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AGROFORESTRY PROGRAMS IN THE COLOMBIAN AMAZON: SELECTION, TREATMENT AND EXPOSURE EFFECTS ON DEFORESTATION

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Agroforestry Programs in the Colombian Amazon:

Selection, Treatment and Exposure Effects on Deforestation

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Abstract

Tropical rainforests play a critical role in the fight against climate change. However, record high levels of deforestation have been experienced in the Amazon which, together with land use change, has led to loss of biodiversity and sustainable livelihoods. Agroforestry and silvo-pastoral conservation programs are particularly promising in this context because of their potential to simultaneously offer sustainable forest cover and support local livelihoods. Together with sustainable animal husbandry, they are critical in addressing the twin challenges of food security and climate change. But empirical estimates of the effectiveness of planned agroforestry on deforestation are largely absent. We study the effects of an innovative and ambitious agroforestry program, part of the UN REDD initiative in Colombia, upon deforestation in the Amazon. Enrolment on the program is not random but based on matching and choice. Achieving reduced deforestation through planned agroforestry is challenging. When selected farms undergo 'treatment' under the program, they initially experience reduction in secondary vegetation in the medium run (5-20 years). Using a quasi-experimental difference-in-differences approach, and both traditional and new econometric methods, we estimate treatment, exposure and selection effects. The findings emphasize that agroforestry programs can stall deforestation and even promote permanent forest cover. However, this requires continuous upscaling with continued and very rapid expansion of the program, entailing substantial costs to society but also significant return..

Significance

The world's tropical forests have been undergoing massive deforestation and degradation. Colombia covers about 10% of the total Amazon forest biome and has experienced loss of 2,220kha of tree cover in the 2000s (about 1,000Mt of CO_2 emissions). Various mitigation measures have been proposed, among which sustainable productive systems hold particular promise. They can offer food security together with reducing carbon emissions and reversing biodiversity loss. However, estimation of its effects on deforestation is challenging since planned agriculture induces rise in deforestation in the medium run through initial clearing of secondary vegetation. Hence, careful measurement of effects and placement is essential to achieve replenishment of forest cover. Using extensive data at the farm-level, and modern quasi-experimental difference-in-differences treatment effects models that can separate selection, treatment and exposure effects, we find that a unique agroforestry program implemented in the Colombian Amazon can restore forest cover fully. The best benefits require rapid roll-out of the program over time, and the costs are high, therefore needing careful resource planning. The finding that full replenishment of forest cover is achievable is very

promising, particularly in offering food security together with reducing carbon emissions and reversing biodiversity loss, together with supporting the fight against narcotics.

Classification: JEL Classification (C21; Q23; Q15; C55; Q56; C23).

Keywords: Agroforestry programs; Selection, Treatment and Exposure effects; Difference-in-differences; Colombian Amazon; Deforestation

Introduction

The Amazon rainforest absorbs vast amounts of atmospheric CO_2, keeping global climate and water cycles in balance and supporting biodiversity, food security, ecosystem services and, ultimately, humanity (1-3). However, the Amazon has been subjected to large and rising deforestation (4-8). The Colombian Amazon has the second highest deforestation and forest degradation rates after the Brazilian Amazon (9), reaching 0.38% per year in the early 2000s (8). Figure 1(a) shows the spatial deforestation profile in our study area and Figure 1(e) shows the aggregate deforestation patterns and trends in the Colombian Amazon. Over 75,000kha (kilo-hectares) of the Colombian rainforest have been destroyed in the past 50 years. One of the obvious consequences of deforestation is the fragmentation of natural ecosystems, leading to further degradation of vintage (primary) and secondary forests. Figure 1(d) shows Colombia within the context of Central and South America, while Figure 1(b) plots barren vegetation in the Colombian Amazon within Colombia; the contrast with deforestation patterns in Figure 1(a) is notable.

Changes to the ecosystem structure and their effects on the environment and sustainable livelihoods have been documented elsewhere (10-18). Also, substantial momentum for international efforts to reverse tropical deforestation have been developed together with various measures to restrict the pace of deforestation (18). Previous work has examined the effectiveness of protected area status and forest governance (20, 28-32), subsidies and finance (33-35), sustainability certifications (36-39), property rights (40-41), and supply-chains (42). In this context, the potential of planned agroforestry to combat and reverse deforestation, together with providing ecosystem services and environmental benefits, is gaining global prominence (25-27). However, there is a lack of information regarding estimates of treatment effects for agroforestry programs are lacking; for a notable exception, see (43). Therefore, in this study, we employ a quasi-experimental treatment effects setup (19-24) to examine quantitatively the effects of a sustainable productive agroforestry program implemented in the Colombian Amazon in reducing deforestation and restoring forest cover.

Colombia has been implementing climate policies since 2010, including the National Strategy for Reducing Emissions from Deforestation and Forest Degradation (ENREDD+), the National Adaptation Plan for Climate Change, and a National Climate Change Policy, leading into Colombia's ratification of the Paris Agreement in 2017 and the country's Nationally Determined Contribution (NDC). The Colombian National Development Plan (NDP) 2014-2018 aimed to establish, in an articulated manner, climate change mitigation and adaptation strategies by increasing resilience and reducing the carbon intensity in the economy, at the same time as building peace and overcoming poverty through resilient development (44). The AFOLU sector (agriculture, forestry and other land uses) is a key component of this economy-wide target. In this context, agro-forestry and silvopastoral systems are recognized as offering great mitigation potential in the country.

To combat deforestation, forest degradation and poverty, Colombia is implementing a United Nations REDD (Reduced Emissions from Deforestation and forest Degradation) Early Movers Program called 'Visión

Amazonia'. The sustainable productive systems component (agroforestry, silvo-pastoral arrangements and conservation agreements) of 'Visión Amazonia' is pioneered by the premier research organization of the Colombian government, the Instituto Amazónico de Investigaciones Científicas SINCHI (Amazonian Scientific Research Institute, henceforth SINCHI). SINCHI has signed bespoke agreements with selected farmers in the Colombian Amazon region that enable preservation of existing forest through alternative and economically viable agroforestry land use models. The validation and quantification of these tailored conservation agreements and their efficiency in reducing deforestation, enhancing biodiversity and promoting sustainable agriculture is still pending, leaving a critical knowledge gap.

In this study, we evaluate the effect of these agreements with farmers (contrasting treated farms subjected to the SINCHI agroforestry program with control farms) upon deforestation outcomes at the farm level using a quasi-experimental treatment effects framework. Our central object is to develop an econometric treatment effects model for planning and predicting productive forest restoration, using agricultural production, monitoring and environmental data collected by SINCHI for the implementation and monitoring of their programs. Importantly, the SINCHI treatment does not involve any financial compensation, but rather focusses on providing farmers with knowledge, training and expertise that enables them to plan and implement agroforestry models on their farms; for further details, see Figure 2 and references therein. These agroforestry models are designed to be economically sustainable and restore forest cover in the long run, thereby providing profitable but environmentally friendly livelihoods as viable alternatives to cattle ranching and illegal coca cultivation.

Deforestation in the Colombian Amazon. Colombia, the fourth largest country of South America, is the second most biologically diverse country in the world after Brazil (46-47). It is home to about 10% of the Amazonian basin rainforest, representing an area of around 48,300kha (45), with Brazil covers another 60% of the Amazon biome. The Colombian Amazon is located in the southern Amazonía region of the country and includes the departments of Amazonas, Caquetá, Guainía, Guaviare, Putumayo and Vaupés (Figure 1(b), (e)). Each department comprises multiple municipalities. Most of the Colombian population is concentrated in the Andean and coastal regions, and the population density in the Amazon is low.

Despite high deforestation, about 90% of the Colombian Amazon is still covered by pristine humid tropical forests. These forest ecosystems represent 42% of the country´s land territory, providing key ecosystem services and climate regulatory functions. This vast area is under increasing threat from multiple stress factors, both human and natural. In the 1980s and 1990s, the presence of illegal armed groups and the expansion of illicit crops led to massive land clearing (48). Insecurity of life and livelihoods partly aided by decades of armed conflict and violence, a general lack of governmental presence and environmental planning, unsustainable land use patterns, illegal land grab and mining, drug cultivation and trafficking, and climate change are aspects of this combined pressure. This has resulted in a 40% increase in deforestation and a significant loss of biodiversity over the past 15 years. The department of Caquetá (0.92%) has the highest rate of deforestation (46), followed by Guaviare (0.80%), in part due to lack of clear government policy on forest conservation and political instability. Between 1990 and 2016, deforestation has been estimated to cover over 6,000kha.

An estimated 200kha, 25kha and 15kha of forest cover are being lost per year, due to pasturing, mining and illegal crops, respectively (49). Around 7% of the deforested areas are used for agriculture, while 50% is converted into grasslands (50). According to the 2018 International Monetary Fund (IMF) country report for Colombia, illegal activities account for 6.3% of the GDP of the country, but the 33.5% share of informal sector may also be related to these activities. In addition, illegal activities are more prevalent in border areas and drug exit corridors, areas of greater conflict and areas deeper in the core forest but with access to water transport (49). Since 2016, Colombia is implementing a difficult peace accord after 50 years of conflict. Land tenure and access to resources are key aspects of this process. Negative effects, including lack of governmental presence, unsustainable land use, land grabbing and illicit crops have increased dramatically. Strong acceleration of deforestation is also reported following the peace agreement between the Colombian government and the FARC forces (46, 51-52).

Progressive deforestation and loss of biodiversity have had severe impacts upon society in the region, combining indigenous communities (which own almost half of the land), immigrant farmers and cattle ranchers. This is despite the fact that farming and ranching activities are part of the problem. While these activities generate some income for local communities and farmers, they also thrive on deforested and reclaimed forest land. The impact of human factors in deforestation and degradation of the Colombian Amazon rainforest is clearly evidenced, with cattle ranching and illicit crops such as coca farming being the leading drivers (53). High poverty and limited access to education and health services are tradeoffs of this negative trend/vicious cycle that persist across the region, slowing or excluding social development and innovation.

SINCHI agroforestry program. Given the high level of environmental degradation in the Colombian Amazon and its socio-cultural and economic implications, initiatives to reduce or reverse deforestation are highly relevant. Sustainable productive systems based on agroforestry and silvo-pastoral arrangements may provide economically viable and ecologically sustainable productive alternatives. Based on current knowledge of agroforestry, climate systems and local agricultural systems, including native and indigenous knowhow, SINCHI has pioneered development and implementation of a set of long-term environmental and economically sustainable agroforestry models in the Colombian Amazon (54-55). These models comprise planned cultivation of a mix of agricultural products and associated technologies that combine subsistence crops (such as tubers, coffee, vegetables – *Pancoger*), fruits (including cocoa, copuazu – *Frutal/Copoazú*), cash crops (mainly rubber – *Caucho*) and timber (*Maderables*). Each model presents an organization plan of trees in a geometric arrangement with scientifically determined planting distances (Figure 2). Figure 2 also shows that different products need different gestation times for full growth, the longest being fully grown forests producing high value products, like timber.

Based on these models, SINCHI approached individual farmers mainly through farmers' associations and offered knowhow and technological support to choose the models that would me most appropriate for their farm and help them in its implementation. This is a purely knowledge exchange intervention (program) and involved no monetary transaction. Some farms are selected into the program (treated farms) based on willingness of both SINCHI and the farms to participate in the program, while others are not (control farms). Once a farm enrols on the program and starts implementing the chosen agroforestry model, the secondary vegetation is partially cleared to allow the implementation of the agroforestry or silvo-pastoral system. This implies that there is an initial increase in deforestation to allow future forest reconstruction. The SINCHI program aimed at incentivizing farmers, through access to technology, to establish the new agroforestry systems in exchange for setting aside a proportion of the native forest present in their farms with the promise of conserving it through a voluntary conservation agreement.

The analysis and evaluation of the program outcomes are currently lacking as are statistical/econometric models to support planning and decision-making at the community and wider landscape levels. As part of its agroforestry program, SINCHI has also pioneered the collection of three datasets. The first is on geo-ecological satellite raster data on a wide range of environmental, topographical and forest cover variables that is spatially granular up to about 100 hectares. For comparison, this is about the average size of an agricultural farm in the Colombian Amazon. Second, SINCHI collated farm-level agricultural production data, collected at a 2-5 year frequency in direct partnership with local communities and regulatory organizations. Third, and more recently, SINCHI created a dataset for monitoring the progress of the selected farms with their implementation of the agroforestry programs and compliance with agreed deforestation reduction targets.

These data are operational tools for SINCHI's own work and as such not immediately applicable for research. This study created a new dataset combining SINCHI's three databases, fully anonymized, conforming to data protection principles, and useful for research. This new database is unique in its content and structure and fundamentally enhances SINCHI's established intervention strategies. SINCHI's farm production database enables the selection of suitable farms, and the monitoring database tracks the progress of these selected farms along the program objectives. The production data has been collected since 2011 on progressively larger sample of farms, some of which were then selected into the SINCHI agroforestry programs. Inclusion of farms commenced in 2011, and coverage was subsequently enlarged around 2015 and 2017. Selected farms are monitored at more regular frequency (once every 6 months). The resulting data have very large variation across farms and locations, they are very rich in information, and even exemplars of agricultural production datasets.

Treatment effect models for environmental change. Most of the available literature on experimental or quasi-experimental evidence for treatment effects of environmental interventions upon deforestation focuses on the Brazilian Amazon. In an early and influential contribution, using a satellite-based measure of deforestation and accounting for potentially endogenous effects of policy particularly development projects, (56) find that land characteristics and transport costs are important determinants of deforestation in the Brazilian Amazon. Using dynamic panel data GMM methods, (29) explored the treatment effects of changes in agricultural land use, especially expansion of sugarcane cultivation, on deforestation in the Brazilian Amazon. (57) find no consistent effect of indigenous people's land rights protections on satellite-based forest cover data in the medium run, therefore arguing that such programs cannot be uniformly justified by deforestation outcomes. These studies set relevant evidence to be considered in the analysis of the SINCHI agroforestry programs, which partly aim to reduce 'land grab' and promote farmer ownership. In addition, our work also highlights the potential for similar agroforestry programs elsewhere in the Amazon.

A theoretical model developed in (58) emphasizes that REDD transfers need to be carefully planned to balance deforestation and growth objectives. The effects of a 2008 Brazilian policy of access to rural credit conditional on commitment to a deforestation target is investigated in (59). Using difference-in-differences (DID) methods on a panel of municipalities, they find that credit constraints affect agricultural production in municipalities where cattle ranching is the leading economic activity, thereby generating positive effects of rural credit in reducing deforestation. Their DID framework is similar to the one we present in this paper but placed in a different context. For the Colombian Amazon we focus on a distinct treatment, the SINCHI agroforestry program, based on farm level agricultural production data. A different agricultural production treatment, the Responsible Soy Project following the opening of a new soybean export facility in the Brazilian Amazon, is considered in (24). Like the SINCHI program, this treatment also forms part of the United Nations REDD initiative, and likewise focused on promoting alternate agricultural production systems. They find significantly reduced deforestation rates for enrolled units, even with staggered (delayed) enrolment. Larger impacts are evidenced for credit constrained smaller units and farms initially non-compliant with deforestation targets. This design is at the farm level and quasi-experimental with self-selected enrolment, and they use a combination of matching and DID methods, which is comparable to our empirical approach. A relevant difference is that treatment application is not in-situ within farms, which renders our study somewhat unique and makes it difficult to establish a direct comparison of the results.

The only relevant contribution on environmental treatment effect models for Colombia is (50). However, this study focusses on the effect of violence and conflict upon reduced deforestation in forest conservation areas, using a combination of matching and DID methods. Some studies from other geographical contexts are also relevant to our work. (33) evaluate a program of payments for ecosystem services in Uganda on deforestation based on a village-level randomized controlled trial. However, a randomized control experimental setting, rather than a quasi-experiment, and a cash program rather than the knowledge transfer SINCHI program distinguish our context from theirs. (61) provide another related program and context, evaluating the impact of a forest certification program upon village-level deforestation in Indonesia. (62) used a quasi-experimental approach combining covariate matching with DID estimation to assess effectiveness of collective payment for environmental services on reducing deforestation in Cambodia. Finally, (63) examined the environmental impacts of a place-based economic policy in India and find that such development policies can sometimes be implemented without adverse impact upon local forest cover.

In summary, the literature on experimental and quasi-experimental evaluation of various programs upon deforestation is substantial; however, our study cuts a niche. While the extant literature is largely based on Brazil, ours is the first relevant study for the Colombian Amazon. Second, unlike most of the literature, our study focuses on an agroforestry program at the farm level. Even in the large literature for Brazil, there is only one study (24) exploring an agricultural production treatment at the farm level. However, the treatment itself is quite different, an export facility in the Brazilian Amazon, whereas the SINCHI treatment is explicitly *in situ* within selected farms. Importantly, we use farm level agricultural production data, rather than satellite information, which makes it very rich in diversity and suitable for understanding heterogenous farm responses to agroforestry program treatment effects. The study by (33) in the Ugandan context is also related but based on a randomized controlled trial at the village level. Together, our work contributes to the emerging literature in treatment effects modelling with staggered treatment and observation times, which enables nuanced analysis taking account of heterogenous pre-existing trends and treatment effects. While based on risk mitigation rather than a technology transfer program, and on village-level data in a Cambodian context, (62) adopt a similar methodology to ours. While applied to the Colombian Amazon, which is an area with significantly less literature, our findings are transferable to other regions of the Amazon and beyond, not least because of our sophisticated modelling of different heterogeneities.

Results

Against the backdrop of the Colombian institutional context and previous literature, we evaluate effectiveness of the novel SINCHI land use regenerative and sustainable agroforestry program upon productive forest restoration in the Colombian Amazon. As discussed earlier, the SINCHI program provides knowledge exchange, rather than direct financial incentives and is based on selection of farms into treatment. Purposive selection motivates a quasi-experimental setting, where we use the current generation of DID methodologies for estimation of treatment and selection effects upon deforestation.

We first considered a traditional two-way fixed effects (TWFE) DID methods (21, 24, 64). The SINCHI program entails planned clearing of undergrowth, which implies modest reduction in vegetation in the medium run (5-20 years), which is then offset in the long run (20-25 years) by the fully grown forest cover is. This implies that, in addition to selection and treatment effects, the econometric model needs to also include the effect of duration (or exposure) to the treatment. However, the recent literature has highlighted important drawbacks of the standard TWFE DID approaches in potential failure to account for heterogeneity in treatment effects and potentially non-parallel pre-treatment trends (64-67). Beyond main effects and interaction, our estimation includes additional covariates to account for the above concerns (64).

In situations when the application of the treatment is staggered over time, which is the case for our data (Table 1), there are improved DID methods addressing the above deficiencies more explicitly (66-67). Specifically, the SINCHI agroforestry program was rolled out to selected farms in several stages, whereby farms previously selected into the program continue to receive the treatment, as new farms are included into the program progressively over time. Hence, and second, we also needed to apply new methods allowing for staggered treatments, heterogenous effects and different pre-existing trends (65-69). Our empirical investigation is based on the new merged farm-level database (discussed in further detail later) combining SINCHI's farm production and program monitoring data with satellite data on a collection of geo-ecological variables. Specifically, we implement the recently proposed Callaway and Sant'Anna estimator (66) accounting for staggered treatment times.

Two-Way Fixed Effects DID estimator. A total of 272 farms have data for two periods, 56 treated farms (selected into the SINCHI agroforestry program) and 216 control farms (Table 1). The locations of the farms vary widely within the Colombian Amazon (Figure 1 (a)), with a vast majority in the Guaviare department (Figure 1 (c), Table 1). The treatments are staggered over time: 15 farms were enrolled into treatment in 2011, another 32 in 2015 and a final 9 in 2017 (Table 1). To account for staggered treatments and trends in deforestation, within the TWFE DID setting, we add a trend to capture the time difference between the two observations for each farm. Likewise, we allow for exposure effects by interacting the SINCHI treatment: (a) with a dummy variable for the second period of observation; and (b) the duration of exposure to the treatment.

Following (21) and (24), but with a small variation to allow for trend, exposure effects and staggered treatment times, we write the two-way fixed effects (TWFE) difference-in-differences (DID) model as:

$$d_{it} = \alpha_i + \beta T_{it} + \delta T_{it}(t - t_{0i}) + \gamma_{DID} T_{it} G_i + \pi_{DID} T_{it}(t - t_{0i}) G_i + \theta' X_{it} + \varepsilon_{it}, \qquad (1)$$

where d_{it} is the percentage deforestation for farm i in year (time) t; T_{it} is a dummy variable indicating the second observation time for farm i; t_{0i} is the first observation year for farm i; G_i is a farm-level dummy variable for a treated farm; X_{it} is a vector of farm and time specific variables controlling for potential heterogenous pre-existing trends and time-varying selection effects; and ε_{it} is an idiosyncratic error term. The model is estimated by least squares, whereby estimates of β, γ_{DID} and π_{DID} represent selection effects, treatment effects and exposure effects, respectively.

The estimates of the TWFE DID model in Eqn. (1) are reported in Table 2. We use several farm-level and environmental variables as controls, which are chosen by a post double selection Lasso procedure (70). For this purpose, we augment the 890 farm-level variables with 36 orthogonal principal component factors from the variables (71), together with 21 spatially granular geo-ecological (climate, land use, and topography) variables extracted by locations of the farms.

We estimate three TWFE DID models with percent forest area deforested as the dependent variable: (a) a linear regression model; (b) a logit model; and (c) a logit fractional regression model (72). While the first two are standard, we feel that the logit model is more realistic because it allows nonlinear marginal effects. The fractional regression model is more robust to distributional assumptions (72). The implications of all three sets of results are similar. As explained in (64, 67), allowing for heterogenous effects and pre-existing trends using controls, helps accounting for heterogeneity and improving validity. The central finding is that there is a treatment effect in reducing deforestation, but this is counteracted by a weaker but persistent effect of exposure to the treatment.

As discussed above, this exposure effect is an essential feature of the SINCHI agroforestry program, whereby planned agricultural land use implies initial partial clearing of secondary vegetation to implement agroforestry systems or silvo-pastoral systems. Based on the nature of agroforestry models underlying the SINCHI program (Figure 2, 54-55), it is expected that forest cover would be fully restored in about 20 years' time. The additional variables fall along expected lines. (Previous) loss of vegetation in the land area of the farm is picked up, together with factors reflecting cattle ranching, access to markets, opportunity for agricultural activities, and some environmental variables reflecting agricultural potential and precipitation.

The main conclusion from the estimates in Table 2 are consistent throughout. Our central estimates indicate a selection effect of about 8.3% reduced deforestation upon inclusion into the SINCHI program, but a countervailing exposure effect of 1.4% increased deforestation per year of treatment. This implies that the immediate gains from deforestation dissipate in about 5-7 years. However, as discussed before, SINCHI has commitments with the farmers to ensure 10% reduced deforestation in its treated farms. Then, a natural way to achieve this reduced deforestation would be to select farms that would be expected *a priori* to be on a downward deforestation trajectory. This is apparent in the very large and statistically significant estimated selection effects.

From our results, we can highlight three main findings. First, the agroforestry knowledge exchange program designed and implemented by SINCHI has a beneficial impact of reduced deforestation. Together with the selection of suitable farms, this treatment can, in the short run, achieve the program objective of 10% lower deforestation. This outcome is highly encouraging, indicating that wider rollout of the program may have substantial benefits for the wider region, and perhaps even recovery of permanent forest cover. The magnitude of the effect is very large, and if widely applied, could well be seen to reverse the strong deforestation trends in Colombia recorded since the active negotiations with FARC dissidents, that is about the period 2015-19 (46, 51).

Second, the exposure effect is also expected *a priori*. Agroforestry programs imply selective replanting of trees that would produce sustainable revenues and forest cover in the future, but in the medium run may cause some depletion of vegetation. The estimated exposure rates deduced from our analysis are comparable with what is anticipated from SINCHI's agroforestry models. While this exposure trend is expected to be reversed in the long run (about 20 years), the merged information in the SINCHI database are relatively short run (essentially 2011-2019) and cannot yet capture this nonlinearity in the exposure effect. This highlights the importance of continued and consistent data collection at the farm level to monitor the forest cover. This is a central aim of SINCHI's regular monitoring program, but further long-term data will be required to obtain stronger evidence of turnaround.

Third, the countervailing exposure effects emphasize the urgent policy need to continue roll out of the intervention program at a sufficiently high rate that can offset reversals to deforestation in the medium run. Then, this has the potential to achieve forest regeneration and sustainable agriculture/forestry because the agroforestry models are designed to sustain both the forest cover and agricultural livelihoods in the long run.

Staggered treatments estimator (66). Despite its popularity and simple implementation, the recent literature points towards serious limitations of the TWFE DID approach (65-66, 69, 73-74). Specifically, TWFE can fail if there are heterogeneous treatment effects (model misspecification), or multiple periods of treatment with violation of the parallel pre-treatment trends assumption. These are particularly exacerbated in data with variation in treatment timing (65-67).

This context aligns closely with the SINCHI staggered treatments program in the Colombian Amazon. Different farms were allocated into treatment at different times, but once allocated, treatment status remained unchanged through the duration under study. This satisfies appropriate conditions for application of the estimator proposed recently by (66). We implement their approach, together with their proposed approximate bootstrap procedure. We make a subtle variation to (66), accounting for the fact that different treated (and control) farms are observed with varying exposure to the treatment. Together, following (66), we account for potential heterogenous effects modelled by additional controls, together with a bootstrap procedure for estimating standard errors. Against the context of limited observation period post-treatment, this variation allows us the opportunity to infer on exposure effects somewhat more precisely.

Figure 3 (a) reports staggered treatment (66) estimates for the percent deforested variable, and for the 3 treatment years (2011, 2015 and 2017). The red and blue lines represent control and treated farms respectively, together with 95% confidence intervals. For the same treatment time, farms are observed at different exposure periods after treatment. Separate estimates for these different observation cohorts are shown in black dashed lines; however, we do not report standard errors because sample sizes here are very small (see Table 1).

Several key observations follow. First, the standard deviations are very small, except for the small number of farms (nine) treated in 2017, hence the estimates are very precise. Second, the control farms have quite a flat trajectory just positive (above zero) and a small upward trend. As discussed in (75), this confirms that pre-existing trends are minimal. Third, there are statistically significant and negative treatment effects reflecting deforestation reducing gains of the SINCHI treatment. Fourth, the estimates also reflect a medium run sharply positive exposure effects counteracting the negative treatment effects. Finally, the trajectories by observation cohorts are similar for the three treatment years. However, the treatment effects are weaker for 2015, likely related to sharp increase in deforestation following the peace agreement between the Colombian government and insurgents (46, 51-52).

Similar evidence is also observed for the logit of percent deforested (Figure 3 (b)). However, evidence on negative treatment effects for farms treated in 2017 is mixed – the standard errors are too large because of the small number (nine) of treated farms. Perhaps most importantly, the Callaway and Sant'Anna (66) estimates and inferences are consistent with the two-way fixed effects estimates reported above. This highlights that the never treated sample is not very small and that pre-treatment trends are quite stable (75-76). Thus, following (65), we contend that potential heterogenous effects are adequately modelled by including additional covariates in our TWFE DID estimation. The counteracting treatment and exposure effects are highlighted. However, the post-treatment period is not long enough to model the long-run benefits of the program. As evident from Figure 2, under the SINCHI agroforestry program, the forest cover is fully recovered only in about 20 years. Given the close alignment between TWFE and Callaway and Sant'Anna (66) estimates, our counterfactual and policy analysis below builds upon the TWFE estimates from Table 2.

Discussion

The empirical estimates reported above have important implications for understanding the potential of regenerative agroforestry programs to reduce deforestation and achieve sustainable livelihoods and forest cover in the Amazon. First, we discuss the main empirical findings and their implications. Next, we conduct a policy experiment to evaluate the potential for the SINCHI program to promote recovery of forest cover.

Model estimates. Both TWFE-DID (21, 64) and staggered treatment (66) estimates are broadly consistent with each other. As discussed in the recent literature (66, 76), this is not unusual given the substantial never-treated (control) sample and low pre-existing trends following our modelling choice of including adequate covariates as controls. We note, however, some evidence of lower treatment effects for farms treated in 2015. Inclusion of dummy variables to account for the peace process does not show statistically significant effects on our TWFE-DID estimation, which reflects high uncertainty and the need for further analyses.

Three further points are worth noting. First, there was a gap of about 4-5 years between the first treatment time, 2011, and the second, 2015. This period approximately matches with the period it takes for exposure effects to outrun treatment effects. While we are not aware of the process and circumstances of SINCHI's roll-out decisions, this situation provides limited validation from the field data regarding the relative magnitudes of estimated treatment and exposure effects.

Second, selection effects are large. The farms selected into the SINCHI program have a commitment to maintain their standing forest cover intact and thereby achieve 10% lower deforestation. Farms are selectively included into the program potentially based on their *a priori* propensity to maintain forest cover, thereby offsetting the adverse exposure effects in the medium run. This explains the high selection effects. However, the pool of farms with sufficiently large selection and treatment effects to offset the counteracting exposure effects is rather limited. This supply constraint emphasizes the urgency to continue roll-out of the treatment to a larger number of farms, to achieve a large and spatially integrated negative impact on deforestation.

Third, based on the above findings, one can evaluate the alternate forest regeneration scenarios based on the balance between financial costs and deforestation benefits using a mathematical model. Below, we develop such a model and analyze the findings.

Forest regeneration policies. To conduct the above counterfactual policy experiment, we set out a mathematical model based closely upon the SINCHI farm-level data, empirical model estimates (Table 2 and Figure 3) and forest cover and vegetation dynamics under the SINCHI agroforestry program (Figure 2). The following is our central model for this purpose:

$$d_t = -7 + 1.7t - 0.04t^2, \qquad (2)$$

where d_t denotes percentage deforestation in a selected farm t years after inclusion into the treatment, the treatment effect being $\gamma_{DID} = -7$ percentage points and the exposure effect $(1.7t - 0.04t^2)$ is calibrated such that the slope is initially close to $\pi_{DID} = 1.7$, and a curvature to ensure that the exposure effect starts decreasing about 20 years after treatment.

We denote the roll-out schedule by $\{f_t : t = 0,1,2,\cdots\}$, where f_t denotes the number of farms newly inducted into treatment at time t. To normalize, we set the initial condition at $f_0 = 1$, that is 1 farm enrolled at the start of the program. Then, aggregate deforestation t years from the start is:

$$D_t = \sum_{s=0}^{t} f_s d_{t-s} = \sum_{s=0}^{t} f_s[-7 + 1.7(t-s) - 0.04(t-s)^2]. \qquad (3)$$

Net present value costs of roll-out are evaluated as:

$$C_t = \sum_{s=0}^{t} f_s/(1+\theta)^s, \qquad (4)$$

where the discount rate $\theta = 0.04$ is set at about the long run average annual inflation rate in Colombia.

Next, we consider two alternate roll-out scenarios: (a) a net-zero deforestation scenario where $D_t \leq 0$ for all t; and (b) a permanent forest cover scenario where the roll-out schedule f_t is extended at the minimum fixed rate for which there would be permanent decrease in deforestation. Under the first scenario, the forest cover is retained at its initial value; hence we have net zero deforestation, but not necessarily recovery of forest cover. The second scenario represents a more aggressive forest regeneration policy, whereby the program is extended, at a fixed rate, to an increasing number of farms. The roll-out rate is set at the minimum necessary to achieve permanent decrease in deforestation. As anticipated, the second scenario is more expensive than the first, but it also has the potential to achieve permanent recovery of forest cover over longer time periods.

Deforestation dynamics for a single farm and the permanent forest cover scenario are shown in Figure 4 (a). From the single farm trajectory, one can see both the negative treatment effect (decrease in deforestation upon inclusion) and the positive exposure effect, initially counteracting against the treatment effect but turning around after about 20 years. The net-zero deforestation scenario can also be seen from the plot – it follows the single farm case until $t = 4$, and then traces horizontally along the x-axis at zero deforestation thereafter. It is also apparent that permanent forest cover regeneration (the solid curve in Figure 4 (a)) can be achieved. The exposure effect is very persistent and long run, hence permanent forest cover is only attained if new farm enrolments on the program expand at a minimum rate of 17.1 percent annually. This rate for continuous roll-out is exceptionally high and may be difficult to attain under current political and economic conditions in Colombia. In fact, one of our key contributions is to provide a quantitative sense of the challenge in promoting net-zero deforestation and permanent forest cover based on agroforestry programs.

Thus, our mathematical model calibrated to empirical estimates reflect that permanent forest cover in the Amazon can be achieved through agroforestry program such as SINCHI's. This is particularly because agricultural technology and topographical features are largely similar in the Colombian Amazon. However, the costs involved are permanent and substantial, requiring continuous expansion of the program at a rate substantially higher than the inflation rate in Colombia, which is itself high. By contrast, net-zero deforestation is achieved at a lower cost, but in this case the lost forest cover is not regenerated. This includes any deforestation in farms that would have been selected into the program at a later stage.

The question arises as to how much larger permanent forest cover costs are relative to net-zero deforestation. To explore this issue, Figure 4 (b) plots, on a logarithmic scale, the number of farms newly included into the program at each time point under the above two scenarios. The long run growth trajectory is the same for both scenarios, which shows that permanent forest cover can be achieved with an additional fixed cost above the net-zero case. Hence, permanent forest cover should in principle be preferred to net zero deforestation. These fixed costs are 11.5 times the costs of net-zero deforestation spread over the first 15 years of program rollout.

Admittedly, the above financial considerations must match and merge with radical political and social changes in the region. It will be this joint-up-approach together with the determination of the governments that will ultimately determine forest cover in the Colombian Amazon, not just the agroforestry programs and actions of the farmers and research institutes like SINCHI in isolation. It is possible that combining agroforestry programs with other policy measures, such as protected area status and forest governance (20, 28-32), financial incentives (33-35), sustainability certifications (36-39), and property rights (40-41), can deliver the best outcomes. This is outside the scope of this study but an important area for future research.

Conclusion

The Instituto Amazónico de Investigaciones Científicas SINCHI in Colombia initiated, a decade back, an ambitious agroforestry program promoting sustainable agriculture and forest cover preservation in the Colombian Amazon. They developed a suite of agroforestry models and offered farmers knowhow to implement a corresponding planned agroforestry program. This was against a commitment that the selected farms would protect their standing forest cover. The key feature of such agroforestry and silvo-pastural programs is that, in the long run (25 years and longer), they sustain livelihoods through agricultural production, and they support replenishment of forest cover even in places where this cover has got denuded. Thus, they support better socio-economic outcomes as well as many other UN SDGs, not least related to climate change, food security and sustainable agricultural livelihoods.

To enable selection and monitoring of selected farms, SINCHI has been collecting valuable data on forest resources and agricultural activities of both treated (selected) and control farms. We use these data, in combination with current quasi-experimental difference-in-differences methods, to estimate (SINCHI) treatment effects on deforestation in these farms. Our approach is statistical, based on new generation big data treatment effects models. We find evidence of statistically significant treatment effects together with (purposive) selection effects. In addition, we find that the benefits of deforestation are negated in the medium run with loss of secondary vegetation over a 5-20 year period as planned agriculture proceeds. The forest cover is recovered in the long run (in 20 or more years) as newly planted trees grow fully. These long run impacts are not yet recorded in our data but will be in the future as SINCHI continues its monitoring program on the selected farms. Hence, we use a mathematical model calibrated to the SINCHI agroforestry program and the available data to investigate the costs and benefits of alternate scenarios for continued roll-out of the program.

We consider two scenarios for roll-out: a net-zero deforestation scenario and a higher cost permanent forest cover scenario. A significant finding is that agroforestry programs like that initiated by SINCHI can achieve both net-zero deforestation and permanent forest cover regeneration. However, for both scenarios, the costs of roll-out are persistent and very large in real terms, relative to recent inflation rates of about 4% per year. On the other hand, permanent forest cover also provides opportunities for reducing food poverty through animal husbandry (meat production and associated grazing) together with reduced deforestation. The potential for such innovative and integrated land use needs further investigation.

Thus, the greatest benefits are obtained if political and social conditions support continuous and expanding roll-out. Colombia faces economic and political challenges at the same time as it is committed to international carbon reduction targets. As such, greater international collaboration may be useful to bear the costs of program roll-out. Left to its own, the benefits of the current SINCHI program will be only transitory. Perhaps the international community and multilateral agencies (like the World Bank and the UN) could support rollout costs for net-zero deforestation, and the host country can bear the incremental fixed costs to make the benefits of forest cover permanent. This seems to be reasonable proportionate allocation of the high costs of Amazon forest regeneration.

Materials and Methods

Planned agroforestry programs hold great potential for delivering sustainable livelihoods as well as climate change mitigation in the tropical forests (18, 25-27). However, empirical estimates of the effectiveness of such programs in reducing deforestation is currently lacking. In this case, experimental and quasi-experimental methods hold particular promise (43, 77-79). We employ quasi-experimental difference-in-differences (DID) methods to examine the performance of a specific program, developed and implemented by SINCHI, in the Colombian Amazon in reducing deforestation.

Data. We use data from an on-site survey among farmers mainly in the Guaviare department (province) of Colombia, which hosts one of the largest deforested areas in the Colombian Amazon (46). We also use satellites images and geological data for the Colombian Amazon rainforest from the United States National Aeronautics and Space Administration (NASA), which allows us to extract geo-ecological variables such as soil quality and forest fragmentation at the farm level.

Trained investigators from SINCHI conducted on-site surveys of farms in seven departments of the Colombian Amazon rainforest between 2011 and 2020. The survey was designed to collect very detailed and high quality data on: (a) the physical characteristics and topography of the farms; (b) economic activities for production, self-consumption and sales, together with their associated values (monetary and physical); (c) farm infrastructure, capital and technology; and (d) detailed socio-economic characteristics of the households living on the farms. The farmers belong to different farmers' associations, and SINCHI approach them mainly through these associations; hence, some information on social networks of the farms is also available.

A total of 2,777 farms were visited and had filled-in questionnaires, including some farms that were visited twice or more. The completed questionnaires were collated into a farm production database with 3,055 observations containing 890 variables. Our empirical analysis is based on the 272 odd farms that were visited more than once, mainly in Guaviare and a few in Caquetá and Meta (Table 1, Figure 1 (a) and (c)). These farm production data constitute our first dataset.

In addition, we use NASA satellites images (raster files) of the Colombian Amazon rainforest to extract geo-ecological (environmental) variables. We used ArcGIS to collate information relating to environmental variables such as patchy area of fragmented forest and secondary vegetation, annual average temperature, livestock load and proximity to agricultural frontier. For the second dataset, we chose 21 such geo-ecological variables based on a priori expected relationship with trends in deforestation and biodiversity (Table 3).

Our third dataset is the SINCHI monitoring data. Farms selected into the SINCHI program are subsequently visited once every half-year to monitor progress made on implementing their planned agroforestry program, including their compliance with agreed deforestation targets. For our purpose, inclusion of a farm in this monitoring dataset is taken as indication of selection into the SINCHI program.

The above three datasets were merged, suitably cleaned, anonymized, and organized, and the resulting dataset was used for analysis. To preserve anonymity, precise treatment times were not available. For each farm with repeat observations in the farm production dataset, we interpret the first period as indicative of consideration for inclusion into the SINCHI treatment in that year. This provides our measure of staggered treatment times. Then, the second period in the farm production dataset indicates observation time, for some farms under the SINCHI treatment and for others, as units in the control group.

Measurement of key variables and Big Data regularization. Our key dependent variable, percent deforested, is measured by farm area deforested as a proportion of total forest area within a farm. For some farms, data on area deforested are missing. For these farms, percent deforested was estimated as loss of vegetation multiplied by the proportion of forested area to total area of the farm.

Our dataset is high dimensional with almost 900 farm-level variables and many missing values. This required imputation based both on field information and context as well as statistical regularization by a combination of principal components and Lasso (least absolute shrinkage and selection operator) (80). This is in line with the PCDID approach (71) together with post double selection (70) to control for potentially heterogenous pre-existing trends as well as sample selection. We subjected the farm-level production and geo-ecological data (about 910 variables) on about 2,800 farms to principal components factor analysis, extracting 36 factors. This produced a design matrix of about 950 variables and 2,800 farms. In our final estimation, controls were chosen from these initial 910 variables and predicted factors using post double selection Lasso methodology. Table 4 presents descriptive statistics on our main variables for 272 farms which have outcome (deforestation) data for two periods.

DID methods. The data on 272 farms that are observed for two periods are included in our DID estimation. Some farms have a close association with SINCHI and monitored under the program; these farms are considered as having received a knowledge exchange intervention which places them in the treated group. The remaining farms represent the control group (Table 1 and Figure 1 (c)). Our central object of inference is the treatment effect, that is the difference in the deforestation outcome between the treated and the control group, together with exposure and selection effects.

DID methods estimate treatment effects by considering the increase (difference) in the outcome variable for each farm between the two periods under observation, and then taking the difference of this measure, in averages, between treated and control farms; hence the name difference-in-differences. In a regression context, this is equivalent to a two-way fixed effects (TWFE) estimator with one dimension being time (first and second period) and the other being a dummy variable for treated farms (21, 64, 67). The coefficient on the interaction between the two effects provides an estimate for the treatment effect, while the coefficient on the treatment dummy measures selection effects. The coefficient on the time effect measures secular changes in outcome (deforestation) over time, or the trend. We also add a variable measuring time difference between the two observation periods to model exposure effects.

The central assumptions underlying DID methods are that: (a) all farms have the same effects on the outcome (homogenous treatment effects); and (b) that all farms had similar trends in outcome before treatment was applied to some of them (homogenous pre-existing trends). The current literature has highlighted several potential issues with TWFE DID methods particularly when treatment times are staggered (66-69, 76). These issues of potentially heterogenous pre-existing trends and heterogenous treatment effects are particularly exacerbated when the never-treated sample is very small relative to treated units. However, (64) shows that TWFE can be interpreted as a two-way Mundlak regression, which is easily adapted to nonlinear models as well as allowing for heterogeneity in a wide variety of ways. We use this form for estimation, not least because one of our considered models is the nonlinear logit fractional regression. In addition, to model potential heterogeneity, we use a combination of principal components and post double selection lasso methods (70, 71).

Given our context with staggered treatment and heterogenous observation times, we also implement the recent estimator in (66). For (SINCHI) treated and control farms that were considered for treatment in period g and subsequently observed in period t, the average treatment effects for the treated can be estimated as:

$$ATT(g,t) = \mathbb{E}\left[\left(\frac{G_g}{\mathbb{E}[G_g]} - \frac{\frac{\hat{p}(X)}{1-\hat{p}(X)}C}{\mathbb{E}\left[\frac{\hat{p}(X)}{1-\hat{p}(X)}C\right]}\right)(d_t - d_{g-})\right] - \mathbb{E}\left[\left(\frac{G_g}{\mathbb{E}[G_g]} - \frac{\frac{\hat{p}(X)}{1-\hat{p}(X)}C}{\mathbb{E}\left[\frac{\hat{p}(X)}{1-\hat{p}(X)}C\right]}\right)m_{g,t}^{nev}(X)\right], (5)$$

where $m_{g,t}^{nev}(X) = \mathbb{E}(d_t - d_{g-}|X, C = 1)$ builds the contrast with never treated units and all expectations are taken over units considered for treatment at time g; C is the dummy variable for control units and G_g for units treated at time g; and $\hat{p}(X)$ is the estimated probability (using a logit model) of being selected at time g.

Three features deserve specific attention. First, heterogeneities are explicitly modelled in two ways – the selection probability in $\hat{p}(X)$, and any pre-existing trends through $m_{g,t}^{nev}(X)$. Second, since the estimator is moment-based, homogenous treatment effects can be evaluated by examining (plotting) the estimates for different treatment (and observation) periods. This is particularly critical in our application; see also (75-76). If the estimates are found homogenous, they can be averaged over different (g,t) cohorts to obtain estimates of average treatment effects. Third, (66) provide a bootstrap procedure to estimate standard errors. We implement this estimator, but also compute a jackknife variance estimator (81) as an alternative, not least to examine whether there are substantial outliers. All computations are conducted using Stata.

Above, we have discussed our estimates of (66) and associated plots (Figure 3). We now highlight the connection between Eqn. (5) and various components of the plot in Figure 3. The treatment (blue line) in Figure 3 refer to the first term in Eqn. (5), while the control (red line) refers to the second term; the average treatment effects on the treated (ATT) is the contrast between the two. However, in addition to staggered treatment times, we also have heterogenous observation (exposure) periods. Estimates of the first term in Eqn. (5), differentiated by observation times and staggered treatment times, is shown by the dotted lines in Figure 3 (a).

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Figures and Tables

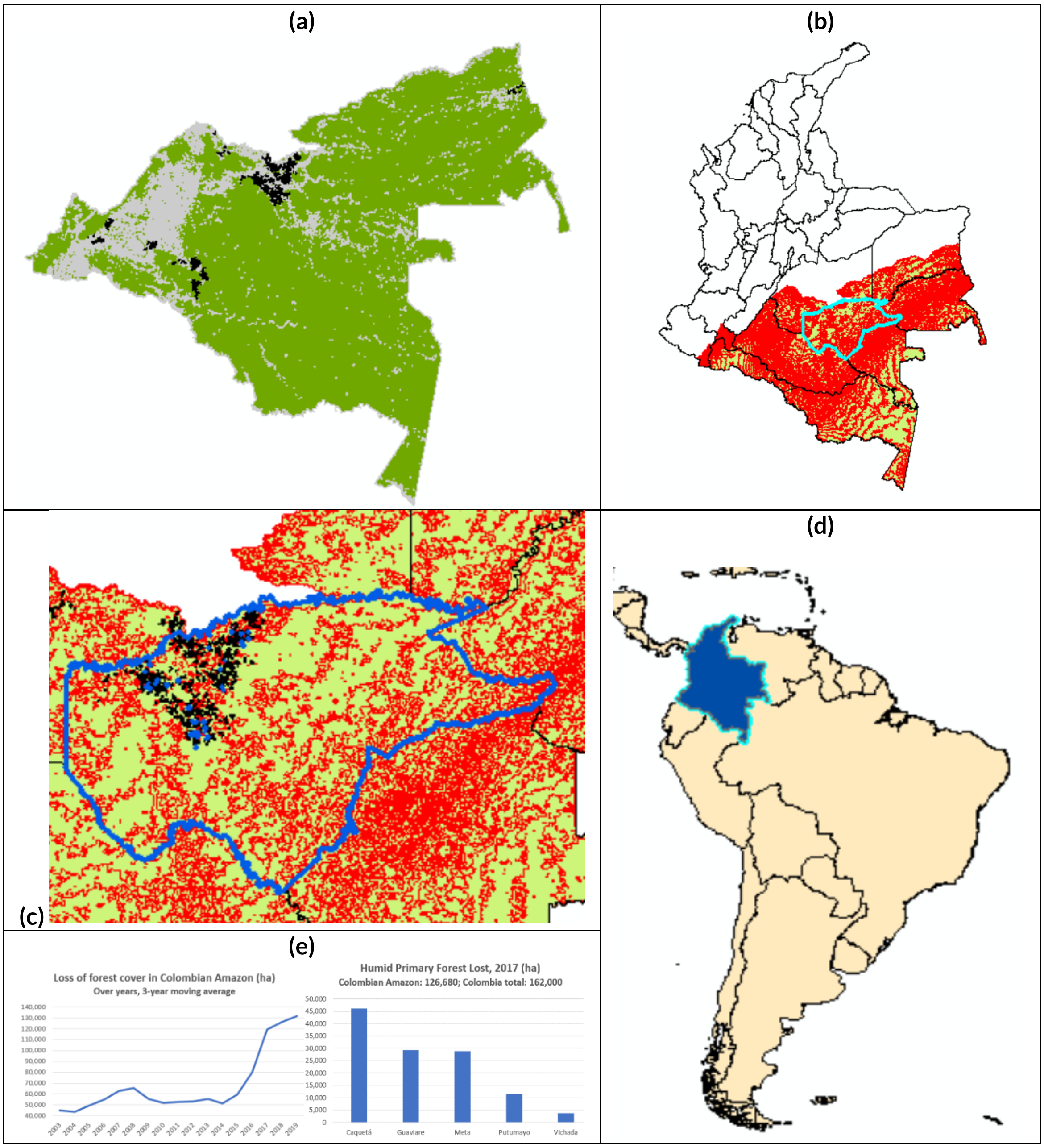
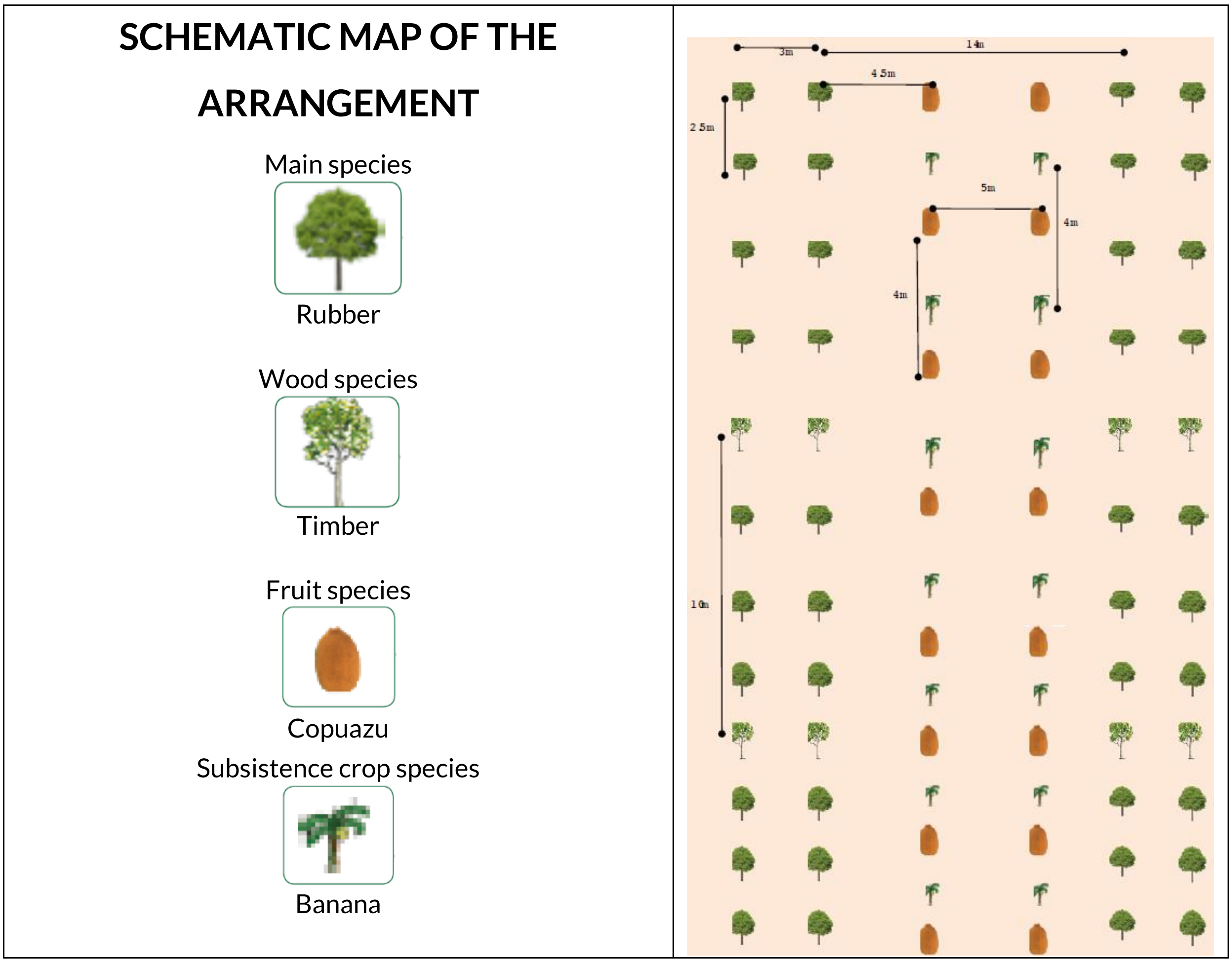


Figure 1. Study area, treated and control farms, forest cover and secondary vegetation.
(a) Deforestation in the Colombian Amazon (forest loss/parched area, 2002, in yellow) and treated farms (black dots). Source: Farm locations (SINCHI) overlaid on satellite image (NASA).
(b) Map of Colombia, highlighting profile of barren vegetation (in 2018) in the Colombian Amazon (in orange) and our study region – the department of Guaviare (blue outline). Source: Satellite images (NASA).
(c) Treated (blue) and control (black) farms within the department of Guaviare, with barren vegetation in the background (orange).
(d) Map of Central and South America with Colombia highlighted (in blue). Source (SINCHI). (e) Temporal and spatial distribution of forest loss in the Colombian Amazon. Source: Global Forest Watch.



Productive cycle

Species	Harvesting Schedule (years)																			
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Cash crops (Rubber)																				
Timber																				
Fruits (cocoa, copuazu)																				
Subsistence crops (tubers,																				

The agroforestry model is based on a productive cycle of 20 years. But, in the case of rubber the production period is longer and extends beyond 25 years (from year 7 to 30), after which its downward production curve begins.

Figure 2. Example of SINCHI agroforestry model (54, p.171-173; 55); translated from Spanish.

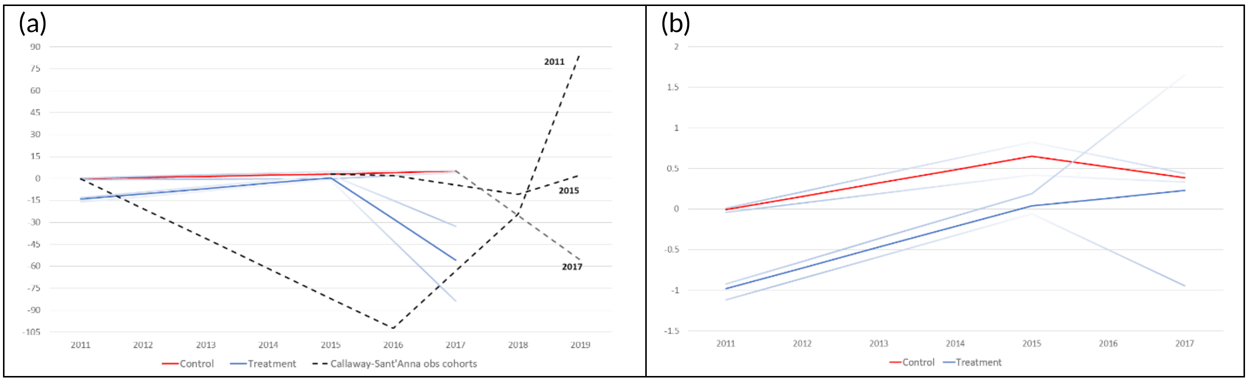


Figure 3. Callaway and Sant'Anna (2021) difference-in-differences estimates for staggered treatment times and varying observation periods. Average Treatment Effect on the Treated (Red) and Control (Blue), varying by treatment years (2011, 2015 and 2017) together with 95% confidence intervals, for two alternate outcomes:
(a) Percent of farm forest area deforested; and
(b) Logit transformation of percent forest area deforested. For panel (a), we also show average treatment effects, on percent deforested, for different observation periods (black dotted lines).

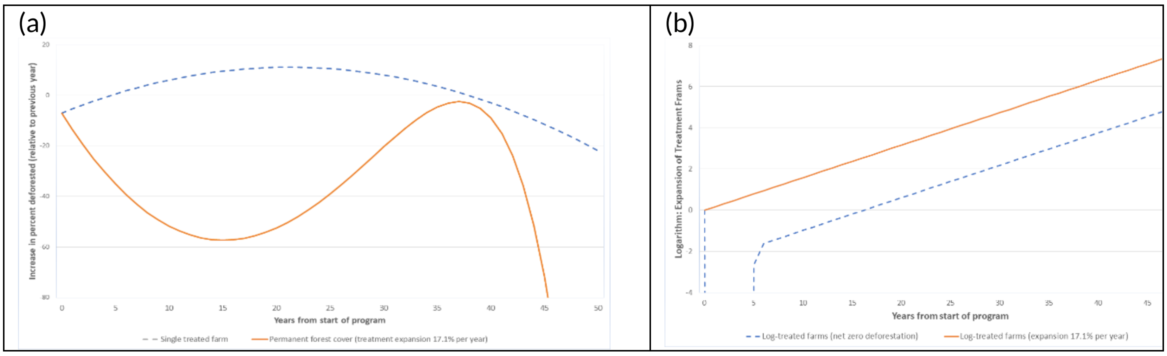


Figure 4. Alternate program roll-out scenarios: net zero deforestation; and permanent forest cover.
(a) Deforestation (relative to control) for a single treated farm (blue dotted line) and a permanent forest cover scenario (orange line), buy years since treatment first started.
(b) Expansion of the agroforestry program, for net zero deforestation (blue dotted line) and permanent forest cover (orange line) scenarios.

Table 1. Distribution of treated and control farms: by staggered treatment and observation periods, and by location

Years	**2011**	**2015**	**2016**	**2017**	**2018**	**2019**	**Total**
Treated							
2011	15		1		10	4	15x2
2015		32		3	5	24	32x2
2017				9		9	9x2
Control							
2011	129		4		92	33	129x2
2015		18			13	5	18x2
2017				69		69	69x2
Total	144	50	5	81	120	144	**544**

Departments	**Number of farm-years**	**Percentage (%)**	**Average farm size (ha)**
Caquetá	8	1.5	66.32
Guaviare	520	95.8	77.59
Meta	16	2.7	217.94

Table 2. Two-Way Fixed Effects Differences-in-differences estimates

Variables	Percent deforested		Logit frac. reg.	Logit – percent deforested	
Effects			Marginal effects		
Selection effects (β)	-1.404 (-6.23,3.42)	-114.98*** (-183.6,-46.3)	-48.48*** (-76.9,-20.0)	-0.380 (-0.92,0.16)	-34.31** (-61.3,-7.3)
Trend (time effects, δ)	0.150 (-0.32,0.61)	-0.006 (-0.42,0.41)	0.418 (-1.00,1.83)	0.0046 (-0.032,0.041)	-0.0090 (-0.04,0.02)
Treatment effects (γ_{DID})	-6.185* (-13.19,0.82)	-8.272** (-15.31,-1.23)	-1.390** (-2.67,-0.11)	-0.602 (-1.58,0.37)	-0.657 (-1.56, 0.24)
Exposure effects (π_{DID})	1.014 (-0.46,2.49)	1.424* (-0.01,2.86)	0.935* (-0.21,2.08)	0.139** (0.01,0.27)	0.154** (0.004,0.304)
Firm effects (α)	Differenced	Differenced	Differenced	Differenced	Differenced
Controls (θ)					
Loss of vegetation (ha)		0.203** (0.04,0.37)	3.890** (0.67,7.11)		0.017*** (0.006,0.029)
Factor – Cattle/pasture technology		4.434*** (1.87,6.99)	7.986*** (3.15,12.82)		0.207*** (0.075,0.339)
Factor – Accessible farms in low coca growth areas		6.578*** (3.76,9.40)	1.808*** (0.64,2.97)		0.632*** (0.29,0.97)
Factor – Value of forests/grasslands		5.685*** (3.44,7.93)	0.791*** (0.26,1.33)		0.466*** (0.26,0.67)
Geo-ecological – Barren vegetation, 2018		0.0061*** (.002,.010)	37.708*** (13.23,62.19)		0.0028** (0.0005,0.005)
Geo-ecological – Annual precipitation, 2019					-0.014** (-0.03,-0.003)
Geo-ecological – Dist. to agri. frontier, change 2002-16			0.841** (0.04,1.64)		0.0013*** (4.5e-5,2.1e-4)
Geo-ecological – Soil drainage, 1979-99			8.705*** (2.59,14.82)		
Intercept	19.643*** (17.82,21.47)	13.327*** (10.34,16.31)		-1.761*** (-1.91,-1.61)	-2.054*** (-2.29,-1.82)
Sample size	535	534	390	535	534
Adj. R^2 [RMSE]	0.0025 [15.61]	0.1977 [14.01]	R^2 = 0.0488 [14.61]	0.0137 [1.42]	0.2321 [1.26]

*, **, *** - Statistically significant at 10%, 5% or 1% levels, respectively. 95% confidence interval in parentheses.

Table 3. Geo-Ecological (Environmental) Variables

Variables names	Units
Advance of the agricultural frontier	m
Livestock load	Animal/km2
Distance to agricultural enclaves	m
Gini index difference 2005-2014	0 to 1
Distance to main land forests	m
digital elevation model (DEM)	ha
Patch area of fragmented forest and secondary vegetation	ha
Patch area of fragmented forest and secondary vegetation	ha
Barrenness (dry and bare (desert) landscape, and has very few plants and no trees)	Dimensionless
Driest month precipitation	mm
Annual effective precipitation	mm/year
Fire density	m
Distance to natural parks	m
Soil drainage quality	No unit
Temperature seasonality	Degrees Celsius
Average temperature of the driest quarter	Degrees Celsius
Average annual rainfall	mm
Seasonality of precipitation	mm
Potential evapotranspiration	mm/year
Driest quarter precipitation	mm
Annual average temperature	Degrees Celsius

Table 4. Descriptive statistics

Variables	Number	Mean	Std. dev.	Minimum	Maximum
Percent deforested	535	19.44	15.63	0.00	75.00
– Control farms	421	20.02	15.79	0.00	74.14
– Treated farms	114	17.27	14.90	0.00	75.00
Logit (percent deforested)	535	-1.84	1.44	-12.72	1.10
– Control farms	421	-1.75	1.25	-5.70	1.05
– Treated farms	114	-2.18	1.95	-12.72	1.10
Increase, percent deforested	263	-0.59	13.35	-61.56	52.84
– Control farms	205	-0.33	12.84	-50.90	52.84
– Treated farms	58	-1.53	15.15	-61.56	34.83
Increase per year, % deforested	263	-1.26	8.34	-61.56	34.83
– Control farms	205	-1.29	7.34	-50.90	27.56
– Treated farms	58	-1.13	11.27	-61.56	34.83
Loss of vegetation (ha)	390	18.66	31.19	0.5	500.0
Statistical factors					
– Cattle/pasture technology	546	0.00	0.92	-2.26	1.43
– Accessible farms in low coca growth areas	546	0.13	0.50	-2.30	2.24
– Value of forests/grasslands	546	0.06	0.56	-3.87	1.91
Geo-ecological variables					
– Barren, 2018	547	3710.5	7206.5	0	21246.7
– Annual precipitation, 2019	547	235.22	459.0	0	1452.5
– Dist. to agri. frontier, change 2002-16	547	1194.22	3302.6	0	26192.0
– Soil drainage, 1979-99	547	1.18	2.32	0	8.85