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A regression discontinuity assessment of the differential impacts of China's Natural Forest Protection Program across forestland property right regimes*

Qi Liu*, Shilei Liu†, Zhaoyang Liu‡, Jintao Xu§ and Andreas Kontoleon‡

Abstract

This study examines the impact of China's Natural Forest Protection Program (NFPP) on forest cover in four Chinese provinces. The NFPP represents one of the world's largest-scale forest conservation/restoration programs in terms of its sheer budget size and geographical coverage. Understanding the heterogeneous impact of the policy on different landowners is important to evaluating its viability and success. This paper presents the first rigorous assessment of the program's performance by comparing its impacts on forestland held by state-owned forest enterprises (SOFEs) and village collectives. We use the spatial regression discontinuity approach to better identify the impact caused by the program per se, rather than by other possible correlated confounding factors. Our results find that the NFPP has a moderately positive effect on forest cover on average over both types of forestland holders. Moreover, we find that the program has a greater positive effect on collective forests than on state forests, even though the program's financial support for the former is not as strong as that for the latter. Our empirical findings provide unique insights that contribute to the highly controversial and ongoing debate on property right reform of China's state-owned forests.

Keywords: Forest conservation and restoration, China's Natural Forest Protection Program, policy impact evaluation, forestland property right regimes, spatial regression discontinuity.

JEL Codes: : Q23, Q28, Q15, P31, P32.

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1 Introduction

China's Natural Forest Protection Program (NFPP), launched at the turn of the century and currently ongoing, is a large-scale forest conservation and restoration program that restricts logging and finances afforestation in 18 Chinese provinces. It aims to conserve and restore the country's forest cover, and thereby to reduce soil erosion which was typically believed to be (at least partly) responsible for the disastrous floods that hit vast areas of China in the late 1990s (Liu et al. 2014; Xu et al. 2006). Two decades after the NFPP was introduced, the program has cost approximately CNY 400 billion in total (Qiao et al. 2021)[1], which accounts for roughly 0.4% of China's GDP in 2020. The NFPP boasts one of the world's largest forest protection and restoration programs in terms of its budget and geographic scope (Liu et al. 2008; Lu et al. 2018).

In tandem with the logging restrictions introduced under the NFPP, China has massively increased imports of forest products from neighboring nations (Mayer et al. 2005). The NFPP has been suspected of being responsible for displacing deforestation from China to other countries. Although scientific studies have provided detailed descriptive accounts of the NFPP (e.g. Bryan et al. 2018; Fang et al. 2018; Liu et al. 2008; Lu et al. 2018; Xi et al. 2022), there has been a paucity of quasi-experimental econometric evidence on whether China's forest cover has been significantly improved by the program. This contrasts with the sheer size of the program and the considerable attention it has attracted from the scientific and policymaking communities worldwide.

This study estimates the effect of the NFPP on forest cover using a spatial regression discontinuity design (RDD) which enables us to better identify the impacts caused by the program *per se*, rather than other confounding factors that possibly correlate with the assignment of the program (Athey and Imbens 2017). Our paper contributes to the relatively small body of studies that have conducted quasi-experimental analyses on the environmental impacts of the NFPP (e.g. Brandt et al. 2015; Ren et al. 2015; Shi et al. 2017; Zhang et al. 2011) and on its livelihood impacts (e.g. Liu et al. 2010; Liu et al. 2014; Mullan et al. 2010). The quasi-experimental approaches adopted by the existing literature could only control for observed confounders (e.g., via matching) and unobserved time-invariants (e.g., using fixed-effects). However, in the case of the NFPP, the estimated impacts are more likely to be influenced by unobserved factors that vary over time. The NFPP covers more than half of China's provinces and affects the entirety of the program area. As a result, the treated and control groups in previous studies tend to be far away from each other (e.g., forestlands in different provinces inside and outside the program area) and thus likely to differ in various key observed and unobserved aspects, many of which could not be adequately accounted for by the estimation methods adopted by those studies.

In contrast, the present study adopts a spatial regression discontinuity design (RDD) to further control for such potential confounders in assessing the impact of the NFPP on forest cover.

[1] Approximately US$58.9 billion.

This approach tests whether there is discontinuity in the distribution of forest cover in areas immediately inside and outside the NFPP borders after the program was introduced. The approach is based on a relatively innocuous (and statistically testable) assumption that factors correlated with both forest cover and the assignment of the NFPP are continuously distributed across the NFPP borders, and therefore any discontinuity in the distribution of forest cover at the NFPP borders can be attributed to the program *per se*. The statistical strengths of this approach are formally discussed in Lee and Lemieux (2010) and Athey and Imbens (2017). Therefore, compared to previous research on the environmental effectiveness of the NFPP, our chosen approach enables us to better identify changes in forest cover caused by the program itself.

In addition, this study speaks to a wider strand of quasi-experimental literature concerning the performance of other forest conservation and restoration programs in the developing world such as Protected Areas (PAs) and Payments for Ecosystem Services (PES). On the one hand, the NFPP shares some characteristics with forest-based PAs in terms of restricting deforestation. On the other hand, the NFPP provides financial support for forest restoration and maintenance, which resembles the payment component of forest-based PES. There is a limited yet growing body of quasi-experimental literature on whether deforestation in developing countries can be curbed by forest-based PAs (e.g. Blackman et al. 2015; Bonilla-Mejía and Higuera-Mendieta 2019; Herrera et al. 2019; Pfaff et al. 2014; Robalino et al. 2017; Sims and Alix-Garcia 2017) or PES (e.g. Alix-Garcia et al. 2015; Börner et al. 2017, Fiorini et al. 2020; Jayachandran et al. 2017; Le Velly et al. 2017; Samii et al. 2014, Simonet et al. 2019; Sims and Alix-Garcia 2017; West et al. 2020). However, these studies have mixed findings as to the effects of forest conservation and restoration programs on forest cover, which often depend on the design and enforcement of the program, as well as on contextual factors such as governance institutions and levels of deforestation threats. Therefore, this study contributes to this literature by undertaking such a case study in the particular context of the NFPP, which as noted, is a forest conservation and restoration program implemented at an unprecedentedly large scale. In particular, we seek to assess whether the program has differential impacts on forestland under different property right regimes, which facilitates the understanding of the reasons underlying the aforementioned heterogenous outcomes of forest conservation and restoration programs observed worldwide.

The NFPP was initially intended for state-owned natural forests, but eventually enrolled large areas of natural forests owned by villages. State-owned forests are owned by the state in principle, and managed by state-owned forest enterprises (SOFEs) in practice. These forests thus constitute a type of common property resource shared among each SOFE's employees, and between each SOFE and the government bodies that supervise them (Xu et al. 2004). By contrast, village-owned forests, or "collective forests", are officially owned by the village, but have mostly been allocated to and managed by individual village households via long-term contracts, and therefore can be regarded as semi-private resources (Xu and Hyde 2019; Yi et al. 2014; Yin et al. 2013).

To the best of our knowledge, this paper presents the first formal econometric study on whether the NFPP has different environmental outcomes in state and collective forests. Though land rights are often believed to have implications for the performance of conservation programs such as PAs (e.g. Geldmann et al. 2019) and PES (e.g. Wunder et al. 2020), such arguments are mostly supported by narrative rather than formal quasi-experimental evidence. The studies of Alix-Garcia et al. (2012) and Bonilla-Mejía and Higuera-Mendieta (2019) represent two rare exceptions.[2] There is richer quasi-experimental evidence concerning the impacts of land rights on forest conditions (e.g. Baragwanath and Bayi 2019; Blackman et al. 2017; Liscow 2013; Probst et al. 2020), although this is not equivalent to how land rights affect the outcomes of forest conservation programs.

Furthermore, in the more relevant impact evaluation studies from developing countries (such as those investigated by Baragwanath and Bayi 2019 and Blackman et al. 2017), the dominating forestland property regimes under investigation are common and open-access regimes, where the former often entails 'communal forests', and the latter is often referred to as 'state' or 'public forests' (which are in essence open-access). This context differs from that of the NFPP in China which is characterized by common and private property regimes. Hence, our study is one of the first quasi-experimental studies in the developing world that compares the differential impacts on 'common' versus 'private' forest property rights resulting from a large-scale forest conservation program.

Exploring our main research question in the context of the NFPP offers considerable insights for the decades-long debate over whether China's state-owned forests should be "privatized", as described in Liu and Xu (2019). This reform has been stuttering amid the central government's purported concern that the privatization of forest resources would exacerbate deforestation. This study empirically tests whether the state property regime indeed outperforms the private property regime (village forests) under the NFPP, which provides highly pertinent empirical evidence for the debate concerning the property right reform of China's state-owned forests. In addition, this study draws and extends upon a wider literature on the reform of China's state-owned enterprises in various economic sectors beyond forestry (e.g. Lin et al. 1998; Jefferson 1998).

The remainder of this article is organized as follows. The next section details the institutional background of the NFPP and discusses why studying its heterogeneous impacts across different forest land regimes is important. Section 3 describes the dataset, followed by Section 4 which outlines the identification strategy (the spatial RDD), and tests whether this approach can be validly applied to our data. Section 5 reports the results of the main analyses and the ancillary robustness and placebo tests. The last section concludes by summarizing and discussing the key findings.

2 The Natural Forest Protection Program (NFPP)

In 1998, vast areas of China were devastated by catastrophic floods, which caused huge losses of life and property. The severity of the floods was widely attributed to the excessive loss of vegetation cover and topsoil in the upstream areas of the Yangtze and Yellow River Basins (Mullan et al. 2010; Qiao et al. 2021; Shen et al. 2006). In response to this ecological crisis, China launched two large-scale forest conservation and restoration programs, the Natural Forest Protection Program (NFPP) and the Sloping Land Conversion Program (SLCP). The NFPP was implemented in more than half of China's provinces, covering a substantial part of the country, as shown by the gray areas in ***Figure 1.*** The implementation of the NFPP consisted of two phases, which covered the first and second decades of this century, respectively. This

[2] Herrera et al. (2019) compared the performance of protected areas managed by different levels of government, which relates to but also differs from investigating the implications of land property right regimes.

study focuses on the first phase of the NFPP, which sought primarily to restrict logging activities in natural forests, and to provide financial support for the restoration and maintenance of forests (Liu et al. 2008; Lu et al. 2018; Xu et al. 2006).

Figure 1. The NFPP areas

Note: This map shows the NFPP areas (gray) and the four provinces (hatched areas) that our data analyses focus on. The black spots in the zoomed-in part of the map indicate forestland plots in our dataset.

The NFPP initially targeted natural forest resources in key state-owned forest regions (Xu et al. 2006). State-owned forests in China are mostly managed by state-owned forest enterprises (SOFEs) at the local level, in theory following specific guidelines set by the central government (Xu et al. 2004). Each SOFE is located in and responsible for specific state forest areas. SOFE managers decide and plan forest management activities, according to their contracts with the government's forestry authority (Jiang et al. 2014; Xu et al. 2004). SOFE workers execute these planned activities in state forests, and their wage levels largely depend on their positions in the SOFE hierarchies (Bennett et al. 2008). On top of the position-based basic wages, SOFE workers may receive performance-based pay or bonuses, which are mostly based on profits from timber production (Söderbom and Weng 2012) rather than forest restoration.

After the introduction of the NFPP, the primary activity of these SOFEs shifted from logging natural forests for timber production to the restoration and maintenance of forests (Liu et al. 2014; Xu et al. 2006), activities which are much less (if at all) profitable and less labor intensive. These SOFEs, therefore, had to downsize and lay off a substantial proportion of their employees[3]. Accordingly, a substantial portion of the NFPP funding was spent on severance pay, healthcare, and pensions for those SOFE employees who were made redundant, and wages and benefits for remaining employees, which can be (to some extent) regarded as compensation for the logging restrictions (Qiao et al. 2021; Shen et al. 2006).

Aside from state forests, the NFPP has enrolled large areas of village-owned forests, which are formally known as "collective" forests. In some regions, collective forests constitute half of the NFPP area (Xu et al. 2006). These collective forests are officially owned by village

[3] Many SOFEs were already in deep financial hardship due to long periods of excessive timber harvesting but inadequate restoration, known as the "double crisis".

collectives, but the use rights of these collective forests had been largely allocated to individual village households using long-term contracts (Hyde and Yin 2019), many of which would last as long as 50 or 70 years and were allowed to be transferred and inherited. Therefore, the property rights of collective forests in NFPP areas resemble a private or semi-private property regime. Collective forest managers in NFPP areas are not substantially compensated for their losses of timber revenues associated with the logging restrictions (Xu et al. 2006). But the NFPP funds for the restoration and maintenance of forests (e.g., planting and maintaining trees, and recruiting forest rangers) are typically made available to both state and collective forest managers (Forestry Department of Guizhou Province 2002; Forestry Department of Shanxi Province 2000).

The first research question of this study focuses on the average overall effect of the NFPP on forest cover. This forest conservation program is of unprecedentedly large scale in terms of both budget and geographic coverage and was widely expected to reverse the net losses of forest cover in the vast areas it targeted within China. However, the project is subject to many constraints which could have compromised its environmental efficacy. For instance, the NFPP's logging restrictions and reforestation activities might be weakly enforced due to information asymmetry, as deforestation and reforestation activities are better known to forest managers (SOFEs and village households), than to supervisory governmental authorities. Though governmental bodies routinely inspect whether SOFEs and village households remain in compliance with the NFPP regulations, they often rely on SOFEs and village leaders for self-reported evidence, and for the sampling and logistic arrangements for onsite inspections, which might have allowed SOFEs and villages to influence the outcome of the inspections.

Furthermore, despite the massive scale of the program's total budget, the NFPP has been frequently accused of under-compensating SOFEs and village households for their losses of timber revenues caused by the logging restrictions. The NFPP has no formal provisions that substantially compensate collective forest managers for such losses. SOFEs tend to be better resourced, but the NFPP funds budgeted for them at the beginning of the program have been devalued considerably by inflation. Therefore, the NFPP might have acquired "paper park" features such as weak enforcement and insufficient financial resources (Blackman et al. 2015). Under the current funding situation, it is largely unclear whether SOFEs and collective forest managers in NFPP areas have sufficient incentives to deliver the expected environmental outcome.

However, as mentioned, there has been a paucity of formal statistical evidence that can convincingly assess how the NFPP has impacted forest cover in the program areas. Earlier studies in this regard typically reported that the program had delivered a positive effect on forest cover, in light of a total decrease of timber output and a total increase of afforested land in the NFPP areas after the program was introduced (e.g. Liu et al. 2008; Xu et al. 2006; Yin and Yin 2010). Similar findings were reached by Shi et al. (2016) and van den Hoek et al. (2014) which compared the forest cover (derived from satellite data) of some NFPP areas before and after the program was launched. Such preliminary evidence, given considerable data limitations in the program's early stages, is likely to have been obscured by confounding factors other than the NFPP, such as changes in timber prices and the existence of other forest restoration programs in the NFPP areas (such as the SLCP). Some of these confounders were better controlled for by some quasi-experimental studies which found further evidence corroborating the NFPP's positive effects on forest cover (e.g. Brandt et al. 2015; Ren et al.

2015; Shi et al. 2017; Zhang et al. 2011).[4] However, the quasi-experimental methods adopted by those studies (i.e. matching and/or fixed effects) can only eliminate confounders that are observed or time-constant (Greenstone and Gayer 2009; Imbens and Wooldridge 2009). As previously discussed, the NFPP was purposefully assigned to particular types of areas which feature a wide range of specific characteristics. Many of those characteristics are likely to be time-varying unobservables, which could not be adequately accounted for with the statistical methods used in existing studies. This could have biased any findings on the estimated impacts of the NFPP. We aim to further address this challenge using a unique dataset at the forestland plot level which allows the first spatial RDD analysis on the impact of the NFPP on forest cover.

Moreover, this study seeks to investigate whether the NFPP has differential effects on state and collective forests. Given the incentive and management structures governing the resources of China's state-owned enterprises, standard economic theory would consider these as being akin to common pool or even open access resources. This would mean that in the NFPP lands, SOFE managers and workers would be more likely to harvest more timber and take in more NFPP funds for their own use (e.g., wages, pensions, and benefits) while at the same time invest less in the restoration and maintenance of state forests (Jefferson 1998; Lin et al. 1998). In contrast, collective forests in the NFPP areas are mostly allocated to and managed by individual households, thus more closely resembling privately owned resources. The incentive structures in the latter case would likely be more closely aligned with investing in and benefiting from more sustainable use of forest resources. Hence, standard economic theory would predict that collective forest managers would likely invest the funds from the NFPP in the restoration and maintenance of forests, suggesting that the program may have a better outcome in collective forests than in state forests. However, it is worth reiterating that the NFPP budget has different provisions for state and collective forest managers in terms of compensating for their financial losses associated with the logging restrictions, although program funds for forest restoration and maintenance are made available to both types of forest managers.

3 Data

We compiled a unique panel dataset at the forestland plot level for four Chinese provinces: Hubei, Jilin, Shanxi, and Guizhou, each of which has its own geographical and ecological importance. Our analysis is restricted to these four provinces because the borderlines of the NFPP areas[5] pass through these four provinces, and therefore each of these provinces has forestland inside and outside the NFPP jurisdiction, as shown in ***Figure 1***. Another important reason for focusing on these four provinces is that we managed to obtain key data from before and after the introduction of the NFPP only for these four areas. Assessing the validity of the RDD requires baseline data before the launch of the program. The validity of the spatial RDD requires all relevant variables existing before the program to be continuously distributed across the borderlines of the program (Lee and Lemieux 2010). Although only four provinces are included in our study, they are reasonably representative of China's latitudinal range.

[4] Viña et al. (2016) estimated the impact of the NFPP on forest cover using a spatial autoregressive model, which accounts for the observed confounders included in the model but is not typically regarded as a sound quasi-experimental approach.
[5] The NFPP borderlines were digitalized from the Atlas of China Forest Resources (Xiao 2005).

Most of the variables in our analysis were sourced from China's National Forest Inventory (NFI) data collected by the country's State Forestry Administration and local forestry bureaus. This forestland plot level dataset contains a wide range of variables concerning forest cover and various geophysical and institutional characteristics of sampled forestland plots (e.g., altitude, slope, soil quality, and property right regimes), as described in Zeng et al. (2015). The NFI dataset sampled forestland plots at the cross points of the two-dimensional kilometer grids of China, as shown in ***Figure 1***. Sampled forestland plots are geo-referenced and periodically revisited.[6] Plot-level variables are collected through field surveys. We obtained a subset of the NFI panel data consisting of three waves. The first wave of the data was collected in 1999 or 2000, which constitutes the baseline period preceding the NFPP. The two post-NFPP waves of data were collected in 2004/2005 and 2009/2010, respectively. In our RDD analysis, the main outcome variable of interest is forest cover[7] obtained from the NFI data.

In addition, as shown in ***Table 1***, our dataset contains many control variables (covariates) that are typically considered to influence both forest cover and the assignment of the NFPP. On the one hand, we seek to assess the validity of the RDD by testing the continuity of baseline covariates across NFPP borders. On the other hand, these covariates will be controlled for in the main regression models to ensure that these factors are adequately accounted for.

The NFPP was initially intended for state-owned natural forests. This selection criterion is captured by the two covariates "state forest" and "forest origin". Moreover, China's state-owned forests are mostly in the country's forested but sparsely populated regions. Because these forests were not predominantly occupied by local residents, it was considered more justifiable and less costly to claim state ownership over these forests (Delang and Wang 2013). These less populated regions typically feature higher altitude, steeper slope, lower levels of accessibility, and less favorable climate conditions and soil quality. These factors, if not adequately accounted for, could potentially confound the observed impacts of the NFPP on forest cover, because they also likely correlate with tree growth, deforestation, and forestry investment (Hansen et al. 2002; McMahon et al. 2010; Naudts et al. 2016). Further, we have discussed in the previous sections that the types of forest property right regimes have often been found to have implications for forest cover (Baragwanath and Bayi 2019; Blackman et al. 2017) and hence forest property rights are also controlled for in our analysis.

Moreover, the accessibility of forests[8] is commonly believed to have implications for the costs of deforestation and thus for forest cover (Deng et al. 2011; Busch and Ferretti-Gallon 2017). Access was controlled for using an Accessibility index constructed from China's National Forest Inventory. Similarly, more populated areas often have higher levels of deforestation, due to higher demand for timber and for converting forestland to agricultural land (Viña et al. 2016). The covariate "night lights" was constructed using night lights data sourced from the National Oceanic and Atmospheric Administration (NOAA) to proxy population density, following Ward et al. (2020) and Geldmann et al. (2019). Lastly, the NFPP prioritized areas with greater implications for watershed ecosystem services and biodiversity (Hyde and Yin 2019; Liu et al. 2014; Qiao et al. 2021; Yin 2016). Forests in such areas are more likely to be designated as

[6] In the four provinces we focus on, sampled forestland plots have the same size (0.0667 acres) and shape (square) (Zeng et al. 2015).

[7] This refers to forest canopy density, which is defined as the proportion of the forestland plot covered by the vertical projection of the tree crowns.

[8] For commercial forests, "accessibility" was assessed by NFI surveyors as a three-level indicator according to the extent to which a forestland plot is reachable for harvesting and transporting forest products. For non-commercial forests, we imputed "accessibility" using that of the closest economic forestland plots.

protected areas or classified as “ecological forests” where logging restrictions are likely to be more rigidly enforced. Therefore, we compiled the two covariates “protected area” and “ecological forest” to account for these potential confounders.[9]

[9] Another such possible confounder is whether the NFPP areas have overlaps with the SLCP areas, since the SLCP is another large-scale forest restoration program launched at a similar time. However, the four provinces we focus on are entirely covered by the SLCP program. We thus assume that the potential confounding effects of the SLCP can be cancelled out when we compare forest cover inside and outside NFPP areas within the four provinces.

Table 1. Variables and data sources

Variable name	Definition	Data sources	Outside NFPP		Inside NFPP	
			Mean	**SD**	**Mean**	**SD**
Outcome variable:						
Forest cover	Canopy coverage (0–100%)	NFI	59.713	21.555	62.670	20.829
Covariates:						
Altitude	Altitude (m)	NFI	605.857	461.141	1031.134	472.591
Slope	1 = flat; 2 = slightly sloped; 3 = sloped; 4 = slightly steep; 5 = steep; 6 = extremely steep	NFI	3.261	1.243	2.967	0.945
Protected area	Distance (km) to the closest protected area	List of National Nature Reserves of China	57.834	43.055	48.213	33.193
Night lights	Brightness of night lights (digital number), ranging from 0 (no lights) to 63 (brightest lights)	NOAA	1.508	5.526	0.817	3.548
Accessibility	Whether forestland is accessible for the harvesting, processing and transportation of forest products and reforestation: 1 = accessible already; 2 = likely accessible in the near future; 3 = unlikely accessible in the near future	NFI	1.255	0.605	1.177	0.545
Precipitation	Total annual precipitation (mm)	CMDSC	868.532	377.386	884.559	331.169
Temperature	Average annual temperature (℃)	CMDSC	10.391	5.554	9.514	18.806
Soil	Soil thickness (cm)	NFI	40.174	24.803	47.265	27.986
Ecological forest	1 = ecological forest; 0 = commercial forest	NFI	0.415	0.493	0.624	0.484
Forest origin	1 = natural; 0 = planted	NFI	0.629	0.483	0.818	0.386
Age	1 = young; 2 = middle-aged; 3 = near mature; 4 = mature; 5 = post-mature	NFI	2.021	1.072	2.044	1.030
State forest	1 = state forest; 0 = collective forest	NFI	0.334	0.472	0.466	0.499

Note: CMDSC: China Meteorological Data Service Centre; NFI: National Forest Inventory; NOAA: National Oceanic and Atmospheric Administration; SD: Standard Deviation.

4 Empirical strategy

4.1 The spatial regression discontinuity design

The spatial RDD is a type of regression discontinuity design that utilizes the spatial borders of the treatment as the cutoff (Lee and Lemieux 2010). The main challenge of empirically identifying the true impact of the NFPP on forest cover is that the observed difference in forest cover inside and outside NFPP areas might be (partly) attributable to factors other than (but correlated with) the NFPP, such as the covariates already discussed. The spatial RDD approach assumes that all relevant covariates existing before the introduction of the NFPP are continuously distributed across the NFPP borders. Under this assumption, the launching of the NFPP would be the only source of discontinuity at the NFPP borders. Therefore, any subsequent discontinuity in forest cover at the NFPP borders can be attributed to the NFPP *per se*, not other factors. This *ex-post* discontinuity in forest cover is the treatment effect of the NFPP that we sought to estimate using the spatial RDD approach.

We first assessed the overall impact of the NFPP on forest cover by performing spatial RDD analyses using the full sample consisting of both state and collective forestland. We next repeated all analyses using two subsamples consisting of only state or collective forestland, respectively, to compare the impacts of the NFPP across property right regimes. The treatment effect of the NFPP on forest cover was estimated using parametric and non-parametric approaches, following Imbens and Lemieux (2008), Pan and Singhal (2019), and Chen et al. (2019). The parametric model was specified as follows:

$$Y_{ikt} = \beta_0 + \alpha\ NFPP_{ikt} + f(Distance_{ikt}) + \boldsymbol{\gamma X_{ikt}} + \boldsymbol{\nu_k} + \boldsymbol{\lambda_t} + \varepsilon_{ikt}. \quad \text{s.t.} \quad -h < Distance_{ikt} < h \tag{1}$$

In this model, Y_{ikt} denotes the forest cover percentage of forest plot i in county k in year t. $NFPP_{ikt}$ is the binary treatment variable equaling 1 if plot ik is inside the NFPP areas, and 0 otherwise. The coefficient α measures the treatment effect of the NFPP on forest cover. $Distance_{ikt}$ measures the shortest distance between plot ik and the NFPP borders. This is the running (i.e. assignment) variable that indicates whether a plot is treated by the NFPP or not ($Distance_{ikt} \geq 0$ if treated, and $Distance_{ikt} < 0$ if not). The spatial RDD focuses on data close to the NFPP borders within a bandwidth, h. We will further explain how this bandwidth was chosen. The function $f(Distance_{ikt})$ models the trends of forest cover with respect to $Distance_{ikt}$ on both sides of NFPP borders and was allowed to have different parameters on the two sides. More specifically, $f(Distance_{ikt})$ includes a polynomial function of the running variable $Distance_{ikt}$, and the interaction between the powers of $Distance_{ikt}$ and the treatment variable $NFPP_{ikt}$:

$$f(Distance_{ikt}) = \sum_{p=1}^{P}\left(\beta_{1p} Distance_{ikt}^{p}\right) + \sum_{p=1}^{P}\left(\beta_{2p} NFPP_{ikt} Distance_{ikt}^{p}\right). \tag{2}$$

The highest power P was chosen from 1, 2, and 3, using the Akaike Information Criterion (AIC) as in Black et al. (2007) and as suggested by Lee and Lemieux (2010). The vectors $\boldsymbol{\nu_k}$ and $\boldsymbol{\lambda_t}$ represent county and period fixed effects, respectively. The vector $\boldsymbol{X_{ikt}}$ contains the covariates listed in ***Table 1***. Model 1 was estimated using data close to the NFPP borders within a bandwidth h defined via the mean square error (MSE) optimal bandwidth selection approach proposed by Calonico et al. (2014a, b). This approach gave an optimal bandwidth of 32.426km for a specification of ***Equation 1*** that included all controls. In addition, we tested the robustness of our findings to bandwidth choice by adopting three alternative bandwidths of 20km, 30km and 40km.

Moreover, we re-estimated the treatment effects of the NFPP using the non-parametric local linear estimator proposed by Calonico et al. (2014a, b). In RDD analyses, non-parametric estimation can be a useful complement to parametric estimation as the former is more flexible in the functional form of the relationship between the outcome and running variables (Lee and Lemieux 2010).

Our non-parametric local linear estimation was performed in a way highly comparable to our parametric estimation (as in ***Equation 1***). To start with, the local linear estimation was performed using data inside and outside the NFPP areas separately, and thus allowed the relationship between the outcome and running variables to differ on the two sides of the NFPP borders. In the parametric model (***Equation 1***), this flexibility was achieved by interacting the treatment variable $NFPP_{ikt}$ with the powers of the running variable $Distance_{ikt}$. Moreover, our local linear estimation controlled for the covariates ($\boldsymbol{X_{ikt}}$) and county and period fixed effects ($\boldsymbol{\nu_k}$ and $\boldsymbol{\lambda_t}$), using a two-step procedure as in He et al. (2020) and as suggested by Lee and Lemieux (2010). In the first step, the outcome variable was regressed against the covariates and fixed effects to derive the residuals. In the second step, the non-parametric estimation was performed using the residuals (instead of the original values) of the outcome variable. This further enhanced the comparability between our parametric and non-parametric estimation because both approaches accounted for the covariates and fixed effects. Lastly, our non-parametric estimation selected the bandwidth in the same way as our parametric estimation.

4.2 Covariate continuity tests

As mentioned, the validity of the spatial RDD depends critically on the covariate continuity assumption (namely that all relevant covariates before the introduction of the NFPP are continuously distributed across the NFPP borders). This assumption was tested using the parametric and non-parametric procedures described, where the outcome variable (forest cover) was replaced by each of the 12 baseline covariates (as listed in ***Table 1***) individually, giving rise to 12 models.

The null hypothesis is that each covariate is continuously distributed across the NFPP borders. ***Table 2*** focuses on the results of the nonparametric model and does not control for other covariates ($\boldsymbol{X_{ikt}}$), following Ambrus et al. (2020) and Moz-Christofoletti et al. (2022). These tests were performed using the average of the 12 covariates' optimal bandwidths computed using the algorithm of Calonico et al. (2014). These tests were repeated three times, using the full sample and the two sub-samples by forestland ownership type, respectively. In addition, we repeated these tests using the parametric approach which has a linear polynomial of $Distance_{ikt}$ (P = 1) and does not control for other covariates ($\boldsymbol{X_{ikt}}$). The results are reported in ***Table S4*** in the Appendix**.**

Starting with the nonparametric tests for the full sample, the estimates in ***Table 2*** (Panel A) find no statistically significant discontinuity in the 12 covariates prior to the NFPP. In the full sample, for all 12 covariates, the estimated discontinuity at the NFPP borders has a *p*-value above 10% (10 covariates have a *p*-value above 35%). For 10 covariates, the estimated discontinuity is less than 10% (in absolute value) of the mean outside the NFPP borders within the bandwidth. We have similar findings from the parametric tests, as can be seen in ***Table S4***

(Panel A). For all 12 covariates, the estimated discontinuity at the NFPP borders has a *p*-value above 10% (9 covariates have a *p*-value above 40%). For 8 covariates, the estimated discontinuity is less than 10% (in absolute value) of the mean outside the NFPP borders within the bandwidth. This provides supporting evidence for the covariate continuity assumption of the Spatial RDD.

We present the results of the tests for state and collective forestland in Panels B and C of ***Tables 4*** and ***S4***, respectively. The main findings are qualitatively similar to those for the full sample: for all 12 covariates, the estimated discontinuity at the NFPP borders has a *p*-value above 10%; the magnitude of the estimated discontinuity is mostly less than or comparable to 10% (in absolute value) of the mean outside the NFPP borders within the bandwidth. In other words, we found no evidence of pre-NFPP discontinuity in the 12 covariates for the state and collective forestland subsamples.

Table 2. Covariate continuity tests: nonparametric approach

Panel A. Full sample

	(1) Altitude	(2) Slope	(3) Protected area	(4) Night lights	(5) Accessibility	(6) Precipitation	(7) Temperature	(8) Soil	(9) Ecological forest	(10) Forest origin	(11) Age	(12) State forest
RDD treatment effect	46.725	-0.098	1.405	0.134	-0.021	-73.621	-0.293	-1.950	0.102	-0.016	0.091	0.031
	(75.687)	(0.079)	(7.409)	(0.200)	(0.065)	(103.434)	(1.535)	(9.371)	(0.079)	(0.052)	(0.105)	(0.137)
	[0.537]	[0.214]	[0.850]	[0.503]	[0.753]	[0.477]	[0.849]	[0.835]	[0.194]	[0.757]	[0.820]	[0.388]
Mean outside NFPP borders	727.876	3.066	63.132	0.940	0.258	806.566	8.919	26.833	0.238	0.708	1.822	0.429
Degree of polynomial	Linear	Linear	Linear	Linear	Linear	Linear	Linear	Linear	Linear	Linear	Linear	Linear
Bandwidth (km)	68.170	68.170	68.170	68.170	68.170	68.170	68.170	68.170	68.170	68.170	68.170	68.170
Obs.	2397	2397	2397	2397	2397	2397	2397	2397	2397	2397	2397	2397

Panel B. State forestland

	(1) Altitude	(2) Slope	(3) Protected area	(4) Night lights	(5) Accessibility	(6) Precipitation	(7) Temperature	(8) Soil	(9) Ecological forest	(10) Forest origin	(11) Age
RDD treatment effect	77.413	-0.122	-8.982	0.208	-0.052	31.114	0.937	5.563	0.117	0.006	-0.119
	(97.633)	(0.125)	(10.204)	(0.248)	(0.113)	(30.954)	(0.669)	(6.038)	(0.129)	(0.076)	(0.164)
	[0.428]	[0.329]	[0.379]	[0.401]	[0.645]	[0.315]	[0.161]	[0.357]	[0.367]	[0.936]	[0.470]
Mean outside NFPP borders	686.135	3.084	64.990	0.971	0.255	632.121	5.416	11.557	0.199	0.737	2.106
Degree of polynomial	Linear	Linear	Linear	Linear	Linear	Linear	Linear	Linear	Linear	Linear	Linear
Bandwidth (km)	56.630	56.630	56.630	56.630	56.630	56.630	56.630	56.630	56.630	56.630	56.630
Obs.	1063	1063	1063	1063	1063	1063	1063	1063	1063	1063	1063

Panel C. Collective forestland

	(1) Altitude	(2) Slope	(3) Protected area	(4) Night lights	(5) Accessibility	(6) Precipitation	(7) Temperature	(8) Soil	(9) Ecological forest	(10) Forest origin	(11) Age
RDD treatment effect	33.897	-0.055	5.975	0.205	-0.042	-97.029	-1.064	-3.549	0.106	-0.034	0.021
	(94.690)	(0.086)	(7.757)	(0.350)	(0.073)	(137.365)	(1.483)	(9.902)	(0.089)	(0.075)	(0.092)
	[0.720]	[0.524]	[0.441]	[0.558]	[0.569]	[0.480]	[0.473]	[0.720]	[0.233]	[0.653]	[0.823]
Mean outside NFPP borders	850.579	2.986	56.777	0.860	0.194	969.758	11.448	42.353	0.302	0.720	1.575
Degree of polynomial	Linear	Linear	Linear	Linear	Linear	Linear	Linear	Linear	Linear	Linear	Linear
Bandwidth (km)	84.310	84.310	84.310	84.310	84.310	84.310	84.310	84.310	84.310	84.310	84.310
Obs.	1369	1369	1369	1369	1369	1369	1369	1369	1369	1369	1369

Notes: (i) Standard errors clustered by county are in parentheses. *P*-values are in brackets. (ii) Each column in the table represents a separate RDD regression for each covariate. (iii) *** p<0.01, ** p<0.05, * p<0.1.

4.3 Manipulation tests

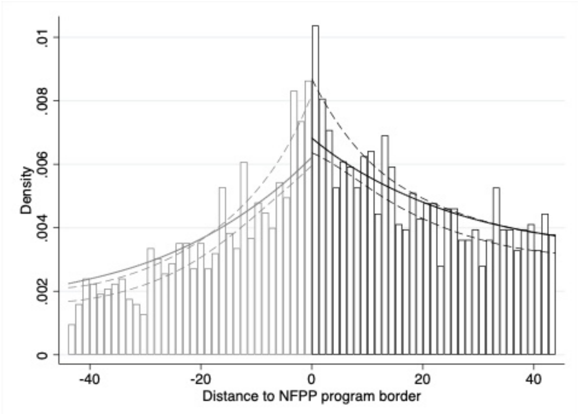
Another important assumption of the RDD approach is that the assignment of the treatment cannot be precisely manipulated by those being treated (Lee and Lemieux 2010). In this study, this "imprecise manipulation assumption" requires that forestland managers are unable to precisely self-select forestland into or out of the NFPP program.

We tested this assumption using the manipulation test proposed by Cattaneo et al. (2020). The intuition is that, if forestland managers were able to precisely self-select forestland into (or out of) the NFPP program, there would be more forestland plots just inside (or outside) the NFPP borders. In other words, the imprecise manipulation assumption would have been violated had there been a statistical discontinuity in the distribution of forestland plots around the NFPP borders. Our manipulation test consisted of using a local polynomial density estimator to estimate the probability density functions of $Distance_{ikt}$ on the two sides of the NFPP borders separately and testing whether there exists a statistical discontinuity at the NFPP borders. The null hypothesis is that $Distance_{ikt}$ is continuously distributed across the NFPP borders. We repeated the manipulation test for the full sample and the state and collective forestland subsamples.

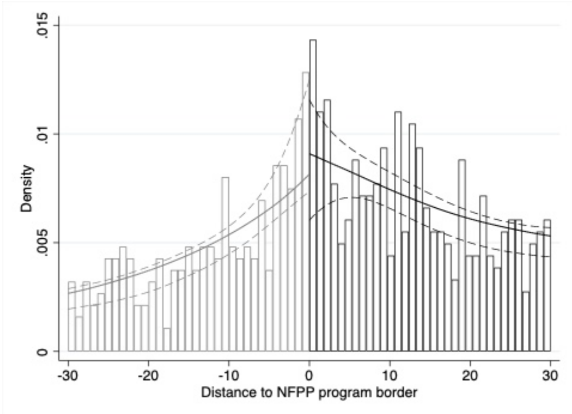
Figure 2 presents the estimated distributions of $Distance_{ikt}$ and ***Table 3*** reports the results of the manipulation tests. It can be seen in ***Figure 2*** that the 95% confidence intervals[10] of the probability density curves largely overlap at the NFPP borders ($Distance_{ikt} = 0$), providing no evidence of statistical discontinuity in the distribution of forestland plots near the NFPP borders. In ***Table 3***, for the full sample, the test statistics turned out to be 0.524 with a *p*-value = 0.600, indicating that the null hypothesis (of continuous distribution) cannot be rejected at conventional statistical significance levels (e.g., p-value < 0.10). We have qualitatively similar findings for the state and collective forestland subsamples, which lend further support to the validity of the RDD in our case.

[10] Confidence intervals in ***Figure 2*** were robust bias-corrected and are hence not necessarily centered around the point estimates of the probability density (Cattaneo et al. 2020).

Panel A. All forestland



Panel B. State forestland



Panel C. Collective forestland

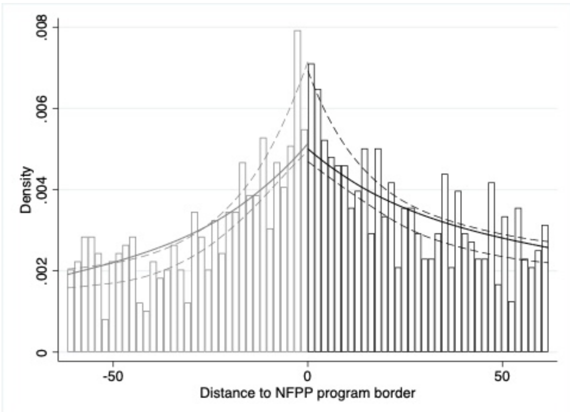


Figure 2. Manipulation test plots

Notes: (i) The histograms visualize the distributions of the running variable on both sides of the NFPP borders. The solid lines represent the estimated probability density functions of the running variable (point estimates), whereas the dashed lines show the robust bias corrected confidence intervals at the 95% level; (ii) The bandwidths in the manipulation tests were computed using the MSE-optimal bandwidth selector proposed by Calonico et al. (2014). (iii) A triangular kernel function was used to construct the local polynomial density estimator.

Table 3. Manipulation test results

	Bandwidths (*h*)	**Observation**	**Test statistic**	***p*-value**
All forestland	43.889	1798	0.524	0.600
State forestland	26.988	671	-0.571	0.568
Collective forestland	61.773	1123	-0.280	0.779

5 Results

5.1 Visual evidence

Figure 3 plots forest cover against the running variable ($Distance_{ikt}$), for the full sample and by forestland ownership regimes, using the second and third periods of our panel data (after the introduction of the NFPP). This provides a preliminary visual assessment of whether the NFPP has led to a discontinuity of forest cover at the program's borders. In ***Figure 3***, the running variable is partitioned into evenly spaced bins, as suggested by Calonico et al., (2014), and each circle represents the average forest cover within each bin. In addition, the curves in ***Figure 3*** show the predicted values from a quadratic regression of forest cover on the running variable. This is the preferred functional form for the parametric RDD regressions, which will be discussed shortly.

As can be seen in Panel A, for the full sample, the data exhibits a visible jump in forest cover at the NFPP borders ($Distance_{ikt} = 0$). More specifically, the average forest cover (%) just inside the NFPP borders (on the right side of the vertical axis) is almost 4% (in relative terms) higher than that just outside the NFPP borders (on the left side of the vertical axis).

Panels B and C visualize the data for state and collective forestland separately. For state forestland, Panel B finds no discernible discontinuity in forest cover at the NFPP borders. In contrast, for collective forestland, Panel C finds a visible and sizable discontinuity in forest cover at the NFPP borders: the average forest cover just inside the NFPP borders is about 5% (in relative terms) higher than that just outside the NFPP borders. Hence, ***Figure 3*** provides some preliminary visual evidence that the NFPP has had a moderate positive effect on forest cover, especially for collective forestland. These patterns were further tested using more formal RDD analyses as will be reported in Sections 5.2 and 5.3.

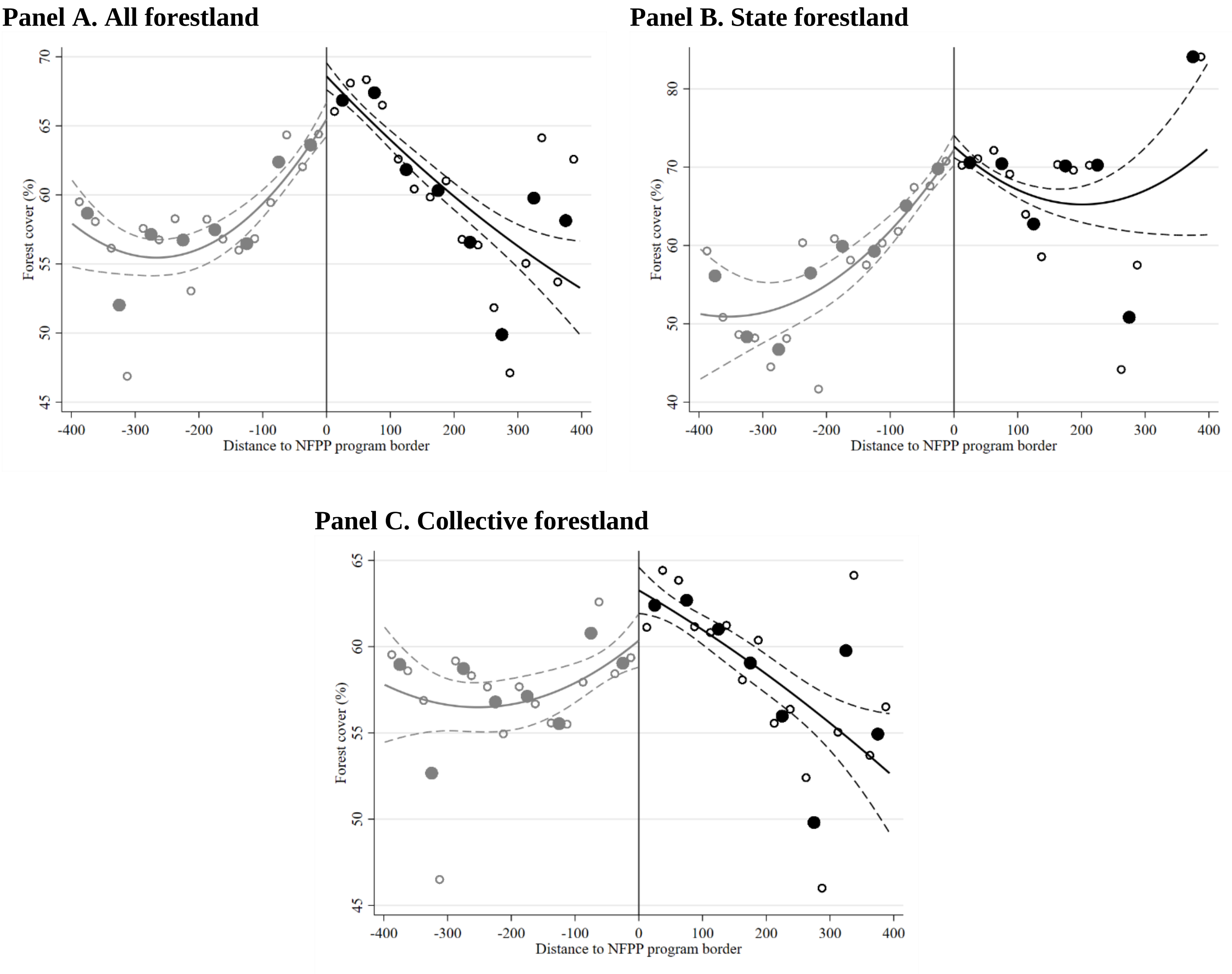


Figure 3. RDD plots: forest cover against the running variable

Notes: (i) The solid curves are predicted forest cover from a quadratic regression of forest cover on the running variable. The dashed curves are 95% confidence intervals of predicted forest cover. Values inside (outside) the NFPP borders are in black (gray). (ii) The solid circles represent average forest cover within 50-meter bins of the running variable and the hollow circles give average forest cover within 25-meter bins.

5.2 Main analysis: Overall effect of the NFPP

Table 4 presents the formal RDD regression estimates of the effect of the NFPP program on forest cover for all forestland regardless of ownership type. Columns (1) and (2) contain the estimates of ***Equation 1*** with and without covariates. Both models control for county and period fixed effects, as suggested by Athey and Imbens (2017), and contain a quadratic polynomial of the running variable $Distance_{ikt}$, because the quadratic polynomial outperforms the linear and cubic polynomials according to the AIC. The bandwidth was computed for the two models separately using the MSE optimal bandwidth selection approach described in Section 4. Columns (3) and (4) present the non-parametric estimates derived from a local linear estimator using a triangular kernel as per Calonico et al. (2014).

We place more emphasis on estimates with a full set of controls (Columns 2 and 4). It can be seen that the parametric and non-parametric estimates are highly comparable in terms of both the magnitude and statistical significance of the treatment effect. The two estimates (Columns 2 and 4) suggest that forest cover just inside the NFPP borders is nearly 6% [11] higher on average (in relative terms) than that just outside. Turning to Columns 1 and 3, it can be seen that the less controlled estimates find a slightly larger positive effect of the NFPP on forest cover. Overall, the four estimates consistently suggest that the NFPP has a moderate positive effect on forest cover on average (regardless of forestland ownership type).

We then adopted three alternative bandwidths (20km, 30km and 40km) and repeated the two most controlled estimation procedures (that gave the estimates in Columns 2 and 4 in ***Table 4***). ***Table S1*** in the Appendix presents the results derived using the three alternative bandwidths. It can be seen that the main findings are considerably stable: forest cover just inside the NFPP borders is about 6% (5.8%–6.3%) higher on average (in relative terms) than that just outside.

[11] 3.659%/63.460% = 5.8%; 3.773%/63.460% = 5.9%.

Table 4. Overall effect of the NFPP on forest cover

	Parametric estimates		Non-Parametric estimates	
	(1)	**(2)**	**(3)**	**(4)**
RDD treatment effect	4.494*	3.659*	4.869***	3.773***
	(2.449)	(0.923)	(1.108)	(1.116)
	[0.069]	[0.058]	[0.000]	[0.013]
Covariates	No	Yes	No	Yes
County fixed effects	Yes	Yes	Yes	Yes
Period fixed effects	Yes	Yes	Yes	Yes
Degree of polynomial	Quadratic	Quadratic	Linear	Linear
Adjusted R^2	0.213	0.274		
Bandwidth (km)	46.025	32.426	46.025	32.426
Mean outside NFPP borders	63.091	63.460	63.091	63.460
Obs.	5544	4365	5544	4365

Notes: (i) Standard errors clustered by county are in parentheses. *P*-values are in brackets. (ii) Each column in the table represents a separate RDD regression which controlled for a specific set of variables and adopted an MSE optimal bandwidth. (iii) *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

5.3 Main analysis: Heterogeneous effects of the NFPP by forestland property right regime

Table 5 compares the effects of the NFPP on state and collective forestland. These estimates were derived from repeating the main RDD analysis using the state and collective forestland subsamples separately. Panel A of ***Table 5*** illustrates the impact of the NFPP on state forestland whereas Panel B shows the impact on collective forestland. The estimates suggest that the NFPP has a positive effect on forest cover for both state and collective forestland, although this positive effect is more pronounced for collective forestland.

In the model that includes the full set of controls (Column 2 in Panels A and B) we find that the estimated treatment effect for collective forestland is 82% higher than that for state forestland. Moreover, the estimate for collective forestland has a lower *p*-value (8.7%) than that for state forestland (45.3%). Similarly, the equivalent nonparametric estimates (Column 4 in Panels A and B) find that the NFPP has a more favorable effect for collective forestland than for state forestland, although the gap becomes smaller in size. We have qualitatively similar findings from the models without the full set of controls for both of the parametric and non-parametric estimates (Columns 1 and 3 in Panels A and B).

In addition, we repeated the parametric and non-parametric estimations using alternative bandwidths (20km, 30km and 40km). As shown in ***Table S2*** in the Appendix, the treatment effect estimates for collective forestland have consistently larger magnitudes and lower *p*-values than those for state forestland, which suggests that the NFPP has better environmental outcomes in collective forestland than in state forestland.

Table 5. Heterogeneous effects of the NFPP on state and collective forestland

Panel A. State forestland

	Parametric estimates		**Non-Parametric estimates**	
	(1)	**(2)**	**(3)**	**(4)**
RDD treatment effect	2.176	2.926	3.972***	2.931**
	(2.842)	(3.876)	(1.514)	(1.400)
	[0.446]	[0.453]	[0.009]	[0.036]
Covariates	No	Yes	No	Yes
County FE	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes
Degree of polynomial	Quadratic	Quadratic	Linear	Linear
Adjusted R^2	0.200	0.267		
Bandwidth (km)	41.552	31.729	41.552	31.729
Mean outside NFPP borders	69.654	70.001	69.654	70.001
Obs.	2590	2149	2590	2149

Panel B. Collective forestland

	Parametric estimates		**Non-Parametric estimates**	
	(1)	**(2)**	**(3)**	**(4)**
RDD treatment effect	4.604*	5.339*	5.554***	5.886***
	(2.535)	(3.087)	(1.832)	(2.010)
	[0.072]	[0.087]	[0.001]	[0.003]
Covariates	No	Yes	No	Yes
County FE	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes
Degree of polynomial	Quadratic	Quadratic	Linear	Linear
Adjusted R^2	0.223	0.271		
Bandwidth (km)	39.306	31.546	39.306	31.546
Mean outside NFPP borders	58.284	58.727	58.284	58.727
Obs.	2471	2140	2471	2140

Notes: (i) Standard errors clustered by county are in parentheses. *P*-values are in brackets. (ii) Each column in the table represents a separate RDD regression which controlled for a specific set of variables and adopted an MSE optimal bandwidth. (iii) *** p<0.01, ** p<0.05, * p<0.1.

5.4 Placebo tests

Lastly, we performed a series of placebo tests to explore whether the aforementioned discontinuity in forest cover at NFPP borders (especially for collective forestland) might represent some random discontinuity in forest cover across space. Following Ebenstein et al. (2017), we displaced the cutoff of the running variable $Distance_{ikt}$ from 0 (NFPP borders) to ±20km and ±30km separately.[12] We repeated the RDD analyses for each of these false cutoffs.

Table 6 presents the estimated discontinuity in forest cover at the four false cutoff points, for the full sample (Panel A) and for the state and collective forestland subsamples (Panels B and C). These estimates were derived from the model with a full set of controls with the same specification and bandwidth as in the main RDD analysis (Column 2, Table 3).

For the full sample, it can be seen that the discontinuity estimates at the four false cutoff points have a small magnitude (lower than 3% of the mean value outside the false cutoff) and a high *p*-value (above 36%). Moreover, we have qualitatively similar findings for the state and collective forestland subsamples. Six of the eight estimates have a *p*-value above 55% and all discontinuity estimates have a small magnitude (lower than 3% of the mean value outside the false cutoff). We repeated the placebo tests using the non-parametric estimation as in the main RDD analysis (Column 4, ***Table 3***). The results are shown in ***Table S3*** in the Appendix. These non-parametric estimates are smaller in size and statistically insignificant. We found no evidence for the presence of random discontinuity in forest cover at the four false cutoff points.

Table 6. Placebo tests: parametric estimates

Panel A. full sample

	False cutoff 1 **20 km** **(1)**	**False cutoff 2** **-20 km** **(2)**	**False cutoff 3** **-30 km** **(3)**	**False cutoff 4** **+30 km** **(4)**
RDD treatment effect	-1.012	-1.714	0.884	0.690
	(1.782)	(1.867)	(1.570)	(3.310)
	[0.571]	[0.361]	[0.575]	[0.835]
Covariates	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes
Degree of polynomial	Quadratic	Quadratic	Quadratic	Quadratic
Adjusted R^2	0.309	0.275	0.279	0.305
Bandwidth (km)	32.426	32.426	32.426	32.426
Mean outside false cut-off	62.958	64.683	66.817	63.002
Obs.	3612	4611	4398	2928

Panel B. State forestland

[12] We did not displace the cutoff to ±10km to avoid picking up the discontinuity in forest cover at the original cutoff.

	False cutoff 1 20 km (1)	False cutoff 2 -20 km (2)	False cutoff 3 -30 km (3)	False cutoff 4 +30 km (4)
RDD treatment effect	-1.613	-0.059	1.396	1.604
	(3.474)	(2.460)	(2.355)	(6.489)
	[0.644]	[0.981]	[0.555]	[0.806]
Covariates	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes
Degree of polynomial	Quadratic	Quadratic	Quadratic	Quadratic
Adjusted R^2	0.265	0.264	0.275	0.249
Bandwidth (km)	31.729	31.729	31.729	31.729
Mean outside false cut-off	69.260	71.035	74.754	69.241
Obs.	1655	2412	2315	1205

Panel C. Collective forestland

	False cutoff 1 20 km (1)	False cutoff 2 -20 km (2)	False cutoff 3 -30 km (3)	False cutoff 4 +30 km (4)
RDD treatment effect	-0.548	-0.229	-0.996	0.249
	(2.697)	(2.655)	(2.306)	(4.261)
	[0.839]	[0.227]	[0.667]	[0.147]
Covariates	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes
Degree of polynomial	Quadratic	Quadratic	Quadratic	Quadratic
Adjusted R^2	0.256	0.200	0.191	0.254
Bandwidth (km)	31.546	31.546	31.546	31.546
Mean outside false cutoff	58.307	59.638	61.171	58.579
Obs.	1888	2109	1966	1597

Notes: (i) Standard errors clustered by county are in parentheses. *P*-values are in brackets. (ii) Each column in the table represents a separate RDD regression which controlled for a specific set of variables and adopted an MSE optimal bandwidth. (iii) *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

6 Discussion and conclusion

The NFPP aims to conserve natural forests and restore forest resources, mainly by restricting logging and financing afforestation. The program is one of the largest forest conservation and restoration programs in the world. However, there is a paucity of formal empirical evidence on the program's environmental outcomes, which contrasts with the sheer size of the program's geographic coverage and financial investment. We contribute to this literature by undertaking the first regression discontinuity study on the environmental impacts of the NFPP, which adds to a very limited body of quasi-experimental literature on this topic (e.g., Brandt et al., 2015; Ren et al., 2015; Shi et al. 2017; Zhang et al. 2011). Compared to previous studies, the present study can better identify changes in forest cover caused by the NFPP, rather than by other observed and unobserved factors that correlate with the program. This is achieved using spatial RDD models that control for observed covariates and county and period fixed effects. Moreover, the NFPP shares some key characteristics of forest Protected Areas (PAs) (e.g., the top-down exogenous assignment of logging restrictions), and of forest-based Payments for Ecosystem Services (PES) programs (e.g., financial support for forest conservation and restoration). Therefore, this study also adds to the quasi-experimental literature on the environmental impacts of forest-based PAs and PES instruments (e.g. Alix-Garcia et al. 2015, Blackman et al. 2015, Herrera et al. 2019 and Sims and Alix-Garcia 2017). Our primary finding is that the NFPP has a moderate positive impact on forest cover overall.

Second, our study is also one of the first quasi-experimental studies in the developing world to compare the performance of a large-scale forest conservation initiative across different forestland property right regimes, which speaks to studies such as those by Alix-Garcia et al. (2012) and Bonilla-Mejía and Higuera-Mendieta (2019). Our empirical results find that the NFPP has a stronger positive effect for collective forests than for state forests. Note that our results and findings were drawn from data for four provinces (out of a total of 18 provinces affected by the NFPP) and thus may not be fully generalizable to other regions. However, our studied regions are still fairly representative both in terms of ecological and social characteristics.

The NFPP includes different provisions across property right regimes. In particular, the financial and administrative support for afforestation on collective forestland is not as strong as that for state forestland. However, our results indicate that the NFPP has induced a more evident increase in forest cover on collective forestland than on state forestland. These state-owned forests can be characterized as a type of common property resource shared within each firm and with government bodies, whereas collective forests are in essence semi-private resources managed by individual rural households (Xu et al. 2004; Yi et al. 2014). Standard economic theory and empirical evidence tend to suggest that China's state-owned enterprises are often outperformed by their private counterparts because state-owned resources often have common property or even public good features which are typically associated with overuse and underinvestment (Jefferson 1998; Lin et al. 1998; Liu and Xu 2019; Xu et al. 2004). The findings in this study are in line with this hypothesis.

Therefore, the NFPP might be able to achieve enhanced performance by (re)directing larger proportions of the program's funds and forest restoration activities towards collective forest managers. China's state-owned enterprises have long been accused of unfairly crowding out private sectors' access to capital and other factors of production (Lin et al. 1998). There could be another such situation in the case of the NFPP, because our empirical results suggest that collective forest managers seem to be more productive in forest conversation and restoration. In theory and in a perfectly competitive setting, the optimal allocation of the NFPP's resources would entail collective forest managers receiving more resources and undertaking more afforestation, until collective and state forest managers have the same level of marginal output (e.g., the increase in forest cover) with respect to the NFPP resources they receive. This implies considerable scope for the NFPP to enhance its performance by allowing more resources to flow to their most productive use, which is likely to be the conservation and restoration of collective forests.

Furthermore, our findings provide insights for the ongoing institutional reform of China's state forest property regime and SOFEs. Under collective forests with semi-private forest rights arrangements, the same household bears the costs of forestry input and receives the benefits that it produces, which avoids the kind of adverse externalities in state forests where individual SOFE workers contribute differently to forestry activities, but the ensuing benefits are shared with the entire SOFE or even with government bodies. Privatizing state forests and allocating forest rights to individual SOFE workers is a long-standing yet heavily debated option for institutional reform. A less radical approach could be a Contract Management Responsibility System (CMR) which uses fixed-term contracts to better align individual SOFE workers' input to and benefits from state forest resources, or at least the forest conservation and restoration activities undertaken under the NFPP. Some SOFEs have adopted some form of CMRS which typically assign to individual SOFE workers the responsibility for patrolling specific areas of state forests and the right to harvest non-timber forest products in those areas (Liu and Xu 2019). There is scope to further develop the SOFEs' CMRS by assigning more substantial forestry management responsibilities and benefits to individual SOFE workers, such as afforestation and timber harvests.

Appendix

Table S1. Overall effect of the NFPP on forest cover: Alternative bandwidths

	Parametric estimates			Non-Parametric estimates		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
RDD treatment effect	4.161**	4.006**	4.357*	4.989***	3.707**	5.352***
	(0.879)	(0.846)	(1.522)	(1.463)	(1.575)	(1.406)
	[0.042]	[0.042]	[0.087]	[0.001]	[0.019]	[0.001]
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Degree of polynomial	Quadratic	Quadratic	Quadratic	Linear	Linear	Linear
Adjusted R^2	0.271	0.275	0.287			
Bandwidth (km)	40.000	30.000	20.000	40.000	30.000	20.000
Mean outside NFPP borders	63.315	63.777	64.196	63.315	63.777	64.196
Obs.	5019	4158	3150	5019	4158	3150

Notes: (i) Standard errors clustered by county are in parentheses. *P*-values are in brackets. (ii) Each column in the table represents a separate RDD regression which controlled for a specific set of variables and adopted alternative bandwidths. (iii) *** p<0.01, ** p<0.05, * p<0.1.

Table S2. Heterogeneous effects of the NFPP on state and collective forestland: Alternative bandwidths

Panel A. State forestland

	Parametric estimates			**Non-Parametric estimates**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
RDD treatment effect	4.187	3.560	4.122	3.632**	3.023**	4.011**
	(3.698)	(3.873)	(4.321)	(1.292)	(1.433)	(1.634)
	[0.261]	[0.361]	[0.344]	[0.042]	[0.035]	[0.014]
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Degree of polynomial	Quadratic	Quadratic	Quadratic	Linear	Linear	Linear
Adjusted R^2	0.266	0.271	0.279			
Bandwidth (km)	40.000	30.000	20.000	40.000	30.000	20.000
Mean outside NFPP borders	69.700	70.185	70.824	69.700	70.185	70.824
Obs.	2531	2072	1578	2531	2072	1578

Panel B. Collective forestland

	Parametric estimates			**Non-Parametric estimates**		
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
RDD treatment effect	4.357*	5.356	6.857**	5.523***	5.774***	5.864***
	(2.522)	(3.238)	(3.237)	(1.822)	(2.072)	(1.725)
	[0.087]	[0.102]	[0.037]	[0.002]	[0.005]	[0.001]
Covariates	Yes	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes	Yes	Yes
Degree of polynomial	Quadratic	Quadratic	Quadratic	Linear	Linear	Linear
Adjusted R^2	0.229	0.226	0.239			
Bandwidth (km)	40.000	30.000	20.000	40.000	30.000	20.000
Mean outside NFPP borders	58.311	58.771	59.012	58.311	58.771	59.012
Obs.	2488	2086	1568	2488	2086	1568

Notes: (i) Standard errors clustered by county are in parentheses. *P*-values are in brackets. (ii) Each column in the table represents a separate RDD regression which controlled for a specific set of variables and adopted alternatives bandwidths. (iii) *** p<0.01, ** p<0.05, * p<0.1.

Table S3. Placebo tests: nonparametric estimates

Panel A. Full sample

	False cutoff 1 -20 km (1)	False cutoff 2 +20 km (2)	False cutoff 3 -30 km (3)	False cutoff 4 +30 km (4)
RDD treatment effect	0.051	-0.536	1.940	1.141
	(1.458)	(1.097)	(1.817)	(1.254)
	[0.972]	[0.625]	[0.286]	[0.363]
Covariates	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes
Mean outside false cut-off	69.260	71.035	74.754	69.241
Degree of Polynomial	LLR	LLR	LLR	LLR
Bandwidth (km)	32.426	32.426	32.426	32.426
Obs.	3612	4611	4398	2928

Panel B. State forestland

	False cutoff 1 -20 km (1)	False cutoff 2 +20 km (2)	False cutoff 3 -30 km (3)	False cutoff 4 +30 km (4)
RDD treatment effect	0.786	0.974	2.524	0.210
	(2.010)	(2.037)	(2.628)	(2.101)
	[0.696]	[0.632]	[0.337]	[0.920]
Covariates	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes
Mean outside false cut-off	69.260	71.035	74.754	69.241
Degree of Polynomial	LLR	LLR	LLR	LLR
Bandwidth (km)	31.729	31.729	31.729	31.729
Obs.	1655	2412	2315	1205

Panel C. Collective forestland

	False cutoff 1 -20 km (1)	False cutoff 2 +20 km (2)	False cutoff 3 -30 km (3)	False cutoff 4 +30 km (4)
RDD treatment effect	0.280	-1.264	2.173	-2.297
	(1.323)	(2.502)	(2.587)	(1.820)
	[0.832]	[0.613]	[0.401]	[0.207]
Covariates	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Period FE	Yes	Yes	Yes	Yes
Mean outside false cut-off	58.307	59.638	61.171	58.579
Degree of polynomial	LLR	LLR	LLR	LLR
Bandwidth (km)	31.546	31.546	31.546	31.546
Obs.	1888	2109	1966	1597

Notes: (i) Standard errors clustered by county are in parentheses. *P*-values are in brackets. (ii) Each column in the table represents a separate RDD regression which controlled for a specific set of variables and adopted an MSE optimal bandwidth. (iii) *** p<0.01, ** p<0.05, * p<0.1.

Table S4. Covariate continuity tests: parametric approach

Panel A. Full sample

	(1) Altitude	(2) Slope	(3) Protected area	(4) Night lights	(5) Accessibility	(6) Precipitation	(7) Temperature	(8) Soil	(9) Ecological forest	(10) Forest origin	(11) Age	(12) State forest
RDD treatment effect	90.989	-0.126	3.654	-0.230	-0.023	-65.568	0.113	-0.804	0.124	-0.008	-0.009	0.092
	(96.750)	(0.083)	(9.172)	(0.285)	(0.077)	(111.885)	(1.841)	(10.146)	(0.090)	(0.060)	(0.139)	(0.118)
	[0.348]	[0.132]	[0.691]	[0.420]	[0.769]	[0.559]	[0.951]	[0.937]	[0.168]	[0.892]	[0.946]	[0.439]
Mean outside NFPP borders	727.876	3.066	63.132	0.940	0.258	806.566	8.919	26.833	0.238	0.708	1.822	0.429
Degree of polynomial	Linear	Linear	Linear	Linear	Linear	Linear	Linear	Linear	Linear	Linear	Linear	Linear
Adjusted R^2	0.052	0.002	0.013	0.003	< 0.001	0.002	0.001	0.008	0.030	0.019	0.003	0.014
Bandwidth (km)	68.170	68.170	68.170	68.170	68.170	68.170	68.170	68.170	68.170	68.170	68.170	68.170
Obs.	2397	2397	2397	2397	2397	2397	2397	2397	2397	2397	2397	2397

Panel B. State forestland

	(1) Altitude	(2) Slope	(3) Protected area	(4) Night lights	(5) Accessibility	(6) Precipitation	(7) Temperature	(8) Soil	(9) Ecological forest	(10) Forest origin	(11) Age
RDD treatment effect	90.096	-0.151	-3.990	-0.139	-0.067	23.881	0.883	6.432	0.108	0.015	-0.087
	(108.675)	(0.143)	(12.442)	(0.342)	(0.107)	(39.286)	(0.826)	(7.268)	(0.140)	(0.088)	(0.160)
	[0.409]	[0.294]	[0.749]	[0.685]	[0.534]	[0.545]	[0.287]	[0.378]	[0.443]	[0.865]	[0.588]
Mean outside NFPP borders	686.135	3.084	64.990	0.971	0.255	632.121	5.416	11.557	0.199	0.737	2.106
Degree of polynomial	Linear	Linear	Linear	Linear	Linear	Linear	Linear	Linear	Linear	Linear	Linear
Adjusted R^2	0.066	0.001	0.002	0.005	0.012	0.001	0.005	0.024	0.048	0.018	0.003
Bandwidth (km)	56.630	56.630	56.630	56.630	56.630	56.630	56.630	56.630	56.630	56.630	56.630
Obs.	1063	1063	1063	1063	1063	1063	1063	1063	1063	1063	1063

Panel C. Collective forestland

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
	Altitude	**Slope**	**Protected area**	**Night lights**	**Accessibility**	**Precipitation**	**Temperature**	**Soil**	**Ecological forest**	**Forest origin**	**Age**
RDD treatment effect	60.396	-0.036	2.970	-0.003	-0.070	-74.393	-1.149	-2.599	0.129	-0.025	-0.027
	(102.888)	(0.097)	(8.582)	(0.384)	(0.089)	(151.038)	(1.648)	(10.872)	(0.087)	(0.081)	(0.106)
	[0.558]	[0.713]	[0.730]	[0.993]	[0.437]	[0.623]	[0.487]	[0.811]	[0.140]	[0.758]	[0.803]
Mean outside NFPP borders	850.579	2.986	56.777	0.860	0.194	969.758	11.448	42.353	0.302	0.720	1.575
Degree of polynomial	Linear	Linear	Linear	Linear	Linear	Linear	Linear	Linear	Linear	Linear	Linear
				<							
Adjusted R^2	0.059	0.006	0.046	0.001	0.011	0.040	0.022	0.042	0.012	0.019	0.030
Bandwidth (km)	84.310	84.310	84.310	84.310	84.310	84.310	84.310	84.310	84.310	84.310	84.310
Obs.	1369	1369	1369	1369	1369	1369	1369	1369	1369	1369	1369

Notes: (i) Standard errors clustered by county are in parentheses. *P*-values are in brackets. (ii) Each column in the table represents a separate RDD regression for each covariate. (iii) *** p<0.01, ** p<0.05, * p<0.1.

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