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Combatting Forest Fires in the Drylands of Sub-Saharan Africa

Quasi-Experimental Evidence from Burkina Faso

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Abstract

Forest fires are among the main drivers of deforestation and forest degradation in the drylands of Sub-Saharan Africa. This paper uses remote sensing data on forest fires and remaining tree cover to estimate the effectiveness of a project targeted at reducing fire incidences in twelve protected forests in arid Burkina Faso. The project consisted of two components that were implemented in the villages surrounding the target forests: a campaign aimed at raising community awareness about the detrimental effects of forest fires, and a program to support establishing and maintaining forest fire prevention infrastructures. Using the Synthetic Control Method the paper finds that the project resulted in a 35% reduction in forest fire occurrences in the period of the year when they tend to be most prevalent —in November, at the very end of the agricultural season. However, this impact is short-lived (as the reduction only occurred in the first four years of the program). The reduction in forest fires also did not result in a detectable increase in vegetation cover—because the reduction in November was not sufficiently large to be captured via remote sensing, or because the duration of the reduction was too short for the vegetation to recover. The paper then tries to uncover the underlying mechanisms to shed light on which of the project's components were effective and to also learn how the program can be improved.

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Combatting Forest Fires in the Drylands of Sub-Saharan Africa: Quasi-Experimental Evidence from Burkina Faso

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1. Introduction

Forest fires rank high among the key causes of global forest degradation and forest loss. They affect about 2% of the world's forested area every year (van Lierop et al., 2015; Tyukavina et al., 2022), and are thus important contributors to both climate change and biodiversity loss (Moritz et al., 2014; Oreskes, 2004; Kelly and Brotons, 2017; Le Quéré et al., 2018). Forest fires are especially harmful in Sub-Saharan Africa where they are responsible for 90% of the continent's forest loss as well as for 50% of the world's fire-related carbon emissions (van Lierop et al., 2015; Andela and van der Werf, 2014). Fires occur because of natural causes, but the bulk of the forest fires in Sub-Saharan Africa are the result of economic activity (Le Page et al., 2010; CIFOR, 2016). Fire is used to clear agricultural land, produce ashes to fertilize the soil, drive out wildlife for hunters, stimulate the growth of young shoots as feed for cattle, and to produce charcoal as fuel (Savadogo et al., 2007; Sawadogo, 2009; Potapov et al., 2012; Sow et al., 2013; Curtis et al., 2018). While forest conservation is recognized as a key strategy to mitigate climate change (as evidenced by the United Nation's REDD and REDD+ programs), relatively little is known about how effective forest conservation policies are in reducing forest fires, especially so in the dryland forests of Sub-Saharan Africa.

In this paper we evaluate the impact of a policy targeted at reducing both the number and the geographical spread of forest fires in twelve of Burkina Faso's 77 protected forests. Because of the country's arid climate, forest fires are especially damaging as the combination of limited annual rainfall and frequent fires prevent tree cover regeneration. Fires thus increase forest fragmentation in forests where tree canopy cover is sparse already (Cochrane, 2003; Hoffmann et al., 2009; Staver et al., 2011; Dwomoh et al., 2019). The program we evaluate can be characterized as a participatory forest management project aimed at increasing community interest and involvement in forest conservation in line with, for example, Agrawal and Ostrom (2001). It was designed by the Government of Burkina Faso as part of its Forest Investment Program (FIP), and it was co-funded by the World Bank and the African Development Bank.

The program was launched in October 2014, and consisted of two main parts. One, the program aimed to sensitize communities living in the vicinity of each of the project forests to the detrimental effects of forest fires. Two, the program also aimed to actively engage community members in local conservation activities using a combination of technical support (by experts from the regional and national authorities) and improved coordination of management activities between adjacent communities. Communities were encouraged to participate in setting up fire barriers within forests to compartmentalize wildfires, in establishing forest management infrastructures and in protecting and monitoring the forests. Taken together, these efforts were expected to reduce both the frequency with which forest fires were started as well as their spread, and especially so at the end of the agricultural season (in November and December) when most of the forest fires take place. We use the Synthetic Control Method (Abadie and Gardeazabal, 2003; Abadie, 2021) to estimate the impact of the policy intervention over the period 2014-2019, the first five years after its inception, using remote sensing data.

Overall, we find that the project was not very effective in reducing fire-induced forest degradation. Forest fires were lower in the project forests, but only in the month of November (the month in which most of the post-harvest forest fires take place), and also in just the first four years after the start of the program. The program did not reduce forest fire occurrences in any of the other months in the dry season. And even though the project managed to decrease the November forest fires by on average 35% in the first four years, we fail to detect an increase in overall vegetation cover. This may be because the decrease in November forest fires was too small to be visible on the satellite images, or because the impact had dissipated too quickly for the forest vegetation to recover.

While the impact of the project was thus limited at best, we perform additional analyses to gain insight into the mechanisms via which the decrease in forest fire occurrences were achieved in this November month. First, the timing of the impact – the first month after harvest – suggests that the effect is driven by farmers; additional support for this hypothesis comes from the fact that most of the reduction of forest fire incidences occurred on the forest fringe, where agriculture is the main economic activity. Second, we find that the reduction was the result of especially improved forest fire containment; the program did not manage to substantially decrease the number of forest fires started. Combined, these results suggest that to make the policy more effective, more attention should be paid to the behavioral aspects of forest fire prevention – among farmers, but especially also among hunters and livestock herders. Third, we also analyze how the estimated treatment effect on November fires is moderated by a number of characteristics of the local communities surrounding the forests. Before the intervention, forest fires were more prevalent around communities with lower average income, where agriculture was relatively intensive (as evidenced by the use of chemical fertilizers and pesticides), and with better access to regional markets (as measured by the proximity to the local road network). Regarding the program's effectiveness, we find that the impact is largest in areas where forest fires were more prevalent before the program, but otherwise the impact is by and large independent of all other community characteristics. Our study thus predicts that when rolled out to other forests (either within Burkina Faso, or elsewhere in the region), the intervention will be most effective in those areas where forest fires are most frequent, independent of their cause.

This paper contributes to two strands of literature. First, it contributes to the large empirical literature on effective forest conservation policies. A popular policy approach in the recent literature is the "Payment for Ecosystem Services" (PES) scheme which incentivizes forest conservation by offering financial payments conditional on conservation effort or on improving environmental outcomes as the result of the effort (Engel et al., 2008; Pattanayak et al., 2010; Engel, 2016). Although the approach is proven to be effective in some cases (Jayachandran et al., 2017), it may not be effective if forest conservation requires cooperation between group members and if (the formal and/or informal) institutions are not sufficiently strong to facilitate this cooperation (Pattanayak et al., 2010; Engel, 2016). Edwards et al. (2020a) implement a field experiment in Indonesia aimed at reducing forest fires. They find that offering communities payments conditional on the reduction of forest fire incidences results in communities putting in more effort in preventing forest fires, but they also find that this did not result in increased tree cover. Our study complements the findings of Edwards et al. (2020a) by evaluating the impact of a forest fire prevention program in the dryland forests of Sub-Saharan Africa.

Second, we contribute to the understanding of the anthropogenic sources of forest fires in the dry forests of Africa. While ecologists have studied the environmental consequences of forest fires in many different biomes (Cochrane, 2001, 2003; Muñoz-Rojas et al., 2016), understanding of the socio-economic drivers of these fires is still limited, especially in developing countries (Balboni et al., 2021). Our work is closely linked to that of Edwards et al. (2020b) who show that fires in the rainforests of Indonesia are more prevalent in the proximity of villages that are either poor and underdeveloped, or that have a long history of using fire to clear land. We confirm the role of these socio-economic factors in the context of Sub-Saharan Africa, where socio-economic institutions and climatic conditions are markedly different. Our results also support earlier findings from Latin America about the role of market access and connectedness to road networks as drivers of forest degradation and deforestation (Nepstad et al., 2001; Joppa and Pfaff, 2010).

The remainder of this paper is organized as follows. Section 2 provides an overview of the role of forest fires in forest degradation and deforestation in Burkina Faso, as well as the details of the program the Burkinabé government implemented to reduce the incidences of forest fires. Section 3 presents the empirical approach we use to evaluate the impact of the program and Section 4 presents the data we use in the analysis. Section 5 presents the results on the FIP program's impact on both forest fires and vegetation cover, and Section 6 explores the role of the characteristics of forest communities surrounding the targeted forests in moderating the overall impact. Section 7 concludes.

2. Study context of Burkina Faso and the FIP project

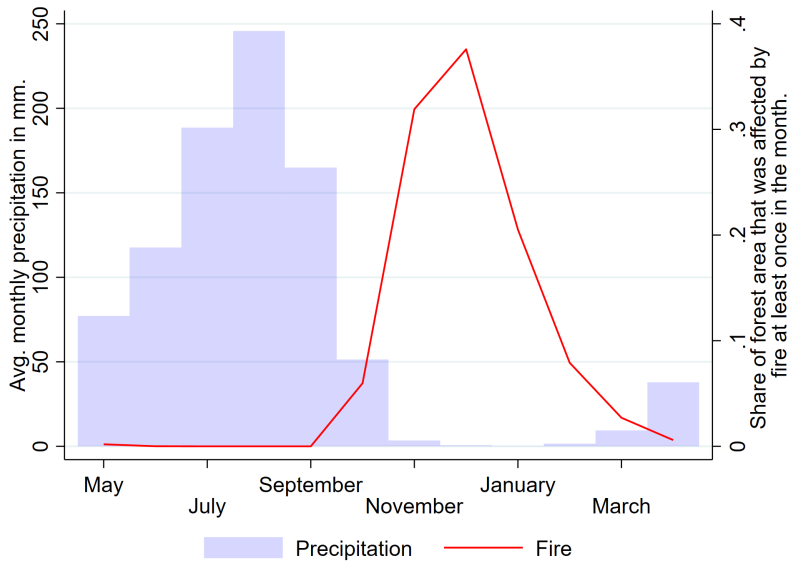
2.1. The role of fires in forest degradation

Despite the Burkinabé government's efforts to mitigate deforestation and forest degradation, the annual rate of deforestation is considerable. In the period between 1990 and 2010, deforestation rates were, on average, about 1.1% per annum (FAO, 2014). This rate of forest loss is especially worrisome as natural regeneration is hampered by the country's very low levels of rainfall (on average about 600–1000 mm per year, concentrated on between 50 and 100 days in the rainy season; MECV (2014)); for more detailed information see Figure 1 (and then especially the grey bars therein). The rate of natural regeneration is thus low, and hence Burkina Faso's forests are threatened by forest fragmentation as well as by a loss of resilience to extreme climate conditions (Miles et al., 2006).

The main proximate causes of forest cover loss in Burkina Faso are land conversion (especially for agriculture and cattle herding), logging (especially for the production of firewood and charcoal), and bush and forest fires; see Pouliot et al. (2012) and CIFOR (2016). Expansion of agricultural and pastoral activities is driven mainly by population growth (Pouliot et al., 2012; Ouedraogo et al., 2009) combined with very limited improvements in land productivity (Goldstein and Udry, 2008; Etongo et al., 2015). Population growth is also the main driver of the increasing demand for firewood and charcoal, the two most affordable energy sources for low-income, rural households (Ouedraogo, 2006; Bensch et al., 2015; Ouedraogo et al., 2011).

Forest fires, the third cause of forest degradation, can occur because of natural causes, but the vast majority of fires in Burkina Faso are man-made (Menaut et al., 1991; MECV, 2007; Devineau et al., 2010; Le Page et al., 2010; CIFOR, 2016). This is the case even

Figure 1: Average precipitation per month of the year (left axis and grey bars), and the average share of Burkina Faso's protected forest areas that are affected by fire (right axis and solid line), in the period between 2003 and 2013.



Note: The average amount of precipitation (measured in cubic millimeters) received by the 77 protected forests in Burkina Faso in each of the calendar months in the period 2003-2013, as well as the share of forest cover having been affected at least once by forest fires in each month in that same period.

though starting fires in forested areas has been declared illegal from 1997 onward. As shown by the solid line in Figure 1, the bulk of these fires occur in the dry season (between November and February) when rainfall is low (as reflected by the grey bars), implying that the vegetation is dry and highly combustible. Farmers use fire to remove crop residue that remains after harvest and to restore soil fertility on previously cultivated land (in October/ November), or clear new land (in March/ April). These fires may run out of control and spread from cultivated lands to neighboring forest lands (Savadogo et al., 2007; Sow et al., 2013). Fire is also used by cattle herders to stimulate regrowth of young sprouts as feed for cattle, and by hunters (or poachers) to spot and drive out game (Sawadogo, 2009). Fires originating from all these different types of economic activity are detrimental to forests as they not only damage the canopy of developed trees, but also hamper the development of seeds (Zida et al., 2007). Forest fires in Burkina Faso thus result in an impoverished and fragmented forest biome, and possibly even in the degradation of forests to savanna grasslands (Sawadogo, 2009; Devineau et al., 2010; Sow et al., 2013).

2.2. Burkina Faso's Forest Investment Project

As part of the country's effort to reduce deforestation and forest degradation and to improve carbon sequestration, Burkina Faso's government implemented the Forest Investment Program (FIP) with financial support from the World Bank, the African Development Bank, and the Climate Investment Fund. Twelve forests were selected to be included in this pilot program aimed at reducing forest fires by a combination of participatory forest management and technical forest fire containment measures.

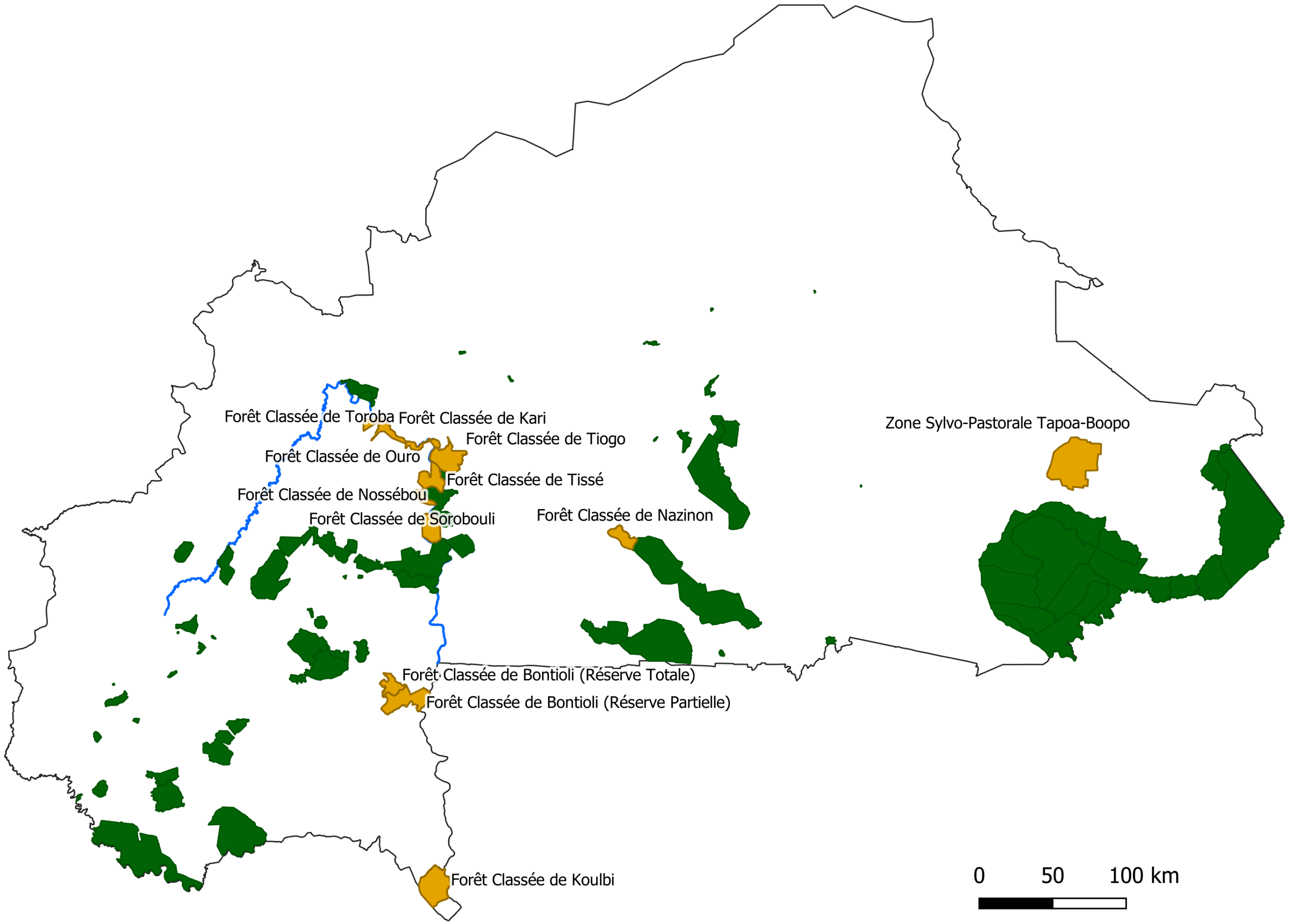
The main axis of the intervention was the establishment of Forest Management Committees (FMC) in each of the twelve project forests. These FMCs consisted of inhabitants of the communities surrounding the forest, and were tasked to disseminate knowledge on forest management in their communities and to coordinate conservation efforts at the forest level. Most importantly, they were to raise community awareness about the adverse consequences of forest degradation and hence about the importance of reducing the number of forest fires started, as well as explain the different methods with which fires can be better contained. As a coordinating body, the FMCs were to share tools and equipment (such as vehicles and communication devices) with the so-called Forest Management Groups (FMGs)[1] who implement the activities at the community level, and to also organize the FMGs' forest management efforts. These efforts included constructing

[1]Forest Management Groups (FMGs) were established in the reform of 1986 (Coulibaly-Lingani et al., 2011) to improve the sustainable management of Burkina Faso's forest areas. Protected forests were partitioned into Forest Management Units (FMU) of between 20 and 40 km^2, each of which was to be managed by an FMG consisting of representatives of the nearby communities, including local leaders and volunteers. As evidenced by the still high rate of forest loss, these FMGs were not very effective in fostering forest conservation due to their inability to formulate effective plans and to protect forests because of poor organization at the community level, lack of knowledge of and lack of resources for forest management, and limited authority (Kalame et al., 2009; Bouda et al., 2011). The FMCs were thus installed by the government to address these issues.

firebreaks (strips of cleared land in the forest to keep fires from spreading), managing the amount of combustible vegetation in the forest at the beginning of the dry season, and delimiting the forest borders (with signposts and cleared forest strips around forest borders). The FIP program was scheduled to run from October 2014 to 2019, but in many of the project forests the program's rollout did not start before early 2015. While the actual starting dates may differ between forests, the program was announced in October 2014. As announcement effects may already affect behavior (think of the possibility of setting more fires now to avoid the risk of not being able to use fire later), we retain October 2014 as the start of the program in our analyses.

Even though there are 77 forests in Burkina Faso with protected forest status, only twelve were to be included in the FIP program, for two reasons. First and foremost, the available budget was not sufficient to include all forests, but the government also explicitly viewed the intervention as a pilot of which the effectiveness was to be assessed. To determine which forests to enroll in the program, the government ranked all 77 protected forests based on criteria regarding forest characteristics as well as the perceived urgency of conservation, such as the frequency of forest fires, deforestation rates, carbon sequestration capacity, forest size, the agro-climatic zone they are located in, and the (perceived) availability of non-timber forest products (for the full list of selection criteria, see Appendix A). The government then selected twelve forests that ranked high on these criteria (see Figure 2).

Figure 2: Burkina Faso's 77 protected forests, and their status in the selection process.



Note: The orange forests are the twelve forests selected for the FIP program. The green forests were excluded from the selection procedure for the project. The river marked in blue in the western part of the country is the Mouhoun river.

3. Empirical approach

We estimate the causal impact of the intervention on forest fire occurrences using the Synthetic Control Method (SCM) as developed by Abadie and Gardeazabal (2003) and Abadie et al. (2010). This method estimates the counterfactual outcome for each of the intervention units in the intervention period (i.e., each project forest's outcome had the intervention not been implemented) using a convex combination of the units that had not received the intervention (the remaining 65 of Burkina Faso's 77 protected forests). More specifically, the estimated Treatment on the Treated effect for project forest i in intervention period t is $\alpha_{i,t>T_0} = Y_{i,t>T_0} - \sum_{j \in C} w_{i,j} Y_{j,t>T_0}$, where T_0 denotes the last period before the start of the intervention, $Y_{i,t>T_0}$ is the outcome of interest of forest i in period $t > T_0$, C is the set of non-treated forests, and $w_{i,j}$ (with $0 \leq w_{i,j} \leq 1$ and $\sum_{j \in C} w_{i,j} = 1$) is the weight assigned to the outcome of each of the non-treated units ($Y_{j,t>T_0};\ j \in C$).

The main challenge is thus to find weights $w_{i,j}$ to minimize the differences between treatment unit i and its synthetic control in the pre-intervention period in terms of both variables that are predicted to affect the outcome variable of interest (in our case, forest size and forest precipitation rates affecting forest fire occurrences) and pre-intervention values of the outcome variable (in our case, forest fire occurrences); see Appendix B for a more detailed explanation of the process. Intuitively, if weights can be found such that the synthetic control ($\sum_{j \in C} w_{i,j} Y_{j,t}$) closely traces the outcomes of the treated unit ($Y_{i,t}$) in the pre-intervention period ($t \leq T_0$), it is also likely to provide an accurate estimate of the treated unit's counterfactual outcome in the post-intervention period.[2]

[2]By not just fitting on pre-treatment forest fire outcomes but also on observable pre-treatment characteristics thought to be predictive of forest fire outcomes, the method reduces the likelihood that unobservable time-varying characteristics cause outcomes of the synthetic control unit to differ from those of the treated unit in the intervention periods. In other words, fitting on both pre-treatment outcomes and observable characteristics helps ensure that the estimated treatment effect is not affected by unobservables even if they systematically differ between treated and non-treated units before the start of the intervention.

Having estimated α_{it} for each of the twelve project forests, the average treatment effect then equals $\alpha_{t>T_0} = \frac{1}{12}\sum_{i \notin C} \alpha_{i,t>T_0}$.

To evaluate the likelihood of the results being false positives, we use the placebo test approach proposed by Abadie et al. (2010) and Cavallo et al. (2013). Intuitively, the smaller the share of placebo estimates exceeding the estimated treatment effects, the more likely it is that the treatment was indeed effective, and hence this share p^{signif} can serve as the estimated treatment effect's pseudo-significance level; for more details, see Appendix B.[3] We calculate the pseudo-significance levels of our estimates using placebo tests on 5 million combinations of twelve of Burkina Faso's 65 non-intervention forests.

The Synthetic Control Method is better suited to estimate causal impacts for this particular study than other, more standard, methods, like difference-in-difference models with matching. Matching of the project forests to non-project forests is not feasible because neither the scores on each of the criteria nor the weights attached to each of these criteria are available. And because selection into treatment was non-random, the parallel trend assumption needed for difference-in-difference methods is very likely to be violated. Finally, the SCM has the added benefit that the method is able to estimate the per-period treatment impacts even if the number of project forests is relatively small. As such, the method is ideally suited to evaluate not just the average effectiveness of the intervention, but also the dynamics of the treatment effect.

[3] For the SCM to work well, the evaluated forests (project, and placebo) need to lie within the convex hull of the set of all control forests. If not, the requirements that $0 \leq w_{i,j} \leq 1$ and $\sum_{j \in C} w_{i,j} = 1$ result in a poor fit in the pre-intervention period, and not correcting for the quality of pre-intervention fit would result in a higher rate of false positives. This is especially relevant for the placebo tests because, by definition, some of the placebo forests will lie outside the convex hull. We address this by scaling all treatment estimates by each synthetic control's Root Mean Squared Prediction Error for the pre-intervention period (Abadie et al., 2010; Galiani and Quistorff, 2017).

4. Data and estimation procedure

We use satellite data from NASA's MODIS collection (publicly accessible via Google Earth Engine; see Gorelick et al. (2017)) to construct a panel of monthly grid-cell data on forest fire incidences for each of Burkina Faso's 77 protected forests in the period from January 2003 to December 2019. The MODIS collection has a resolution of 1 km^2 and provides global coverage every one or two days.[4] Our main measure of forest fire incidences is the number of days in a month on which a forest grid cell was detected to be on fire, averaged over all grid cells in a forest. This measure thus simultaneously captures two dimensions of forest fires – the number of grid cells that were on fire in a month, but also the number of days each of the grid cells was on fire in that month. Following the terminology of Giglio et al. (2018) we will refer to this measure as "forest fire occurrences", which is thus forest- and month-specific.

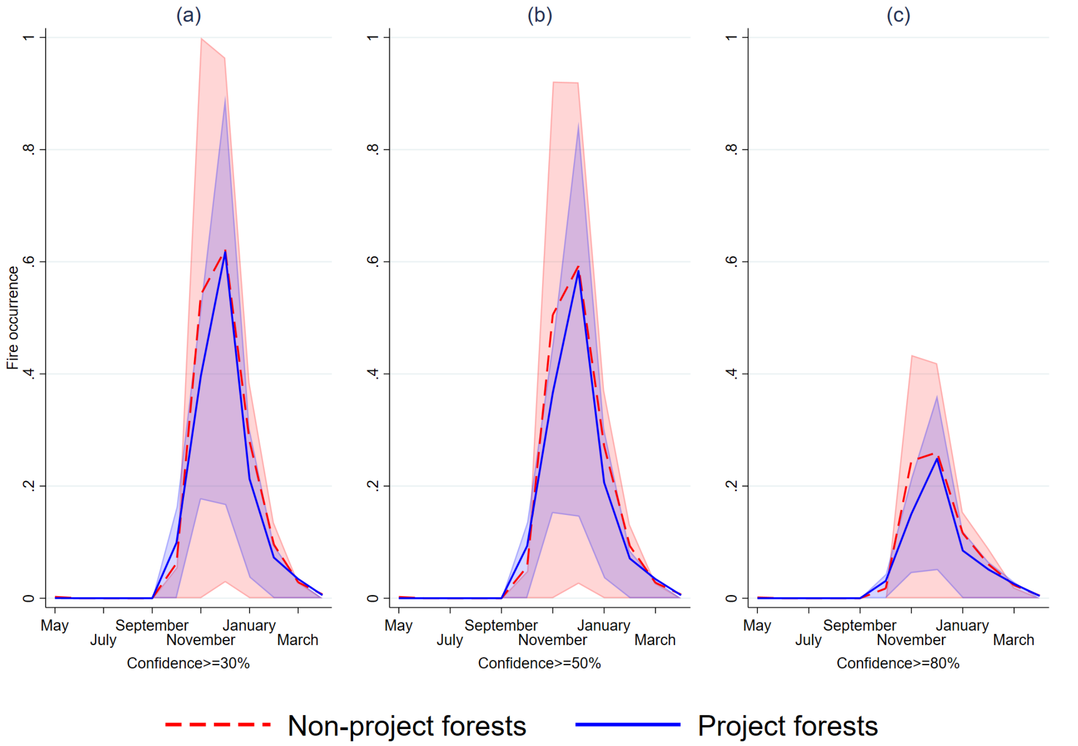
The resolution of 1 km^2 is small enough to assume that if a fire is detected in a grid cell, most (if not all) of the vegetation is burned (Burgess et al., 2012; NASA, 2019). However, false positives may still arise. MODIS addresses this concern by reporting a confidence level (between 0 and 100%) for each detected fire. Figure 3 presents the pre-intervention fire occurrences, averaged over the pre-intervention period 2003-2013, for each month of the calendar year, using three different confidence thresholds – 30%, 50% and 80%. Consistent with Figure 1, the three panels of Figure 3 show that fires occur mostly in the dry season (November-February), and especially so in November and December, the first two post-harvest months. The panels also show that the mean number of forest fire occurrences is similar in the (then yet to be) treated forests and in the 65 other classified forests (depicted by the continuous and dashed lines, respectively). Also note that the variance around these means is quite substantial (as indicated by the

[4] We preferred MODIS over NASA's Visible Infrared Imaging Radiometer Suite (VIIRS) as the latter data are only available from 2012 onwards. Hence, using FIRMS would not allow us to properly train the SCM because of the paucity of pre-intervention observations.

blue- and red-shaded areas, representing the 25% and 75% percentiles). Not only were the mean levels of forest fire occurrences very similar in the project and non-project forests, they also co-move over the pre-intervention years; see Figure C.1 in Appendix C. However, the trend of fire occurrence in project forests does not trace perfectly the trend in non-project forests, which suggests that a difference-in-differences approach is not feasible. Regarding the confidence thresholds, relatively few forest fires were detectable with an 80% confidence level or better. Because using the 80% threshold would cause us to severely underestimate the prevalence of forest fires (Devineau et al., 2010; Schroeder et al., 2014), we decided to focus our analyses in the remainder of this paper on forest fire occurrences that have been detected with 30% confidence or better – the threshold that MODIS identified as the cut-off for nominal-confidence levels. Below we do, however, test whether our results are robust against using the 50% confidence criterion as well.

Forest fire occurrences are thus our main indicator variable, but it should be noted that it may hide important differences. A forest fire occurrence of 0.2 days per month may mean that two of every ten grid cells in a forest experienced a forest fire on one day of the month, or that fire was detected on one out of ten grid cells on two days in that month. Which of the two is the correct interpretation of the observed forest fire occurrence is important because fires in the Sahelian savannah zone degrade forests primarily by damaging the seeds and destroying the canopy of young saplings (Zida et al., 2007). That means that fires taking place on two different grid cells may be more damaging than a single fire affecting the same grid cell on two consecutive days. It is thus important to know not just (the changes in) the number of forest fire occurrences, but also (the changes in) the share of forest grid cells that experienced one or more fires in a specific month. And if the program proves to have been successful, it would also be useful to know the mechanism via which the program managed to reduce forest fire occurrences. Was it effective because it resulted in a decrease in the number of fires

Figure 3: Monthly fire occurrences in the project and non-project forests, averaged over the period 2003-2013, and for different levels of detection confidence.



Note: Average forest fire occurrences are depicted by the blue solid and red dashed lines. The top and bottom of the blue and red shaded areas capture the 25th and 75th percentile of fire occurrences between 2003 and 2013 for the project and non-project forests. The threshold confidence levels for detection are 30%, 50%, and 80% for panels (a), (b), and (c) respectively.

started, or was it effective because the fires were better contained?

To answer these questions, we calculate three additional forest fire indicators. The first is the share of grid cells in a forest on which at least one forest fire was detected in the month under consideration. Our second additional indicator is the number of fires that were started in a month. We define a fire event as a contiguous set of grid cells that were on fire on one day of the month, whereas none of these grid cells were on fire on the previous day. The latter criterion makes sure that a forest fire that lasted for more than one day is coded as one fire event, and the contiguity criterion implies that we assume that fires on contiguous grid cells emanate from the same initial incident. And we can then also measure the spatial spread of the forest fires, our third additional indicator, by calculating the size of area affected by fire for each fire event and subsequently taking the average thereof.

We use the Synthetic Control Method to estimate the FIP program's impact on each of the four forest fire measures: forest fire occurrences, the share of a forest grid cells having been on fire at least once, the number of forest fires started, and the extent to which forest fires spread out.[5] As forest characteristics that predict fire incidences, we use the annual panel of 2006-2013 pre-treatment outcomes[6], the average annual precipitation in the forest before the treatment, and the size of the forest (measured at baseline, in 2013) to construct the synthetic control forest for each of the treatment forests. Although the relationship between each of these two forest characteristics and the actual forest fire occurrences is ex-ante ambiguous[7], including them in the weighting process will improve the fit, independent of the exact relationship. Regarding the composition of the synthetic control forests, 34 of the 65 non-intervention forests received a positive weight in at least one of the 12 synthetic control forests; on average, a project forest's synthetic control

[5]While it would also be interesting to have information on the duration of forest fires, the MODIs data set does not contain the necessary information (Balboni et al., 2021). We can approximate it, however, by taking the ratio of the number of forest fire occurrences and the share of forest grid cells that were affected at least once during the month. This would provide an upper-bound estimate of the average duration of fires because it does not take into account whether grid cells were on fire on consecutive days or not. An analysis of this fifth (and imprecise) indicator would not yield any new insights because we already analyze the numerator and denominator separately.

[6]Despite having data on forest fires from 2003 onward, we do not include all pre-treatment periods as predictors. This is because if we were to do so, the "relevance weights" ($\boldsymbol{V}_k$) that assign positive weights to the pre-treatment outcomes and zero to the the forest characteristics would minimize the pre-treatment RMSPE in Equation (B.5) (cf. Kaul et al. (2021)). Instead of including all pre-treatment outcomes, we aim to find synthetic controls that fit well to the project forests in the period leading up to the beginning of the FIP program.

[7]Forest size is expected to affect forest fire occurrences because of two reasons. First, man-made fires are more likely to be started on the forest fringe than in the interior (especially if agriculture is the main activity causing forest fires), so that larger forests may have, on average, fewer forest fires per grid cell. Alternatively, larger forests may have more fire occurrences because they are more difficult to monitor. And also the relationship between precipitation and forest fires is also ambiguous ex ante. In drier forests the vegetation is more prone to catching fire and the fire is likely to spread wider too. But then it may also be the case that agricultural activity is higher in areas with more precipitation, so that forest fire occurrences are more pronounced in forests with higher precipitation rates. Whichever of the two opposing mechanisms is dominant for each of these two variables, including precipitation rates and forest size in the SCM's weighting process will improve the accuracy of the synthetic control.

consists of 7.5 non-intervention forests; see also Table C.1 in Appendix C.

We have monthly data on forest fires, and this relatively high frequency poses a challenge to the SCM approach for two reasons. First, applying the SCM to high frequency and highly varying data may yield a synthetic control that gives relatively more weight to idiosyncratic shocks (i.e., to the number of forest fires in the pre-treatment period) and relatively little weight to the predictors of the outcome variable (precipitation and forest size), leading to biased estimates of the counterfactual (Dube and Zipperer, 2015; Robbins et al., 2017). Second, high variation in the data prevent the detection of small or even moderate effect sizes as these effects would be similar in size to the prediction errors in the pre-treatment outcomes due to imperfect fit (Abadie, 2021). We address these concerns by applying the SCM to the forest fire indicators for each of seven months in the dry season, those months of the year in which forest fires (may) occur; see Figure 1. For instance, to estimate the impact of the forest fire prevention program on forest fires in November, we construct synthetic controls by using the forest fire occurrences in the month of November as well as by using time-invariant forest characteristics (forest size and precipitation).

5. Overall impact of the FIP

5.1. Impact on forest fire occurrences and tree cover

We first test whether the FIP program was effective in reducing the number of days the average forest grid cell was on fire, for each of the seven months of the dry season. We present the results on forest fires with a detection confidence of 30% or better in Figure 4. In each of the seven panels of the figure, the solid blue line represents the average of fire occurrences observed in the project forests, the dashed red line reflects those in the corresponding synthetic controls, and the grey vertical line indicates the last observation prior to the start of the intervention (in October 2014). As is clear from this figure, the synthetic controls closely match the observed pre-intervention outcomes (i.e.,

Figure 4: Fire occurrences in the project forests in each of the seven dry months of the year, and the counterfactual outcome as derived using the Synthetic Control Method.

Note: The panels in this figure present the average number of days a fire was detected on a grid cell. The continuous blue lines depict the observed fire occurrences in project forests with at least 30% fire detection confidence, whereas the red dashed lines show the counterfactual outcomes as derived from the Synthetic Control Method. The last observation before the start of the program is indicated by the black vertical line. As the program was launched in October 2014, this last observation is for 2013 for the months of October to December, and for 2014 for January-April.

in 2003-2013/2014) of the treatment forests in each of the seven months, and especially so in the last two to three years of the pre-intervention period. Indeed, the root mean squared prediction errors (RMSPEs) in the pre-intervention period are below 0.06 days per month in November, December, and January (when average fire occurrences are higher; see Figure 1), and below 0.03 days in March, April, May, and October (when fire occurrences tend to be less frequent). The synthetic controls we constructed not only properly reproduce the pre-treatment outcomes averaged over all twelve treatment forests, but also those for each of the treatment forests separately (see Figure C.2 in Appendix C). And this holds not only for the case of forest fires that are detected with a 30% confidence level, but also when using the 50% criterion; see Figure C.3 in Appendix C. Our results are thus robust to changes in forest fire detection confidence levels. And our results are also robust to excluding those non-treatment forests from the analysis that are contiguous to treatment forests; see Table C.2 in Appendix C. This is important because it allows us to rule out the possibility of treatment spillovers affecting the post-intervention outcomes in non-treatment forests, which would have resulted in a violation of the SUTVA assumption (Pearl, 2009).

Regarding the effectiveness of the intervention in reducing the number of forest fire occurrences, Figure 4 shows that the post-intervention differences between the treatment forests and their synthetic controls tend to be small in all months except for, possibly, November – and then only for the first three or four years. This is confirmed by the SCM treatment estimates $\left(\alpha_t = \frac{1}{K}\sum_{i=1}^{K}\alpha_{it}\right)$ presented in Table 1. Columns (1) and (2) of this table present the estimated impact on fire occurrences with a minimum detection confidence of 30% and 50%, respectively. Note that the associated p-values are presented in brackets, and that those with $p < 0.10$ are printed in bold.

As already suggested by the graphical evidence presented in Figure 4, Table 1 documents that the FIP's intervention only managed to significantly reduce forest fires in November, the post-harvest month. In the first year of the intervention, the number of days the average grid cell was on fire in that month decreased by 0.073 compared to the synthetic control; see Column (1). While this effect is sizeable (as it is equal to a 43% reduction in forest fire occurrences), treatment effects were too divergent between the twelve treatment forests for this reduction to be significant. In the subsequent years the treatment effect increased from 0.073 (in 2014) to 0.126 (in 2016), after which it started to decline. And while the effects were still considerable in 2018 (with the average grid cell

Table 1: Estimated impacts of the forest fire prevention program on forest fire occurrences per calendar month, for the period 2014-2019

		(1)	(2)
		Fire occurrences	
Month	Year	C30	C50
Oct	2014	–0.033	–0.027
		[0.116]	[0.178]
	2015	–0.024	–0.013
		[0.184]	[0.218]
	2016	–0.024	–0.035
		[0.776]	[0.727]
	2017	–0.014	–0.039
		[0.102]	[0.461]
	2018	0.000	–0.000
		[1.000]	[0.856]
	2019	0.001	–0.002
		[0.322]	[0.859]
Nov	2014	–0.073	–0.040
		[0.284]	[0.706]
	2015	-0.093***	-0.098***
		[0.002]	[0.004]
	2016	-0.126***	-0.115***
		[0.000]	[0.006]
	2017	-0.026***	-0.103**
		[0.003]	[0.020]
	2018	–0.054	–0.075
		[0.459]	[0.636]
	2019	0.023	0.015
		[0.212]	[0.298]
Dec	2014	–0.017	0.028
		[0.901]	[0.401]
	2015	0.090	0.067
		[0.165]	[0.199]
	2016	0.044	0.017
		[0.856]	[0.947]
	2017	–0.093	–0.085
		[0.241]	[0.277]
	2018	0.162	0.127
		[0.202]	[0.139]
	2019	–0.143	–0.121
		[0.384]	[0.370]
Jan	2015	–0.013	–0.016
		[0.994]	[0.878]
	2016	–0.056	–0.047
		[0.957]	[0.882]
	2017	0.036	0.035
		[0.641]	[0.612]
	2018	0.005	–0.000
		[0.731]	[0.837]
	2019	–0.001	–0.010
		[0.621]	[0.813]
Feb	2015	0.020	0.031
		[0.728]	[0.568]
	2016	0.031	0.027
		[0.568]	[0.690]
	2017	0.062	0.062
		[0.162]	[0.169]
	2018	–0.029	–0.044
		[0.239]	[0.201]
	2019	0.031	0.022
		[0.121]	[0.293]
Mar	2015	–0.014	–0.016
		[0.304]	[0.247]
	2016	–0.017	–0.012
		[0.442]	[0.881]
	2017	-0.022***	–0.002
		[0.000]	[0.854]
	2018	–0.005	–0.006
		[0.920]	[0.724]
	2019	0.021***	0.020
		[0.000]	[0.702]
Apr	2015	0.005	0.005
		[0.540]	[0.834]
	2016	0.002	0.002
		[0.707]	[0.238]
	2017	–0.001	–0.001
		[0.864]	[0.838]
	2018	–0.001	–0.001
		[0.586]	[0.254]
	2019	0.015	0.015
		[0.159]	[0.497]

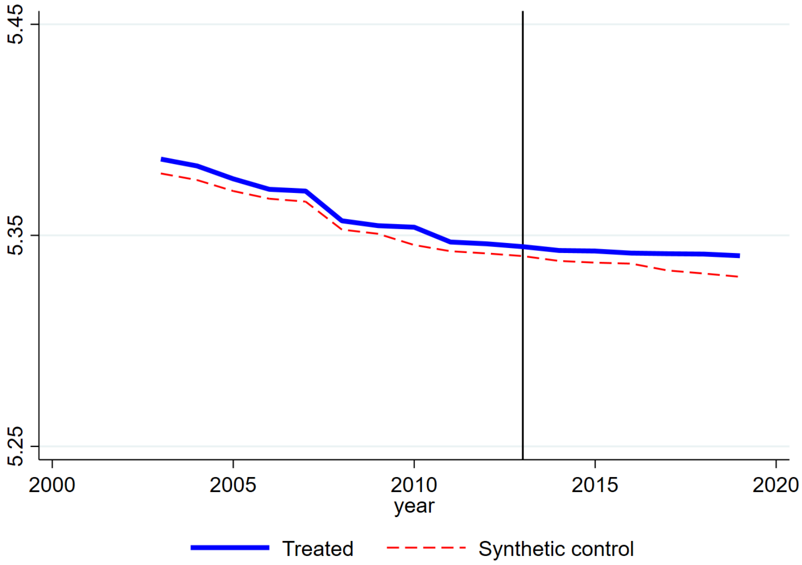
Note: This table presents the average decrease in the number of days a forest grid cell is on fire, as a result of the FIP program. The effects of the program are estimated separately for each month on an annual-panel of forest level fire occurrence in the given month. We dropped two project forests in the estimation of December effects and one project forest in the estimation of April effects because pre-treatment fire occurrence in these forests fell outside the convex hull. Variables in the SCM process include past fire occurrences from 2006 onwards, the size of the forests, and the amount of annual precipitation before the FIP program. The p-values of the impact estimates (as derived from the inference tests) are presented in square brackets; those that are not "significant" at the 10% level have been grayed out. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

in the treatment forest experiencing 0.054 fewer days on fire than the synthetic control unit), they are also measured with less precision, and the effect is fully extinguished by 2019. A similar pattern emerges when using the 50% confidence criterion (see Column (2) of Table 1). There are no discernible effects in any of the other months of the year except for March, where the program seems to have resulted in a *reduction* in forest fire occurrences in 2017 and in an *increase* thereof in 2019. However, when using the 30% confidence criterion, these impacts are small (a decrease or increase of less than 0.025 days of fire on the average grid cell; see Column (1)), and virtually zero (and highly insignificant) when using the 50% criterion (in Column (2)). That means that the March results are not likely to be real (and definitely not economically significant), and hence November is the only month in which the FIP managed to change forest fire occurrences.

Based on Figure 4 and Table 1, we conclude that the program was not effective in reducing forest fire occurrences throughout the year; it only managed to reduce the number of forest fire occurrences in the first month after the harvest has been completed. The next question is whether this sizeable yet relatively short-lived impact of the FIP program on the frequency of November forest fires resulted in an increase in forest cover. We use the annual forest level tree cover data from the Global Forest Change dataset of Hansen et al. (2013), which combines Landsat images and MODIS data with ground-truth verification (Hansen et al., 2010). We apply the SCM estimator on the annual forest-level tree cover measure; the results are presented in Figure 5.

Two features of Figure 5 are most notable. First, while average tree cover in the treatment forests is systematically larger than that in their synthetic controls, the differences are small in the pre-intervention period (about 0.01 percentage points on average), and the synthetic control also closely traces the observed tree cover in the treatment forests over time. Second, the post-intervention difference continues to be small, although the figure also seems to suggest that the reduction in tree cover is slowed down (if not stopped) in the treated forests, whereas the decline in the synthetic control seems to

Figure 5: The observed tree cover in the treatment forests and their counterfactual cover as derived by the Synthetic Control Method.



Note: The blue continuous line depicts the observed tree cover in the 12 treatment forests, whereas the counterfactual is represented by the red dashed line. The vertical line marks 2013, the year before the FIP program was launched. Although the estimated synthetic control does not fit perfectly on the observed tree cover before the treatment, the differences are small in absolute terms: 0.01 percentage point in each pre-treatment year. Also, the difference between the two lines does not change notably in the intervention period, indicating no effect of the FIP on tree cover.

continue. Indeed, while none of the point estimates are significantly different, the differences in tree cover between the treated forests and their synthetic controls gradually increases over time, from about 0.1 percentage points in 2015 to about 0.2 percentage points in 2020.[8]

5.2. Mechanism behind the reduction in November forest fire occurrences

Overall, the forest fire prevention program was thus not very effective. It managed to reduced fire occurrences in just one month of the dry season (November, at the end of

[8] As is clear from Figure 5, forest fire occurrences decreased not just in the project forests, but also in the non-project forests (and then especially so over the period 2004–2010. In the period 2014–2019 the difference in the share of vegetation cover is somewhat larger, but remains small in absolute terms. As already stated in Section 5.1, this is not likely to due to technical and/or informational spillovers having attenuated the project's impact.

the agricultural cycle) and for just a limited number of years (between 2014 and 2017), and the program also did not result in an increase in forest cover. Still, uncovering the mechanisms via which the November forest fires occurrences were reduced is of interest. Has the reduction in November forest fires been the result of a reduction in the number of fires started (e.g., due to improved community awareness), or because of improved forest fire containment? And was the largest reduction achieved in the forest fringe (suggesting that farmers were the main agents of change), or in the forests' interior (suggesting it was the livestock herders and hunters that changed their use of forest fires)? We now turn to addressing these issues.

The timing of the impact – in November, when the bulk of the harvesting has just been completed – already suggests that the intervention was particularly effective in reducing agricultural fires. Farmers typically burn the crop residues on agricultural plots, so we would expect large reductions in fire occurrences at the forest fringe. This is corroborated by Table 2, which shows that most of the forest fire reductions took place within a 1 to 2 kilometer band away from the forest fringe. Comparing the size of the impact estimates in that table to those in Column (1) of Table 1, we can infer that the reduction has been largest on the forest fringe, and that the reductions in the forest interior are smaller and less likely to be significant; see also Figure C.4 in Appendix C. So while a change in agricultural practices is likely to have been the most important driver of the decrease in the November forest fire occurrences, other economic activities seem to have been affected (much) less.

In Table 3 we present the program's estimated impact on the share of grid cells that were burned at least once in November (see Column 1), and we also separately estimate the intervention's impact on the number of forest fires started, and their geographical spread (see Columns 2 and 3, respectively); see Figure C.5 in Appendix C for the graphical illustrations of these treatment effects. Comparing the Column (1) results in Tables 1 and 3, the FIP intervention was about as effective in reducing the total share

Table 2: Estimated average treatment effect on number of fire occurrences excluding the forest fringe

Month	Year	(1) No thresh.	(2) Fire occurrences 1 km thresh.	(3) 2 km thresh.
Nov.	2014	–0.073	–0.053	–0.010
		[0.284]	[0.285]	[0.971]
	2015	–0.093***	–0.174***	–0.081
		[0.002]	[0.001]	[0.116]
	2016	–0.126***	–0.158**	–0.106
		[0.000]	[0.023]	[0.139]
	2017	–0.026***	–0.025	–0.039
		[0.003]	[0.424]	[0.474]
	2018	–0.054	–0.118	–0.060
		[0.459]	[0.318]	[0.698]
	2019	0.023	–0.011	0.048
		[0.212]	[0.276]	[0.955]

Note: Estimates are based on the synthetic control method using forest-month level data. We use fires with 30% or better confidence to construct the outcomes. Treatment start from October 2014. P-values from the placebo analyses, in which treatment effects are standardized by pre-treatment RMSPE, are in brackets. Average fire spread is measured in km^2. *** p<.01, ** p<.05, * p<.1

of grid cells affected by fire in the post-harvesting month in the period 2015-2017 as it was in reducing overall forest fire occurrences. Indeed, the percentage-point reduction in the share of grid cells affected by fire in the 2015-2017 November months ranged between 8.2% and 10.1%. From Columns (2) and (3) we can infer that the main reason why the intervention was effective was that it resulted in a better containment of forest fires. As shown in Column (2), fewer fires were started throughout the post-intervention period, but these reductions are not significant in any of the post-intervention years except for 2016. Column (3), however, shows that the intervention resulted in a reduced spread of forest fires over neighboring grid cells in both 2016 and 2017: the 2.10 km^2 and 1.83 km^2 decreases in the size of fire events translate into a 38% and 29% decrease, respectively. We thus find that the reductions documented in Table 1 are more likely the result of improved forest fire containment than of a sizeable and long-lasting reduction in the number of fires started. Also note, however, that while the point estimate with respect to the number of fires started in 2018 was negative and sizeable (see Column (2)), this effect is not statistically significant, and we observe a sizeable *increase* in the geographical spread of fires in the same year (see Column (3)).

Table 3: Impact of the intervention on the share of forests affected by fire in November in each of the post-intervention years, as well as on the number and size of the forest fires.

Month	Year	(1) Share of fire affected grids in November	(2) # of ignitions	(3) Avg. fire spread
Nov.	2014	–0.060	–0.867	–0.295
		[0.470]	[0.745]	[0.678]
	2015	–0.082**	–0.471	0.331
		[0.035]	[0.416]	[0.971]
	2016	–0.086**	–1.324**	–2.108**
		[0.014]	[0.043]	[0.032]
	2017	–0.101*	–0.445	–1.829***
		[0.071]	[0.136]	[0.000]
	2018	–0.059	–1.237	1.730***
		[0.373]	[0.268]	[0.002]
	2019	–0.006	–0.410	–0.481
		[0.305]	[0.452]	[0.364]

Note: Estimates obtained using the Synthetic Control Method, using the 30% confidence criterion; p-values are presented in parentheses. or better confidence to construct the outcomes. Treatment start from October 2014. P-values from the placebo analyses, in which treatment effects are standardized by pre-treatment RMSPe, are in brackets. Average fire spread is measured in km^2. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.10$.

Together our results on better fire containment and no reduction in the number of forest fires started complement the findings of Edwards et al. (2020a). These authors evaluate the effect of a payment for ecosystem service program in Indonesia, in which villages were offered a large cash transfer if they did not set any fires within their villages' boundaries. Although payments induced villagers to better monitor their peers and to prevent them from setting fires, Edwards et al. (2020a) find that payments did not decrease the number of villages with one or more fires, and tree coverage did not increase either. Our findings suggest that forest conservation programs can be effective in increasing villagers' fire prevention effort and in containing fires, but not so much in preventing fire setting and limiting the subsequent damages. Even so, it is yet to be understood why better fire containment may not improve tree cover neither in Indonesia nor Burkina Faso.

6. The role of socio-economic characteristics in driving (the reduction in) forest fire occurrences

Having established that the FIP program was effective in reducing end-of-the-agricultural cycle forest fires, the next question is whether the program was equally effective in all forest areas, or whether there are marked differences in the response to the program by the communities surrounding the forests. We use responses from the 2014 Living Standards Measurement Study (LSMS), elicited between January and March of that year, to characterize villages surrounding the forests. Next, we assign each forest grid cell to the "sphere of influence" of the geographically most proximate village (see Appendix D for details about the matching process) and define the set of grid cells in the same sphere as a "subforest". By doing so, we assume that economic activities in a specific forest location are undertaken by inhabitants of the nearest village. We then calculate fire occurrences at the subforest level and relate the observed fire occurrences to the characteristics of the associated village.

Table 4 presents the socio-economic characteristics of the villages surrounding all 77 protected forests in Burkina Faso, as well as those of the subsamples of project and non-project forests. As shown in Column (1), the average village consists of about 175 households, nearly all households engage in agriculture, about half of them use inorganic fertilizers and the same holds for the use of organic fertilizers. The level of education is fairly low, household assets amount to FCFA 270,000 (or about US$ 400), the average distance from the village to the nearest protected forest is about 1.5 kilometers, and the average distance from a village to the main road is about 3 kilometers. More importantly, comparing Columns (2) and (3) of Table 4 we see that differences between the FIP and non-FIP villages tend to be small.

We implement two types of village-level analyses. First, we explore whether the characteristics listed in Table 4 are correlated with the subforest-level November forest fire occurrences before 2014. We do so by regressing the average of November fire

Table 4: Characteristics of the villages surrounding FIP and non-FIP subforests.

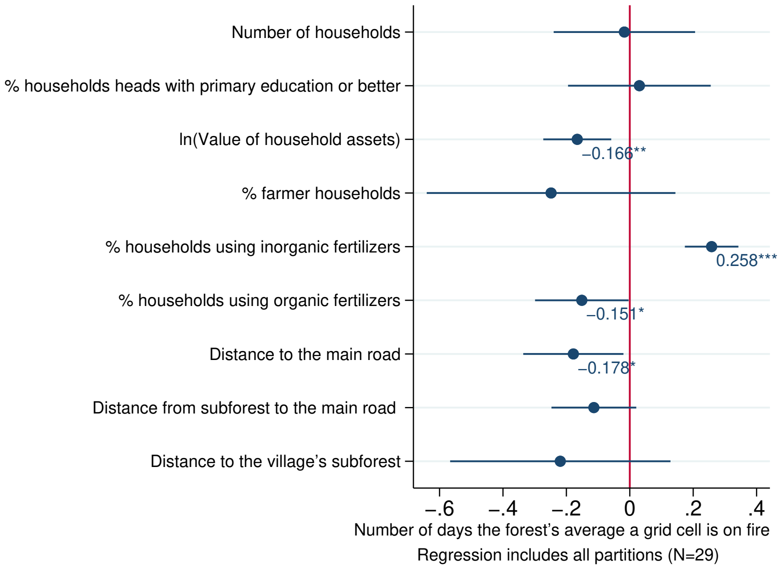
Variable	(1) Overall village characteristics Mean (SD)	(2) Villages surrounding FIP forests Mean (SD)	(3) Villages surrounding non-FIP forests Mean (SD)
Number of households	173.413	177.517	172.430
	(83.996)	(63.819)	(88.346)
Share of farmer households	0.980	0.981	0.979
	(0.072)	(0.045)	(0.077)
Share of households using organic fertilizers	0.552	0.479	0.569
	(0.269)	(0.301)	(0.259)
Share of households using inorganic fertilizers	0.582	0.595	0.579
	(0.297)	(0.316)	(0.294)
Share of households heads with primary education or better	0.149	0.118	0.156
	(0.150)	(0.101)	(0.159)
Value of household assets (FCFA, in natural logarithms)	12.445	12.060	12.537
	(0.987)	(1.014)	(0.962)
Distance to the main road (in km)	2.792	3.422	2.641
	(1.171)	(1.280)	(1.096)
Distance to the village's subforest (in km)	1.573	1.055	1.697
	(1.422)	(0.640)	(1.528)
Distance from village's subforest to the main road (in km)	8.977	9.286	8.903
	(6.293)	(3.867)	(6.756)
N	150	29	121

Note: Means and standard deviations of the socio-economic characteristics of the sample of villages surrounding all forests are presented in Column (1); those for the subsamples of intervention and non-intervention villages are presented in Columns (2) and (3), respectively.

occurrences before the treatment on a set of village characteristics. The results of the cross-sectional OLS regression are shown in Figure 6. We find that forest fires tend to occur more frequently the poorer the village, the more intensively it makes use of chemical fertilizers and the less it relies on organic fertilizers. And we also find that forest fires tend to occur more frequently in subforests of villages that are better connected to the road network. These results are in line with the findings of Bandiera et al. (2017), Balboni et al. (2021) and Oliveira et al. (2007), who also document the relevance of agricultural dependence and access to markets as drivers of forest fires.

Second, we test for heterogeneous treatment effects, to explore whether the FIP intervention proved to be more effective in changing the behavior of some villages than of others. We use the SCM to estimate $\alpha_{srt}^{\text{November}}$, the subforest-specific treatment effect for subforest s in region r in post-intervention year t ($t > T_0$). To construct synthetic con-

Figure 6: The relationship between the average rate of November fire occurrences in subforests and the socio-economic characteristics in the neighboring villages.



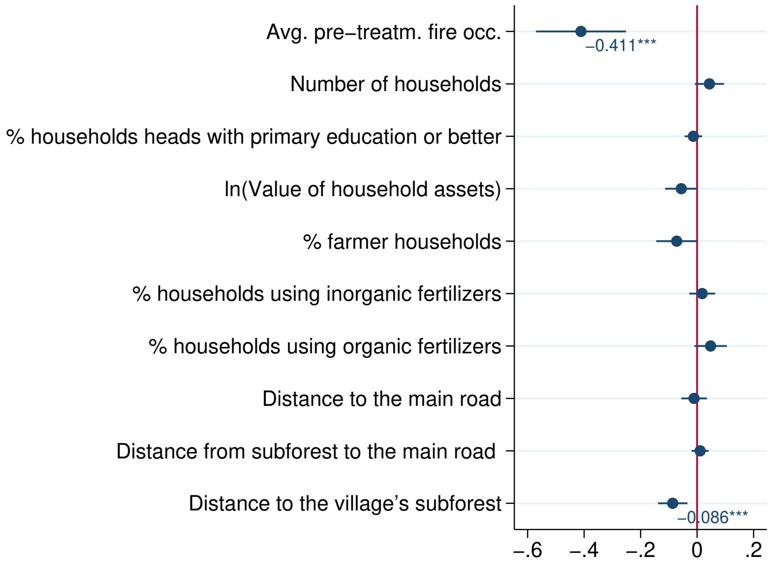
Note: This figure presents the coefficients from regressing average pre-treatment November forest fire occurrences in the treatment forests' 29 subforests on the neighboring communities' standardized socio-economic characteristics, in the pre-intervention period. The dots represent the point estimates, and the horizontal lines represent the 90% confidence intervals. ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

trols for each of the treated subforests we not only fitted the weights on pre-intervention outcomes, forest size and precipitation data (as we did in Section 5), but also on all village characteristics as presented in Table 4. After having estimated the treatment effects for all 29 treated subforests between 2014 and 2019, we regress $\alpha_{srt}^{\text{November}}$ on all village characteristics from the LSMS survey and pre-treatment average of November fire occurrences using the following random effects panel model:

$$\hat{\alpha}_{srt}^{\text{November}} = \mu + \zeta \bar{Y}_{sr}^{Nov,t \leq T_0} + H_s'\Gamma + \nu_s + \delta_r + \delta_t + \varepsilon_{srt}. \tag{1}$$

Here, $\bar{Y}_{sr}^{Nov,t \leq T_0}$ is the average pre-intervention level of November forest fire occurrences in subforest s in region r, H_s denotes the set of normalized (and time-invariant) characteristics of the village matched with subforest s, ν_s is the subforest random effect, δ_r

Figure 7: Estimates of the heterogeneous treatment effects on November forest fire occurrences for the various socio-economic characteristics of each of the subforests' neighboring villages.



Note: This figure presents the heterogeneous treatment effects, estimated at the subforest level, for each of the socio-economic characteristics of the adjacent village. Village characteristics in the regression are standardized by their means and standard deviations; the regression controls for the pre-intervention subforest fire occurrences as well as for region and year fixed effects. The dots in this figure represent the point estimates, with point estimate values depicted adjacently for those coefficients that are significant at the 10 percent, or better; the horizontal bars depict the 90% confidence intervals. . ***, **, and * indicate significance at the 1, 5, and 10 percent critical level.

and δ_t are the region and time fixed effects, and ε_{srt} is the idiosyncratic error term. The results of this analysis are presented in Figure 7.

As shown in Figure 7, we find a stronger response to the intervention in subforests that tend to have more frequent forest fires at baseline. The heterogeneous treatment estimate of -0.411 implies that, all else equal, subforests that faced 0.1 more days of pre-treatment fire occurrences per month experience an additional treatment-induced reduction in forest fires of 0.04 days for the average grid cell. Although this effect may seem small, it is relatively large compared to the average treatment estimate of between -0.08 to -0.14 days per month; see Table 1. We also find that larger distances between the subforest and the corresponding village is associated with stronger reductions in forest fire occurrences. The treatment-induced reduction in the number of forest fire occurrences is 0.08 days larger for villages that are one standard deviation (about 6 km) farther away from their subforest. Apart from baseline levels of forest fires and the distance between subforests and villages, none of the other covariates are found to affect the intervention's overall effectiveness.

7. Conclusions

In this paper we evaluated the impact of a forest fire prevention program in twelve of Burkina Faso's protected forests. Forest fires cause environmental damage in the form of both the increased emissions of greenhouse gasses and biodiversity loss. Forest fires are particularly damaging in arid regions because low precipitation results in fires spreading wider and vegetation regeneration being slower, resulting in forest fragmentation and degradation. Most of the forest fires in Burkina Faso are anthropogenic, with fire being used in economic activities such as agriculture (with the ashes acting as a natural fertilizer), cattle herding (to produce new shoots for grazing), hunting (to drive out game), or charcoal production. Reducing the frequency and size of man-made forest fires is thus essential for sustainable development, but evidence on effective fire reducing forest conservation policies is scarce.

The program we evaluate aimed to raise community awareness about the importance of preventing and mitigating forest fires, and to provide both the tools and knowledge necessary for forest fire containment. We use satellite images to monitor forest fire occurrences in each of Burkina Faso's 77 protected forests, for the period 2004-2019. We thus observe the frequency of forest fires in the intervention forests, and we use the Synthetic Control Method Abadie et al. (2010) to estimate each treatment forest's counterfactual outcome by assigning proper weights to each of the non-treatment forests.

We show that overall the program was not very effective in reducing forest fires. We find that the program reduced forest fires at the end of the agricultural season (in November) – after harvest, when farmers tend to use fire to burn the crop residue on their land. We do not detect any effects for any of the other months in the dry season, and also the vegetation cover was not significantly improved. Analyzing the forest fires' geographical spread suggests that the program was effective in reducing forest fires especially by means of better fire containment. The number of days a fire is detected on the average grid cell of treatment forests was reduced by 35% between 2014 and 2017, and we also find that the project's effectiveness tends to be stronger the more prevalent were the forest fires before the beginning of the program. Despite the initial success, the project's impact became statistically insignificant from 2018 onwards – even though the new institutions aimed at improving forest management, like the Forest Management Committees, were still in place. The project's impact was therefore quite temporary, and it also failed to significantly reduce the number of forest fires in any of the other months in the dry season. Probably as a result of this, we also find no significant increase in the amount of vegetation cover – either because the reduction in November forest fires was not sufficiently large to be captured via remote sensing, or because the size and duration of the treatment impact were not sufficient for the vegetation to recover. We thus conclude that just mitigating the geographical spread of post-harvest fires is not enough to substantially improve forest conservation, and that additional measures are needed to reduce not only the number of agriculture-related forest fires, but also the frequency and geographical spread of the fires emanating from other non-agricultural economic activities.

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Appendix A. Selection criteria for the forests to be included in the program

The selection process of forests into the FIP program consisted of two main steps. In the first, the government narrowed down the number of forests from 77 to 23 following the seven selection criteria on the perceived urgency of conservation below:

- Capacity in terms of carbon sequestration of the forest in relation to the productivity
- Level of CO_2 emission by wildfire
- Current level of destocking or export of carbon (forest clearing, excessive cutting of firewood, etc.)
- Level of the ecosystem degradation/anthropization
- Opportunities to take stock of anterior interventions in the forests
- Security level (elimination criterion)
- Main factor of deforestation/degradation

The second step of the selection process consisted of the government narrowing down the number of forests from 23 to 12 on the basis of a set of eight criteria:

- Forest must have or must be designing a development and management plan
- Opportunity to further develop existing resources (e.g. non-timber products of vegetal and animal origins)
- Spatial span (large forest must be privileged)
- Level of the ecosystem degradation/anthropization
- How management of common forest areas is allocated (inter-communities and inter-regions)
- Whether the forest is representative in terms deforestation dynamics
- Presence and activity of professional organizations
- Risk level of activating safeguard policies when interventions are done in the forest.

Appendix B. Estimation of the synthetic control outcomes

The Synthetic Control Method can be summarized as follows. Let us use K to denote the set of treated units that were selected into the intervention, C to denote the set of non-treated units, and $|C|$ and $|K|$ to denote the number of units in each. Suppose further that we observe all units for T periods (indexed $t = 1, \ldots, T$), and that the intervention started in period $T_0 + 1$ $(1 \leq T_0 < T)$. Finally, let us denote the observed outcome of unit i in period t by $Y_{i,t}$, and the value of an observable characteristic of the same unit that is expected to affect this outcome by z_{li} (indexed $l = 1, \ldots, L$). Then the SCM constructs a synthetic control unit for each treated units $k \in K$, represented by the weighting vector $\boldsymbol{W_k} = (w_{1,k}, \ldots, w_{|C|,k})'$ (where $w_{ik} \geq 0 \;\; \forall \; i \in C$ and $\sum_{i \in C} w_{ik} = 1$), such that the set of following conditions are met:

$$\sum_{i \in C} w_{i,k} Y_{it} = Y_{kt}, \quad \forall \; 1 \leq t \leq T_0, \text{ and} \tag{B.1}$$

$$\sum_{i \in C} w_{i,k} z_{li} = z_{lk}, \quad \forall \; 1 \leq l \leq L. \tag{B.2}$$

Abadie et al. (2010) show that if equations (B.1) and (B.2) hold for all $t \leq T_0$ and for all L baseline variables, the synthetic control unit's predicted outcome $\sum_{i \in C} w_{i,k} Y_{it}$ is an unbiased estimate for the counterfactual of treated unit k in treatment period $t > T_0$. Ideally, treated unit k's synthetic control is thus the one with a vector of weights $\boldsymbol{W_k}$ that exactly replicates k's pre-intervention outcomes (see equation (B.1)) as well as each of its observable baseline characteristics (see equation (B.2)). Fitting on both pre-treatment outcomes and observable characteristics helps ensure that the estimated treatment effect is not affected by differences in unobservables even if they systematically differ between treated and non-treated units before the start of the intervention.

The process via which $\boldsymbol{W_k}$ is derived consists of two steps. In the first step the SCM assigns a randomly selected set of "relevance weights" $v_m \geq 0$ to each of the $M = T_0 + L$ constraints (see equations (B.1) and (B.2)) and collects them in an $(M \times M)$ symmetric, diagonal, and positive semi-definite matrix ($\boldsymbol{V}_k$). The SCM subsequently finds the set of control units' weights $\boldsymbol{W}_k(\boldsymbol{V}_k)$ that minimizes the distance between the $(M \times 1)$ vector of attributes of treated unit k that need to be matched and the corresponding $(M \times |C|)$ matrix containing the attributes of the non-treated units for the given relevance vector. Denoting the former by $\boldsymbol{X}_k = (z_{1k}, ..., z_{Lk}, Y_{k1}, ..., Y_{kT_0})'$ and the latter by $\boldsymbol{X}_0$, the distance function to be minimized in the first step is thus:

$$\min_{\boldsymbol{W_k}} \parallel \boldsymbol{X}_k - \boldsymbol{X}_0 \boldsymbol{W}_k \parallel_{\boldsymbol{V}_k} = \sqrt{(\boldsymbol{X}_k - \boldsymbol{X}_0 \boldsymbol{W}_k)' \, \boldsymbol{V}_k \, (\boldsymbol{X}_k - \boldsymbol{X}_0 \boldsymbol{W}_k)}, \tag{B.3}$$

$$\text{s.t.} \quad w_{ik} \geq 0 \quad \forall \; i \in C \quad \wedge \sum_{i \in C} w_{ik} = 1. \tag{B.4}$$

Having repeated the first step for a large number of randomly selected relevance vectors $\boldsymbol{V}_k$ (each resulting in a specific $\boldsymbol{W}_k(\boldsymbol{V}_k)$), the second step is to find the $\boldsymbol{V}_k$ that results in the best fit in the pre-intervention period. Collecting the pre-intervention outcomes in a $(T_0 \times 1)$ vector denoted by $\boldsymbol{Y_k^{\leq T_0}}$ for treated unit k and the pre-intervention outcomes of non-treated units in a $(T_0 \times |C|)$ matrix denoted by $\boldsymbol{Y_0^{\leq T_0}}$, Doudchenko and Imbens (2017) propose to choose the set of relevance weights $\boldsymbol{V_k^*}$ that minimizes the root mean squared prediction error on the pre-intervention outcomes of the treated unit:

$$\min_{\boldsymbol{V}_k} \quad \text{RMSPE}_{\boldsymbol{k}} = \sqrt{\frac{1}{T_0} \left(\boldsymbol{Y_k^{\leq T_0}} - \boldsymbol{Y_0^{\leq T_0}} \boldsymbol{W_k(V_k)} \right)' \left(\boldsymbol{Y_k^{\leq T_0}} - \boldsymbol{Y_0^{\leq T_0}} \boldsymbol{W_k(V_k)} \right)} \tag{B.5}$$

$$\text{s.t.} \quad v_{mm} \geq 0 \; \forall \; m \quad \wedge \quad \sum_{m=1}^{M} v_{mm} = 1. \tag{B.6}$$

Having determined $\boldsymbol{V_k^*}$, the resulting treatment effect estimate of this unit in each period $t > T_0$ is equal to the difference between treated unit k's observed outcome and its counterfactual outcome as generated by its synthetic control:

$$\alpha_{k,t} = Y_{k,t} - \sum_{j \in C} w_{j,k}(\boldsymbol{V_k^*}) Y_{j,t} \quad \forall \; t > T_0. \tag{B.7}$$

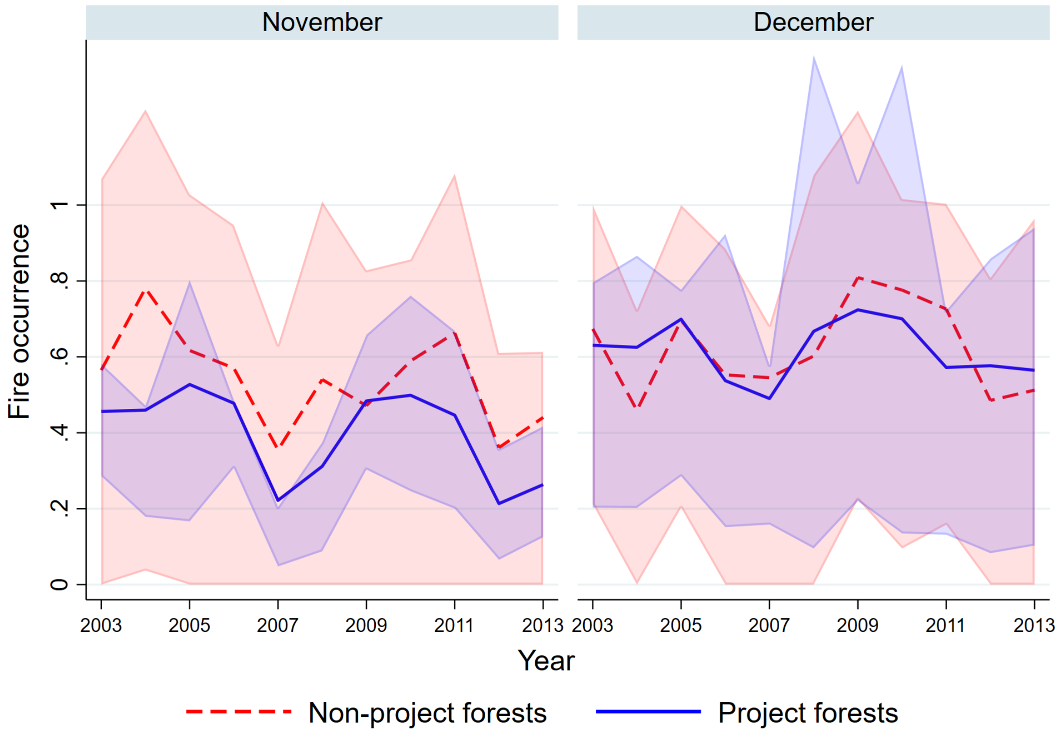
We can then take the unweighted average of the treatment effects in period $t > T_0$ to calculate the average treatment on the treated effect of the intervention in the period $\left(\alpha_t = \frac{1}{|K|}\sum_{i \in K} \alpha_{it}\right)$.

To test the "significance" of the estimates, we follow the placebo-test type approach proposed by Abadie et al. (2010) and Cavallo et al. (2013). We apply the SCM estimator to obtain placebo effect estimates on non-treated units and calculate the share of placebo test results that are larger than the actual impact estimates. This method, similar in spirit to randomization inference (Fisher, 1935; Rosenbaum, 2002), consists of selecting $|K|$ non-treated units from the donor pool (C) and using the SCM to estimate the "treatment effect" for each of these "placebo-treated" units ($\alpha_{it}^{\text{Placebo}}$) with synthetic controls that are obtained from the (properly weighed) remaining $|C| - |K|$ non-treated units; the average placebo treatment effect is then equal to $\alpha_t^{Placebo} = \frac{1}{|\mathcal{K}|}\sum_{i \in \mathcal{K}} \alpha_{it}^{Placebo}$, where $\mathcal{K}$ denotes the set of placebo-treated units ($|\mathcal{K}| = |K|$). For each average placebo effect estimate, the method also calculates the corresponding root mean squared prediction error (RMSPE^{Placebo}; see equation (B.5)) to capture the quality of the synthetic controls based on the pre-treatment fit on the observed outcomes (see also footnote 3). These steps are repeated N^{Placebo} times (with N^{Placebo} sufficiently large), and significance is then measured as the share of (normalized) average placebo impact effects that are larger than the actual (normalized) average treatment effect (α_t/RMSPE):

$$p_t^{\text{signif}} = \frac{\sum_{g=1}^{N^{\text{Placebo}}} I\left(\left|\frac{\alpha_t^{\text{Placebo},g}}{\text{RMSPE}^{\text{Placebo,g}}}\right| > \left|\frac{\alpha_t}{\text{RMSPE}}\right|\right)}{N^{\text{Placebo}}}. \tag{B.8}$$

Appendix C. Supplementary figures and results

Figure C.1: The evolution of fire occurrences in project and non-project forests over the period 2003-2013.



Note: Average November fire occurrences over the 2003-2013 period in the month are presented in the left panel, and average December fire occurrences in the same period are presented in the right panel. The blue solid and red dashed lines depict fire occurrences in project and non-project forests, respectively. The top and bottom of the blue and red shaded areas capture the 25$^{\text{th}}$ and 75$^{\text{th}}$ percentile of fire occurrences.

Figure C.2: November forest fire occurrences in the project forests and in the corresponding synthetic controls.

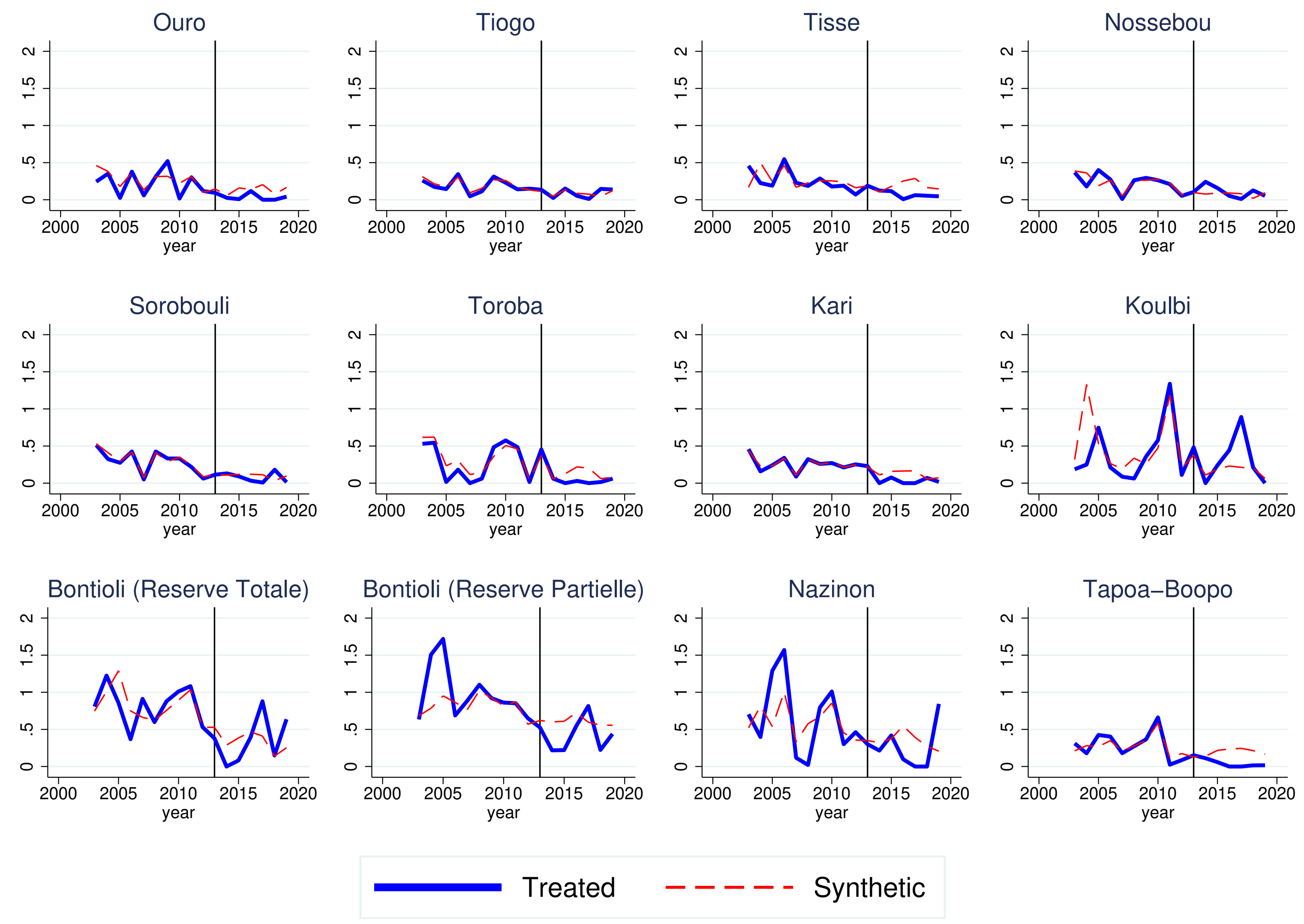
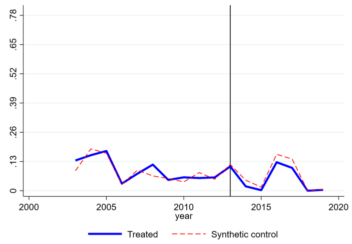
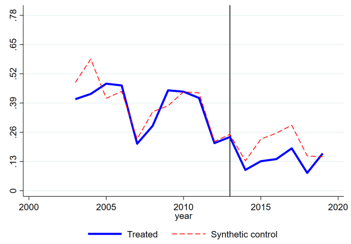


Figure C.3: Fire occurrences with a detection confidence of 50% or better in the project forests and in their synthetic controls.

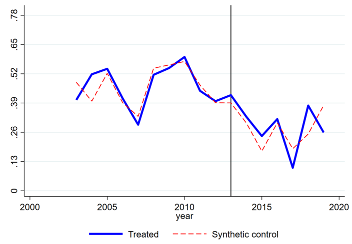
(a) October



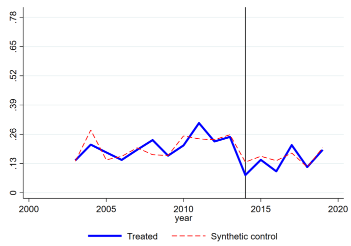
(b) November



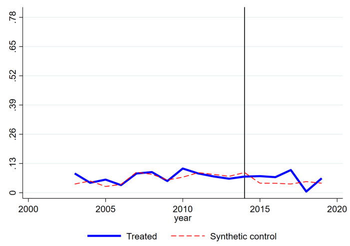
(c) December



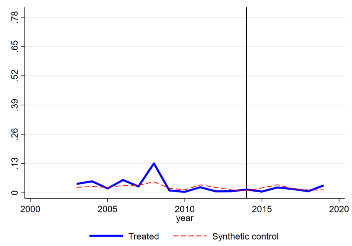
(d) January



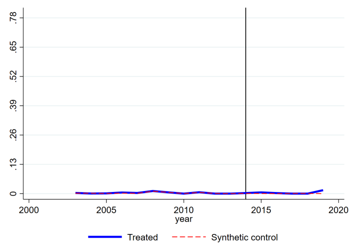
(e) February



(f) March



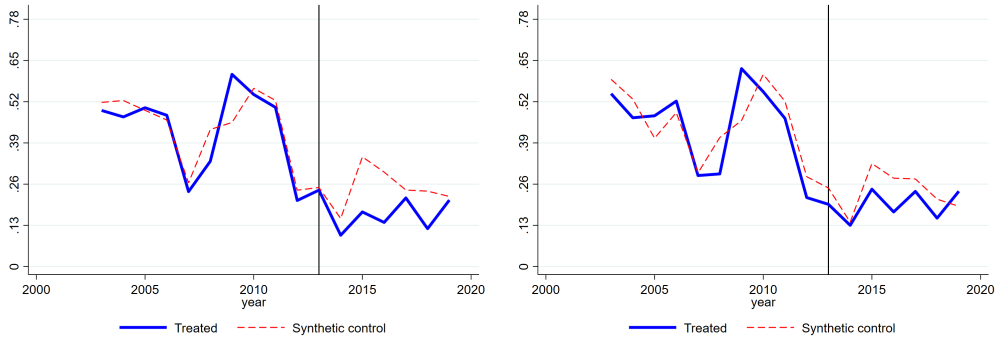
(g) April



Note: These figures present fire occurrences in the project forests measured in days per month per grid. The blue continuous lines show the observed fire occurrences in project forests with at least 50% fire detection confidence, whereas the red dashed line show the estimated counterfactual outcomes in the absence of the FIP program. The synthetic control units, that build into the counterfactual outcomes, are estimated separately for each months. The beginning of the program (October 2014) is indicated with the black vertical line.

Figure C.4: Observed fire occurrences in November in the interior of the forest.

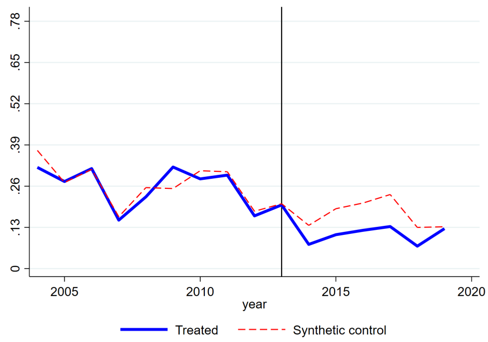
(a) Fire occurrence using a 1km threshold (b) Fire occurrence using a 2km threshold



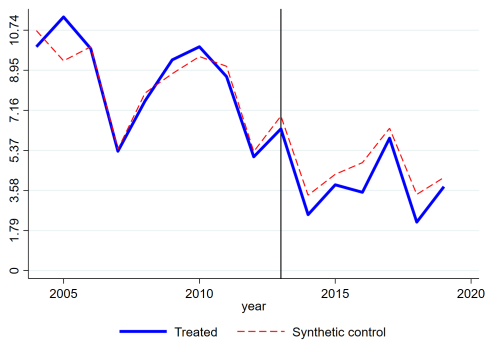
Note: These figures present fire occurrences within the interior of the project forests in November. In Panel (a) we consider fire occurrences on grid cells that are at least 1 km from the forest border. In Panel (b) we calculate the same fire occurrence using 2 km as the threshold. The blue continuous lines show the observed outcomes in project forests (taking fires with 30% or better confidence), whereas the red dashed line show the estimated counterfactual outcomes in the absence of the FIP program. The beginning of the program is indicated with the black vertical line and it corresponds to October 2014.

Figure C.5: Observed number of fires that were started, their average size, and the estimated counterfactuals in project forests in November.

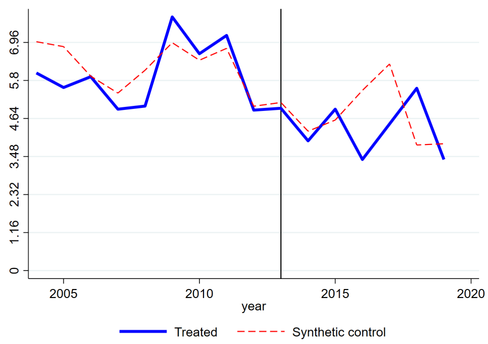
(a) Share of fire affected grids in November



(b) # of ignitions



(c) Average spread of fires



Note: These figures present the number of fire ignitions and the average size of fires (measured in km^2) in the project forests in November. The blue continuous lines show the observed outcomes in project forests (taking fires with 30% or better confidence), whereas the red dashed line show the estimated counterfactual outcomes in the absence of the FIP program. The beginning of the program is indicated with the black vertical line and it corresponds to October 2014.

Table C.1: Weights assigned to each of the non-treated forests in the synthetic control for the November fire occurrences for each of the treated forest.

Donor forests (ID)	ID of FIP forests											
	1	2	3	4	5	6	7	8	9	10	11	12
14	0	0	0	0	0	0	0	.031	.12	.064	.053	0
20	0	0	0	0	0	0	0	0	.34	.194	0	0
22	0	0	0	0	0	.134	0	0	0	0	0	0
23	0	0	0	0	0	0	0	.346	.132	0	0	0
25	0	0	0	0	0	0	0	.052	0	0	.031	0
26	0	0	0	0	0	0	0	0	0	.048	0	0
28	.046	.021	.06	0	0	0	.02	0	0	0	0	0
30	.001	0	0	0	0	0	0	0	0	0	0	0
31	0	0	.013	0	0	0	0	0	0	.168	0	0
32	0	0	0	0	0	0	0	0	.029	0	0	0
33	0	0	.072	0	.005	0	0	0	0	.221	.136	.2
34	.238	.181	0	.104	.097	.165	0	0	0	0	0	0
39	0	0	0	.099	.08	.004	0	0	0	0	0	0
41	0	0	0	0	0	0	0	0	0	.24	0	0
42	0	0	0	0	0	0	.028	0	0	.008	0	.004
43	.114	0	.093	0	0	0	.004	0	0	0	.013	0
47	0	0	0	0	0	0	0	0	.177	0	0	0
48	0	.311	.207	.017	.166	0	.034	0	0	0	0	0
49	.474	0	0	.078	.274	0	.207	0	0	0	0	0
50	0	0	0	.11	.197	0	0	0	0	0	0	0
51	0	.029	0	.055	.141	0	.18	0	0	0	.244	.021
54	0	0	0	0	0	0	0	0	0	0	0	.317
56	0	.015	0	.049	0	.437	.056	0	0	0	0	0
59	0	0	0	0	0	.158	0	0	0	0	0	.111
61	0	0	0	0	0	.101	0	.571	.028	0	0	0
62	0	.052	.175	0	0	0	0	0	0	0	.523	.028
63	0	.084	0	0	0	0	.211	0	.174	.021	0	0
64	.077	0	0	.441	0	0	.134	0	0	0	0	0
66	.052	.306	.38	0	0	0	.126	0	0	0	0	0
73	0	0	0	.047	0	0	0	0	0	0	0	0
74	0	0	0	0	.04	0	0	0	0	0	0	0
75	0	0	.001	0	0	0	0	0	0	0	0	0
76	0	0	0	0	0	0	0	0	0	.037	0	0
77	0	0	0	0	0	0	0	0	0	0	0	.319
# donors	7	8	8	9	8	6	10	4	7	9	6	7

Note: This table presents the weight of each non-treated forest (one per row) in the synthetic control unit of each treated forest (one per column). The last row shows the number of non-treated forests that have a positive weight in the synthetic control of the given treatment forest.

Table C.2: Estimated impacts of the program on forest fire occurrences for the set of non-contiguous treatment and control forests.

		(1)	(2)
		Fire occurrences	
Month	Year	Confidence¿=30%	Confidence¿=50%
	2014	–0.081	–0.043
Nov.		[0.622]	[0.890]
	2015	–0.133***	–0.104**
		[0.004]	[0.019]
	2016	–0.137***	–0.109**
		[0.009]	[0.048]
	2017	–0.094***	–0.129**
		[0.008]	[0.026]
	2018	–0.115	–0.103*
		[0.250]	[0.091]
	2019	–0.028	0.000
		[0.142]	[0.329]

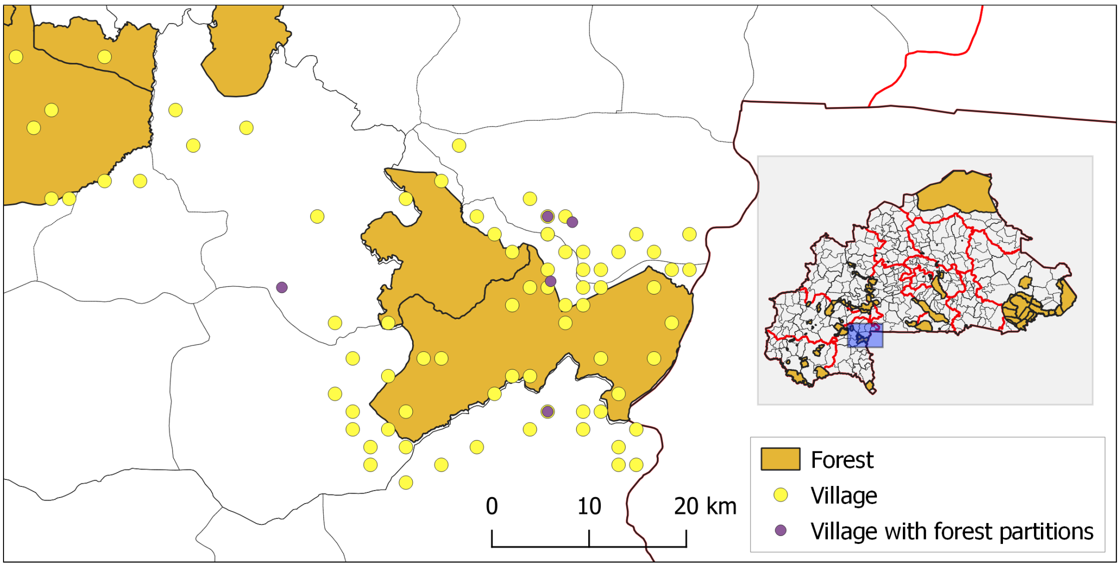
Note: The table presents the average estimated effects of the FIP program over time on forest fire occurrence in November from the SCM, measured in "days per month". The effects of the program are estimated separately for each month on an annual-panel of forest level fire occurrence in the given month. We exclude non-project forests in the donor pool that lie next to project forests to avoid bias from potential treatment contamination (see Figure 2). Variables in the fitting process of SCM include past fire occurrences up until 2005, the size of the forests, and the amount of annual precipitation before the FIP program. P-values from the inference tests are presented in square brackets. Point estimates not "significant" at the 10% level are grayed out. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Appendix D. Sub-forest level analysis with the LSMS survey

The LSMS is a nationally representative household level survey that collected information on household composition, households' economic and employment status, housing, agricultural production, health, education, and food security. The surveys were implemented by the National Institute of Statistics and Demography of Burkina Faso. We construct our community level variables based on the responses from the first round collected between January and March 2014.

An important limitation of the LSMS is that compared to the ten thousand settlements in the country, the survey sample only consists of 905 enumeration areas (normally a village, a small group of villages, or a district in a city) and only 150 could be linked to forest partitions. More precisely, 189 forest partitions can be formed, but 39 of these forest partitions (3 in project forests and 36 in non-project forests) are small, less than 10 grid size. Although our results are not sensitive to the inclusion of these forest grid cells in our analysis, we omit these outliers from the sample to avoid the mis-characterization of small forest partitions. The remaining forest partitions consist of 10 to 600 forest grid cells. This means that villages assigned to forest partitions are not necessarily the closest to the forest among all villages (see Figure D.6) and the assignment of survey villages to forest partitions inherently assumes that the survey village is similar to other villages between the survey forest and the forest. This concern may be relevant, as the average Euclidean distance between the forest partition and the corresponding LSMS village around project forests is about 10.3 km (see Table 4) – a considerable distance indeed because of sparsity of roads which are oftentimes also of poor quality. Therefore analyses in this section may be subject to bias from measurement error in community characteristics to the degree that villages surveyed in the LSMS are different from those closer to the forest.

Figure D.6: Visualization of the LSMS villages around the Bontioli Reserve.



Note: The map shows the communities surrounding the Bontioli Reserve, which lies in the South-South-West of Burkina Faso (highlighted in the small blue box on the right). The Bontioli Reserve is highlighted by the orange area in the center of the map. The villages within 10 kilometres of the forest border are represented by the yellow dots. Villages in the sample of the LSMS survey are depicted by the purple dots.