stat, Δ Disb. level		20.440	19,974	12.285	25.016
Cragg-Donald F-test stat, Δ Disb. level		2.1269	4.3883	4.9826	4.5222
Dependent variable mean	0.13212	0.13212	0.13809	0.13820	0.13820
ADMIN1 $\times$ year FE					✓
Country $\times$ year FE	✓	✓	✓	✓	

Notes: Column (1) displays an OLS regression, and columns (2-5) 2SLS regressions. First-stage regressions of the columns (2-5) are displayed in Table E.28. Columns (1-5) dependent variable is the first difference of the deforested area, in million square meters. The independent variable is the first difference of the level of disbursement of climate aid by cell. ***, **, and * reveal significance at the 1%, 5%, and 10% level, respectively. Country $\times$ year fixed-effects are used in columns (2-4), and ADMIN1 $\times$ year fixed-effects are used in columns (5). Weather shock controls, included in columns (3-5), denote the first difference in average precipitation, temperature, and SPEI, as well as two dummies of extreme temperature. Weather $\times$ frequency of exposure, included in columns (4-4), denotes the interaction of the first difference in average weather controls with the share of the instrument. Non-climate aid (lag), included in columns (4-5), denotes the one-year lag, the first difference of the level of disbursement of non-climate aid. Conflicts and population, included in columns (4-5), denote the first difference of the number of conflicts and of inhabitants. Standard errors are clustered at the cell level. Kleibergen-Paap Wald and Cragg-Donald F-test statistics are reported for all columns.

Table E.28: First difference for climate aid and deforestation: first stage

	Δ Disb. level 2SLS			
	(1)	(2)	(3)	(4)
Δ Instrument	0.0028*** (0.0006)	0.0029*** (0.0007)	0.0031*** (0.0009)	0.0029*** (0.0006)
Controls: Δ weather shocks		✓	✓	✓
Controls: Δ weather $\times$ freq. of exposure		✓	✓	✓
Controls: Δ non-climate aid (lag)			✓	✓
Controls: Δ conflicts, Δ population			✓	✓
Observations	115,120	108,920	108,833	108,833
Kleibergen-Paap Wald stat (1st stage)	20.440	19.974	12.285	25.016
Kleibergen-Paap Wald p-value (1st stage)	6.16×10^{-6}	7.86×10^{-6}	0.00046	5.7×10^{-7}
Cragg-Donald F-test stat (1st stage)	2.1269	4.3883	4.9826	4.5222
Cragg-Donald F-test p-value (1st stage)	0.14474	0.03619	0.02561	0.03346
ADMIN1 $\times$ year FE				✓
Country $\times$ year FE	✓	✓	✓	

Notes: All columns display the first stages of the 2SLS regressions of Table E.27. All columns' dependent variable is the first difference of the level of disbursement of climate aid. The independent variable is the first difference of the instrument. ***, **, and * reveal significance at the 1%, 5% and 10% level, respectively. Country $\times$ year fixed-effects are used in columns (1-3), and ADMIN1 $\times$ year fixed-effects are used in columns (4). Weather shock controls, included in columns (2-4), denote the first difference in average precipitation, temperature, and SPEI, as well as two dummies of extreme temperature. Weather $\times$ frequency of exposure, included in columns (2-4), denotes the interaction of the first difference in average weather controls with the share of the instrument. Non-climate aid (lag), included in columns (3-4), denotes the interaction of the first difference of the level of disbursement of non-climate aid with years. Conflicts and population, included in columns (3-4), denote the first difference of the number of conflicts and of inhabitants. Standard errors are clustered at the cell level. Kleibergen-Paap Wald and Cragg-Donald F-test statistics are reported for all columns.