6 Concurrent green initiatives in Tianma National Nature Reserve, China

This chapter presents hidden spillover effects between China's Grain-To-Green Program (GTGP) and Forest Ecological Benefit Compensation (FEBC) Fund in Tiantangzhai Township in Anhui Province of China which belongs to a nature reserve called the Tianma National Nature Reserve (TNNR). We draw on household survey data (250 households collected in 2013 and 481 households in 2014) and satellite observations to examine hidden spillover effects among the two concurrent payments for environmental services (PES) programs. We first describe the study site and the two PES programs within the local context, then present the socio-ecological outcomes of the PES programs, and finally summarize the findings and their implications.

6.1 Tianma National Nature Reserve (TNNR)

Tianma National Nature Reserve (TNNR) was set to protect the last remaining patches of secondary natural forests in Southeast China and many protected plant and animal species. The township of Tiantangzhai, which covers an area of 189 km^2, encompasses the core of the TNNR and spans a geographic extent of N31º05′–31º09′, E115º42′–115º46′ in the eastern Dabieshan Mountain Ranges with elevations ranging from 363 m to 1,729 m (Figure 6.1). Tiantangzhai is located in a subtropical monsoon climate with a mean annual temperature of 16.4ºC and mean annual precipitation of 1,350 mm, sustaining lush vegetation. The township is rich with ecotourism resources, which were well developed to attract tourists. Tiantangzhai is home to 4,369 households with a population of 17,295, according to the local household registration record in 2012. The township encompasses 165 resident groups distributed in seven administrative villages. Local farmers live primarily on cropland cultivation, animal husbandry, and forest resource extraction. They also engage in other economic activities such as local off-farm employment, local businesses, and out-migration.

6.2 Concurrent PES programs in the Tianma National Nature Reserve

The GTGP is the largest PES program in the world. It was implemented in the aftermath of back-to-back natural disasters in the late 1990s in China. The program

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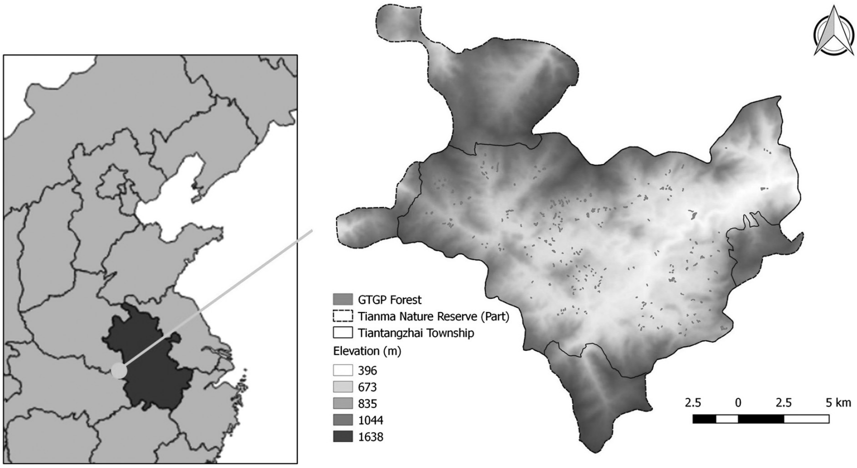

Figure 6.1 Location of Tianma National Nature Reserve (TNNR). The core zone is situated within Tiantangzhai Township, Anhui Province, China.

was initially tested in Shaanxi, Shanxi, and Sichuan provinces before becoming a national policy in 2001 (Zhang & Song, 2006). By enrolling in the GTGP, farmers plant trees in croplands on steep slopes for soil and water conservation, and the Chinese central government provided the farmers with as much grain as they would harvest from the cropland as compensation. Thus, the program is named the GTGP, although the grain compensation was replaced with cash in the subsequent years due to high transaction costs. Due to the rough terrain, some croplands in Tiantangzhai are located on steep slopes, causing severe soil erosion. Therefore, the GTGP was applicable in this region and was implemented in 2002, resulting in the enrollment of 1,680 mu (112 ha) croplands from 753 households. Most enrolled lands in the GTGP in Tiantangzhai were established as ecological forests, mainly sweetgum (*Liquidambar styraciflua*). The duration of payment was eight years for ecological trees and five years for economic trees (e.g., pecan trees) according to the GTGP policy. The compensation rate was set the same as in the Yangtze River Basin (Song et al., 2014), i.e., 210 yuan/mu/year during the first eight-year contract (ecological trees) and then 125 yuan/mu/year for the renewed eight-year contract. Under the supervision of the local government, qualified croplands were first identified for enrollment, and then the households that farm these croplands were requested to enroll in the program. Theoretically, the farmer can decline the request, but it rarely happens in reality.

The FEBC program in TNNR was initially embedded in a forest management policy (Dai et al., 2009), called Ecological Welfare Forest Program, aiming to protect natural forests from commercial logging (Zhang et al., 2019). The nature of the program is similar to the national forest conservation policy, the Natural Forest Conservation Program. In 2000, the Chinese government adopted the PES

Figure 6.2 Photos of tree saplings and forests protected under the FEBC. (a) Tree saplings recently planted on cropland enrolled in the GTGP and (b) protected natural forests under the FEBC program in the Tianma National Nature Reserve.

principle and compensated households who own FEBC forests. The compensation rate in Tiantangzhai was initially set at 5.00 yuan/mu/year, and the compensation rate increased to 8.75 yuan/mu/year in 2009. Since most households have some natural forests in the study area, nearly all households automatically participated in the FEBC and received government payments (Figure 6.2). The area of FEBC land varies widely among households due to the natural variation in forest areas from village to village. Those living in the mountains often have extensive natural forests and are compensated with sizable cash payments each year. According to our survey, the total payment amount for a household can be as high as several thousand Chinese yuan per year, which may account for the majority share of total agricultural income for the household (Zhang et al., 2018c).

6.3 Data collection

We conducted two waves of household surveys collecting data to evaluate the socioeconomic and ecological impacts of the GTGP and the FEBC in Tiantangzhai Township in 2013 and 2014. Since nearly every household is enrolled in the FEBC program, we designed our sampling schemes focusing on the GTGP. In the 2013 survey, we adopted a simple random stratified sampling scheme. We had two household strata, the households enrolled in GTGP and those not enrolled. We aimed to collect a roughly equal number of households from each stratum. We successfully interviewed 250 households comprising 139 GTGP participating households and 111 non-participating households in 2013. We obtained information on demography, economic activities, land use, and compensation from each of the PES programs from each interviewed household. We particularly asked whether people stole any trees from FEBC land (i.e., FEBC tree theft) and whether a local forestry station monitored FEBC forests. For each of the interviewed households, we also visited every cropland parcel the household farmed at the time and recorded its geolocations with a hand-held GPS unit. The geographic coordinates allow us to derive the topographic features (e.g., slope and aspect) with a digital elevation model (DEM) and connect the biophysical data at the cropland parcel level with the household socioeconomic data. We visited 1,196 cropland parcels in the 2013 household survey.

In the 2014 household survey, we designed a more comprehensive questionnaire because we received funding from the US National Science Foundation (grant number DEB-1313756), covering more topics than that used in the pilot study in 2013. We adopted a more sophisticated sampling method, a two-stage disproportionate random sampling scheme (Bilsborrow, 2016), to select households for the survey. Since many more households were not enrolled in the GTGP, and we aimed to select a sample with a roughly equal number of enrolled and those not enrolled in the GTGP, we need to oversample in the GTGP participating households and under-sample in the GTGP non-participating households. We first obtained a list of the household population of Tiantangzhai, including information on household head name, resident group, village, and whether they are participating in the GTGP. In the first stage, we selected resident groups based on the proportion of households enrolled in the GTGP, which was stratified into five strata, with their participation proportion being 1.0–0.80 (Stratum-I), 0.79–0.50 (Stratum-II), 0.49–0.30 (Stratum-III), 0.29–0.00 (Stratum-IV), and 0.00 (Stratum-V). We randomly selected ten, nine, seven, ten, and four resident groups from each of the strata, resulting in an estimated mean proportion of GTGP participation of 47%. In the second stage, we randomly selected roughly 20 households from each resident group from the two strata of GTGP participants and non-participants. If a resident group consists of fewer than 20 households, all households would be selected. We purposely oversampled GTGP participating households for resident groups with lower proportions of participation in the GTGP and oversampled non-participants for resident groups with a higher proportion of households participating in the GTGP. This sampling would lead to a final sample with a balanced number of households for GTGP participants and non-participants from each resident group. We successfully collected data for 481 households, with 271 (56%) participating in the GTGP and the remaining households not enrolled in the GTGP. A more detailed description of the sampling process can be found in previous studies (Song et al., 2018; Zhang et al., 2020).

In both surveys, we obtained the geolocation information of each interviewed household with a hand-held Global Positioning System unit. Ancillary data, including a high spatial-resolution remotely sensed image (WorldView-2 on 7/13/2013), a digital elevation model, and topographic maps, were used to delineate each of the GTGP forest stands in Tiantangzhai. Given these data, we performed the following analyses concerning the spillover effects among the two concurrent PES programs, the GTGP and the FEBC.

6.4 Data analysis and modeling

With careful data collection, this section explores five fundamental dimensions of local livelihoods: cropland abandonment, household labor allocation (for labor out-migration), household energy transition (from fuelwood to nontraditional, alternative sources), tree theft, and the direct impact from FEBC to GTGP. In particular, we focus on how the two green initiatives, GTGP and FEBC, may interact with each other and account for the above four dimensions.

6.4.1 Cropland abandonment

Cropland abandonment has been a significant phenomenon in mountainous areas (Zhang et al., 2014), like Tiantangzhai Township in China. The abandonment of cropland potentially contributes to the additionality of the PES programs for ecological restoration. It is a reverse process of conversion from natural surface to human-dominated land. The GTGP and the FEBC may change rural households' land-use decisions on cropland abandonment through two mechanisms. First, the cash compensation provides households with financial resources to reallocate farm labor to other activities than cropland cultivation, causing some cropland parcels in marginal areas to be abandoned due to lack of labor. Second, the converted forests under the GTGP and the recovery of natural forests under FEBC can influence the decision-making on cropland use located near the forests due to multiple feedback effects such as crop raiding by wildlife (Chen et al., 2019) and shading effects (Bista et al., 2021). However, the compensation from the GTGP and the FEBC provides financial resources to purchase agricultural tools and supplies, which may lead to agriculture intensification. It is essential to understand the respective effect of the two PES programs and their ensemble effects on cropland usage.

We first used the data of the 250 households from the 2013 household survey because the survey contains the geolocation data for 1,196 cropland parcels managed by these households. Although households are central decision-makers for cropland use, the abandonment of a cropland parcel also depends on its biophysical conditions. Therefore, the key factors influencing cropland abandonment include the biophysical features of the cropland parcel and the socioeconomic and demographic characteristics of the household to which the cropland parcels belong (Table 6.1). By setting the dependent variable as a binary variable indicating whether a cropland parcel has been abandoned (0 = cultivated, 1 = abandoned), we utilized a random-coefficient modeling approach to examine the effects of PES programs on cropland use decisions, with the equation as follows:

Table 6.1 Explanatory variables for modeling cropland abandonment at the TNNR, China

Variable	*Description*	*Mean (std. dev.)*
Parcel level		
Parcel area	Area of land parcel (ha)	0.0861 (0.0841)
Parcel type	If the parcel is dryland (0 = no, 1 = yes)	0.4534 (0.4980)
Walk distance	Reported walking time from parcel to house (minutes)	10.6199 (10.6994)
Parcel elevation	Elevation at parcel location (100 m)	6.466 (0.9646)
Parcel TWI	Topographic wetness index value at parcel location	9.8707 (3.9722)
Parcel aspect	Aspect facing the direction of the parcel (0 = south, 180 = north)	75.6614 (52.7316)
GTGP distance	Geographic distance to nearest GTGP forest stand (100 m)	0.7849 (0.7269)
FEBC distance	Geographic distance to nearest FEBC natural forest edge (100 m)	3.4408 (3.1647)
Household level		
Head age	Age of household head	52.2238 (9.2554)
Head gender	Gender of household head (0 = male, 1 = female)	0.0341 (0.1816)
Head education	Education completed by the household head (years)	6.9642 (2.6433)
House elevation	Elevation at house location (100 m)	6.4308 (0.9427)
Farm labor	Number of a current household member aged 18–60, living at home, and being able to provide farm labor	1.8319 (1.0751)
Cropland	Total area of cropland managed (ha)	0.4146 (0.1854)
Crop raiding	Incidence of crop raiding by wildlife (0 = no, 1 = yes)	0.4634 (0.4989)
Livestock	Livestock ownership (0 = no, 1 = yes)	0.7696 (0.4213)
Off-farm	Share of local off-farm income in total household gross income	0.2823 (0.4016)
Fuelwood use	Total amount of fuelwood used per year (1,000 kg)	9.2003 (5.7606)
FEBC	Total amount of payment received from FEBC per year (1,000 yuan)	0.3349 (0.3581)
GTGP	Total amount of payment received from GTGP per year (1,000 yuan)	0.1583 (0.2327)

$$\boldsymbol{y}^* = \alpha + \beta \boldsymbol{X} + \gamma \boldsymbol{Z} + \mu + \varepsilon \tag{6.1}$$

where $\boldsymbol{y^*}$ is the transformed logistic indicator denoting whether a parcel is abandoned or not; $\boldsymbol{X}$ is the vector of parcel-level variables and $\boldsymbol{Z}$ is the vector of household-level variables; $\boldsymbol{\alpha}$ is the intercept; $\boldsymbol{\beta}$ and $\boldsymbol{\gamma}$ are fixed effects corresponding to parcel-level and household-level variables, respectively; $\boldsymbol{\mu}$ is the random coefficient that can capture the household-level variance; and $\boldsymbol{\varepsilon}$ is the random error term at the parcel level.

6.4.2 Household labor allocation for labor out-migration

Rural-to-urban migration is a hallmark of the socioeconomic transformation in China following the adoption of the open and reform policy in the late 1970s (Peng, 2011). Currently, there are about 200 million migrants from rural areas working in cities in China, pulling hundreds of millions of people out of poverty in China (Liang, 2016). Tiantangzhai experienced a growing trend of out-migration when the FEBC and the GTGP were implemented. According to theories in micro- and macroeconomics, migration can be viewed not only as an individual-level decision-making outcome but also regarded as a livelihood strategy of a household (Barbieri et al., 2009; Bilsborrow, 2016; Bilsborrow et al., 2004; Massey, 1990).

The intervention of PES programs can influence the livelihood strategy of households who enrolled their lands in the programs. Farmers used to be intimately connected to their land, which produces livelihood necessities, and active farming secures land tenure simultaneously (Ma et al., 2015). On the one hand, the two PES programs, especially the GTGP, directly change land-use types from cropland to forest, relaxing the labor liquidity constraints, and hence indirectly support the livelihood diversification (Lin & Yao, 2014). Furthermore, the cash compensation can serve as a safety net for risk diversification by investing the labor force into multiple alternative off-farm activities, particularly migration, which can bring in lucrative economic returns from remittance (Zhang et al., 2019). On the other hand, households may also invest financial capital received (i.e., cash compensation) to intensify agriculture by using more fertilizer and/or allocating more labor time to land cultivation after enrolling marginal croplands in the GTGP; on the contrary, the effects of the payment schemes between FEBC and GTGP may be different in influencing household livelihoods. Here, we analyze how the two concurrent PES programs affect individual migration.

We draw on socioeconomic and demographic data from the 2014 household survey to examine the effects of the current PES programs on labor migration. We define a migrant as an individual who lives away from the household outside the county for at least six consecutive months and is 15–59 years old at the survey time. Individuals outside this age range are more likely to be dependent and thus not considered migrants in this study. We recorded the migration history of each individual from 2000 to 2013 in the interviewed households, and the migrants can be easily identified from the interview data recorded. For time-varying variables such as age and education, we reconstructed panel data to reflect the status of migrants before the migration. We also randomly selected a non-migrant from each interviewed household and obtained their attributes (e.g., age, education, and occupation) when the migrant left the household. For households with no migrant, we recorded a randomly selected house member and his or her attributes five years before the survey time, which is roughly the midpoint of our study period, making the non-migrant group comparable to the migrant group. The dependent variable is the migration status for all individuals aged 15–59 (1 = yes, 0 = no).

We used logistic regression to analyze factors that influenced the migration decision. To control for the contextual factors, we developed a multilevel regression model (Equation 6.2), including individual attributes (I), household characteristics (H), and resident group factors (G), to understand the factors influencing individual migration (M) (Table 6.2). We mainly included payments received from the FEBC and the GTGP at the household level to examine their effects on migration.

$$M = f\left(I, H, G\right) \tag{6.2}$$

Table 6.2 Statistics of explanatory variables for modeling labor migration at TNNR, China

Variable	*Description*	*Mean*	*Std. dev.*
Individual level			
Gender	Individual gender (0 = male, 1 = female)	0.4969	0.5002
Age	Individual age	36.6676	13.2997
Education	If individual completed elementary school (0 = no, 1 = yes)	0.7573	0.4289
Marriage	Marital status of individual (0 = never married, 1 = married)	0.7274	0.4455
Single female	If individual is a single female (0 = no, 1 = yes)	0.1108	0.3140
Household level			
Head gender	Gender of household head (0 = male, 1 = female)	0.0457	0.2090
Head age	Age of household head	49.6992	9.1721
Head education	If household head completed elementary school (0 = no, 1 = yes)	0.7537	0.4310
Head marriage	Marital status of household head (0 = never married, 1 = married)	0.9120	0.2833
Elevation	Elevation at house location (m)	673.5856	104.0458
Walk	Travel time to nearest paved road by walk (minute)	11.3773	14.4167
Household size	Number of current household members	3.7168	1.2308
Migration experience	If any household member or previous member has migration experience (0 = no, 1 = yes)	0.3219	0.4674
Cropland	Total amount of cropland under cultivation (mu)	4.8173	3.3076
GTGP	Payment amount received from GTGP per year (1,000 yuan)	0.1486	0.1993
FEBC	Payment amount received from FEBC per year (1,000 yuan)	0.4979	0.6243
Group level			
Group size	Number of households within the resident group	26.0185	8.6601
School	Distance to nearest elementary school (minute)	20.0545	25.0469
Hospital	Distance to nearest hospital or clinic (minute)	18.7599	15.8205

6.4.3 Energy transition: fuelwood vs. alternative sources

Many rural regions in developing countries like China are still at the early stage of energy transition (Tang & Liao, 2014). Fuelwood collected from natural forests remains the primary energy source for households living in forest areas (Zhang et al., 2009). At TNNR, fuelwood is used for cooking daily meals and livestock feed and heating during the winter (Song et al., 2018). According to the energy ladder theory (Leach, 1992), a household tends to go through a transition from using primitive (e.g., fuelwood) to transitioning (e.g., kerosene or coal) and to modern fuels (e.g., electricity or Liquid Petroleum Gas) as the household income increases. The fuel stacking theory posits that a household adopts new fuels as income increases without altogether forgoing the old fuels, i.e., households do not switch fuels but "expand" their fuel portfolio as income increases (Masera & Navia, 1997). The change in energy sources from fuelwood to modern energy sources aligns with the goal of forest conservation policies because the transition relaxes the pressure on forest resources. The compensation from the two PES programs, particularly the FEBC program, reduces rural households' dependence on their land and encourages them to seek alternative livelihoods, potentially influencing rural household energy uses conducive to forest sustainability.

We used the 2014 household survey data to examine how PES affected rural households' fuelwood use and fuel choices. We designed two sets of questions relating to energy use in the questionnaire. The first is fuel choices, including (1) using fuelwood or other biomass (e.g., crop stalk) as the only energy source; (2) using fuelwood as the primary energy source, supplemented with modern fuels; (3) roughly half and half of fuelwood and gas/electricity as sources for energy; (4) using gas/electricity as the primary energy source, supplemented with fuelwood; and (5) using gas/electricity as the only energy source. The second set aimed to quantify the amount of fuelwood used for cooking, heating, and feeding per year. To lower the burden of estimation by the respondents, we asked them to estimate the quantity per day and then computed the amount of usage per year by the interviewers after the interview. The sum of the usage for the three activities was the total fuelwood use. By controlling for various socioeconomic factors, we fitted a multinomial logistic regression model and a weighted multiple regression model to understand the factors affecting fuel choices (categorical) and per capita fuelwood use (continuous) in rural households. The models for fuel choice and fuelwood amount are respectively specified as follows:

$$ln\left[\frac{\Pr(Y = j \mid X)}{\Pr\left(Y = i \mid X\right)}\right] = \beta X + \varepsilon \tag{6.3}$$

$$U = \gamma X + \varepsilon \tag{6.4}$$

where Y represents the household fuel choices (j, $j \neq i$; i is the reference fuel choice, which is set as fuelwood/coal as the only energy source); X is the vector of explanatory variables, while β captures the fixed effects of the explanatory variables; U represents the quantity of per capita fuelwood use in a household, while γ captures the fixed effects corresponding to X, and ε represents random errors. Note that in the first equation, we merged fuel choices (4) and (5) into one choice (using gas/electricity as the primary or only energy source) because very few households used gas/electricity as the only source of energy.

6.4.4 Tree theft

Despite the overall increase in forest cover since implementing the PES programs at TNNR (Zhang et al., 2018b), tree theft has also been reported by rural households from the 2013 household survey. This finding is another spillover effect of restricting forest resources under the two PES programs, particularly the FEBC program. Rural households enrolled in FEBC cannot harvest timber from the natural forests they manage. However, the compensation may not effectively relax their dependence on forest resources, such as fuelwood or other wood product need. Thus, households may have to extract resources from forests in surrounding areas managed by others, resulting in a negative spillover of deforestation or forest degradation, jeopardizing the effectiveness of forest conservation under the PES programs. Thus, we aimed to understand if the GTGP and the FEBC played a role in this spillover effect of tree theft.

Our 2013 household survey data recorded the tree theft information, thus enabling us to investigate whether tree theft on FEBC land is related to GTGP after controlling for other factors. We hypothesized that tree theft on FEBC land might be affected by the FEBC land area, GTGP participation, the closeness of houses to the GTGP forests, and neighbors' GTGP forest area. The variable of neighbors' GTGP forest area was defined as the GTGP area enrolled by neighboring households within the same resident group, i.e., the total GTGP area in the resident group subtracting the GTGP forest area of the household of interest. Since neighbors' GTGP forest area is a group-level factor, we developed a mixed-effects model that captures random effects at household and resident group levels to test our hypotheses.

6.4.5 Direct interactions between GTGP and FEBC

In addition to the complex spillover effects described in the previous sections, we examined the direct interactions between the GTGP and the FEBC to understand synergistic or offsetting effects. The enrollment in the FEBC was pre-registered before 2002 as a continuing effort of the forest conservation policy (Dai et al., 2009), whereas the GTGP was newly initiated and implemented in 2002. Hence, participation in the FEBC program can be considered a pre-existing condition that may influence the enrollment in GTGP by rural households in TNNR.

We used data from household surveys in 2013 and 2014 to investigate the interaction between the GTGP and the FEBC. Since the spillover effect between the two concurrent programs is of interest, we excluded households that did not participate in both PES programs from the sample. This way, we obtained a subsample of 408 households, including 139 and 269 households, from the 2013 and 2014 surveys, respectively. We developed a multivariate linear regression model to examine the relationship between the cropland area enrolled in the GTGP, and the forest area enrolled in the FEBC, controlling for other factors such as household demographic and socioeconomic conditions. Households with large areas of FEBC forests tend to live in high elevations and thus may naturally manage croplands that are more likely to be targeted for GTGP enrollment. Therefore, we also included household elevation in the model to control its confounding effects.

6.5 Findings

With the above data analysis and modeling efforts presented, we show the results in the same order: cropland abandonment, household labor allocation for out-migration, energy transition: fuelwood vs. alternative sources, tree theft, and direct interactions between the GTGP and the FEBC.

6.5.1 Cropland abandonment

We found that the geographic locations of the GTGP and the FEBC forests relative to the cropland parcels exhibit statistically significant effects on cropland abandonment, but only the FEBC payment influences household decisions on cropland abandonment (Figure 6.3a). Every 100 m increase in distance of a cropland parcel to the nearest GTGP or FEBC forests decreases the odds ratio of abandoned versus not by 8% and 46%, respectively. This result means that cropland parcels in proximity to FEBC and GTGP forests are more likely to be abandoned, and the effect of the FEBC forests is much stronger than that of the GTGP on cropland abandonment. The FEBC forests are natural forests where more wildlife likely resides. Wildlife can cause significant damage to the crop, contributing to farmers' decision to abandon the cropland (Bista & Song, 2021).

After controlling for a series of other socioeconomic variables (Figure 6.3b), we found that the GTGP payment, which is relatively small in amount, did not significantly affect household cropland use decision on abandoning cropland parcels. However, every additional 1,000 yuan of a household's FEBC payment can increase the cropland abandonment odds ratio by over two times. The FEBC pays approximately three times more cash compensation to the participating households than the GTGP pays (Song et al., 2018), making the households receiving more compensation from the FEBC affordable to abandon the marginal croplands. By inducing more cropland abandonment, the two PES programs may synergize the additionality of environmental restoration. The abandoned cropland parcels will go through secondary succession and eventually become forested lands, constituting positive spillover effects in line with the aims of the two PES programs.

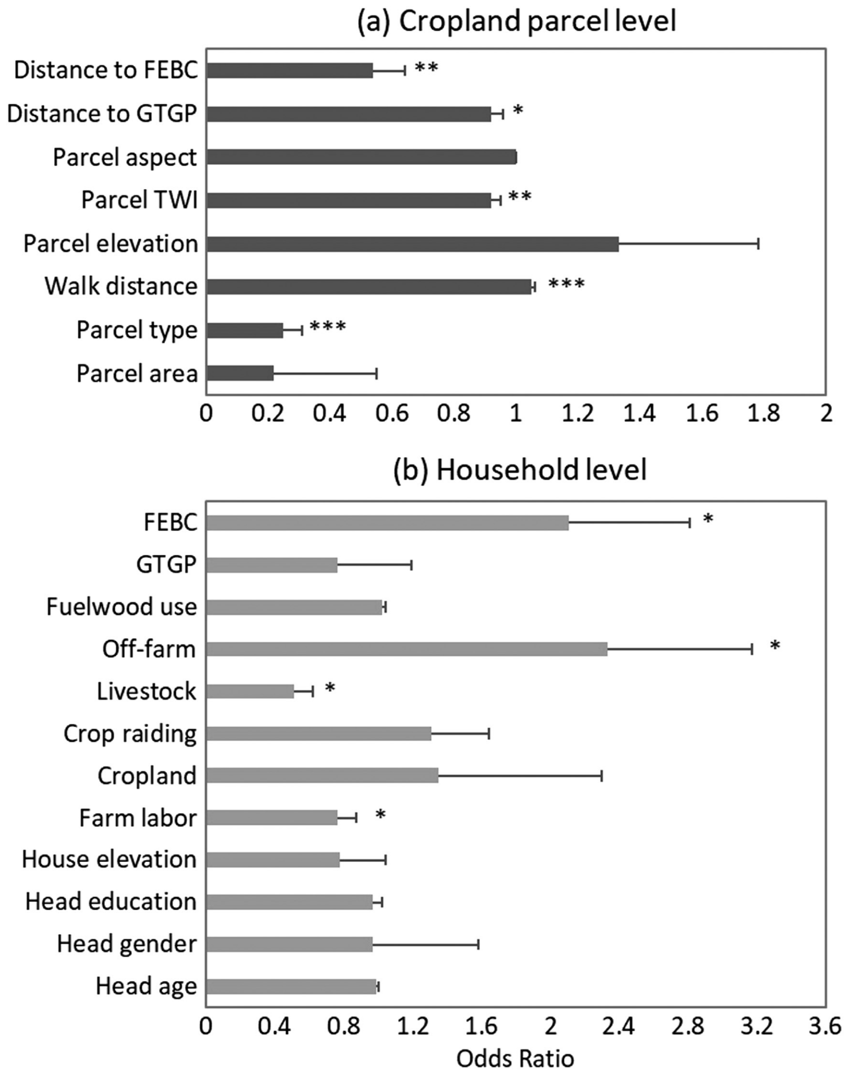

Figure 6.3 Effects of the GTGP and the FEBC on cropland abandonment by farm households. The effects are based on random-coefficient models at TNNR, China. (a) Modeling result at individual cropland parcel level; (b) modeling result at the household level. The model uses data collected from the 2013 survey with 1,196 cropland parcels managed by 250 households. *$p<0.10$; **$p<0.05$; ***$p<0.01$.

6.5.2 Household labor allocation for out-migration

Results from the multilevel analysis suggest negative spillover effects between the two PES programs. The logistic regression analysis found that the GTGP and the FEBC had opposite effects on labor out-migration after controlling for other factors (Table 6.3). Specifically, every additional 1,000 yuan of GTGP payment increased the odds of sending out migrants by 4.4 times, consistent with classic PES literature regarding GTGP's positive impact on out-migration (Uchida et al., 2009). On the other hand, every additional 1,000 yuan of FEBC payment decreased the odds of out-migration by 34%.

The GTGP seeks to enroll marginal cropland for reforestation, thus freeing farm labor from land cultivation. Without involving cropland retirement, the FEBC provides sizable cash compensation to participating households, particularly those with large areas of FEBC forests (Zhang et al., 2018c). The significant compensation from the FEBC with nearly minimal opportunity cost can

Table 6.3 Results of the multilevel logistic regression model of migration decisions at Tianma, China

Variable	*Coefficient*	*Odds ratio*	*Robust standard error*
Individual level			
Individual gender (1 = female, 0 = male)	−1.4318***	0.2389	0.0631
Individual age	−0.1528***	0.8583	0.0150
Individual education	1.1852**	3.2714	1.9021
Individual marital status (1 = married, 0 = otherwise)	1.3118**	3.7128	2.2346
If individual is a single female (1 = yes, 0 = no)	1.1314**	3.1001	1.7288
Household level			
Gender of head	−1.4776	0.2282	0.2315
Age of head	0.1264***	1.1347	0.0297
Education of head	0.4410	1.5543	0.5446
Marital status of head (1 = married, 0 = otherwise)	−1.0293	0.3573	0.3417
House elevation (m)	0.0037	1.0037	0.0048
Walking distance to nearest paved road (minute)	−0.0337	0.9669	0.0232
Household size	−0.0545	0.9470	0.0880
If household has previous migration experience (0/1)	1.2267***	3.4098	1.1259
Cultivated land area (mu)	−0.2016***	0.8174	0.0372
GTGP payment (1,000 yuan)	1.6870***	5.4031	2.9277
FEBC payment (1,000 yuan)	−0.4116*	0.6626	0.1535
Resident group level			
Resident group size	0.0015	1.0015	0.0180
Distance to nearest elementary school (minute)	0.0065	1.0065	0.0049
Distance to nearest hospital or clinic (minute)	0.0151**	1.0152	0.0067
Intercept	−3.4330	0.0323	0.1474
Intercept variance	0.4943		0.3729

Notes: $^*p<0.10$; $^{**}p<0.05$; $^{***}p<0.01$. The model uses data collected from a 2014 survey with a sample of 1,137 individuals from 412 households in 40 resident groups. The results are from Zhang et al. (2018a).

substantially improve the livelihoods of the participating households, reducing the need for income from out-migration. Understandably, the FEBC compensation may have lessened the pressure of cash shortage for the enrolling household, allowing household members to stay together with advantages for caring for the elderly, children's education, and quality family life. The GTGP has strongly stimulated residents to become out-migrants, releasing local population pressure on natural resources, while the FEBC has the opposite effect on out-migration.

6.5.3 Energy transition: fuelwood vs. alternative sources

The distributions of fuel choices and fuelwood use quantity indicate that rural households at TNNR are still in the early stage along the energy ladder, predominantly using fuelwood for energy (Figure 6.4). Among all the interviewed households, over 70% reported that they used fuelwood as the primary energy source, and about 10% of the households interviewed used fuelwood as the only energy source. The percentages of households selecting the other sources as primary sources of energy are much lower: only 8% and 6% fall in Category 3 (roughly half fuelwood and half modern fuel) and Category 4 (gas/electricity as the primary source of energy), respectively, whereas a trivial number (2%) used modern fuels as the only source of energy. On average, the total amount of fuelwood consumption is as high as 10,147 kg per year; cooking for daily meals and heating during winters are the two major activities for fuelwood consumption.

Based on the modeling results (Table 6.4), we found that only the forest area enrolled in the FEBC program had a statistically significant effect on fuel choices and fuelwood use, but the GTGP did not significantly affect either fuel choice or fuelwood amount used. Households with larger areas of FEBC forests are more likely to retain fuelwood as the only source of energy compared to other options. We also found that every mu (~667 m^2) of FEBC forests would increase the quantity of per capita fuelwood use by 12.1 kg, making the household more dependent on forest resources. The two PES programs did not seem to substantially shift the daily use of fuel of the participating households from fuelwood to cleaner modern fuels because fuelwood is accessible to them with plenty of supply in the study area. New policies specifically designed to change farmers' behavior from using fuelwood to cleaner modern fuels are needed if policymakers aim to reduce fuelwood use and preserve forest resources.

6.5.4 Tree theft

Among the 250 surveyed households in 2013, 32% reported that they experienced tree theft in the natural forests they managed (Table 6.5). According to the model on tree theft on FEBC land, every 100 m closer to a household residence to the nearest GTGP land increased the odds of FEBC tree theft by 15.5% (i.e., $1 - \exp(-0.1685)$) after controlling for other socioeconomic factors (Table 6.6), suggesting that trees on FEBC land are more likely to be illegally logged by neighboring residents if the household is in closer proximity to GTGP land. Such

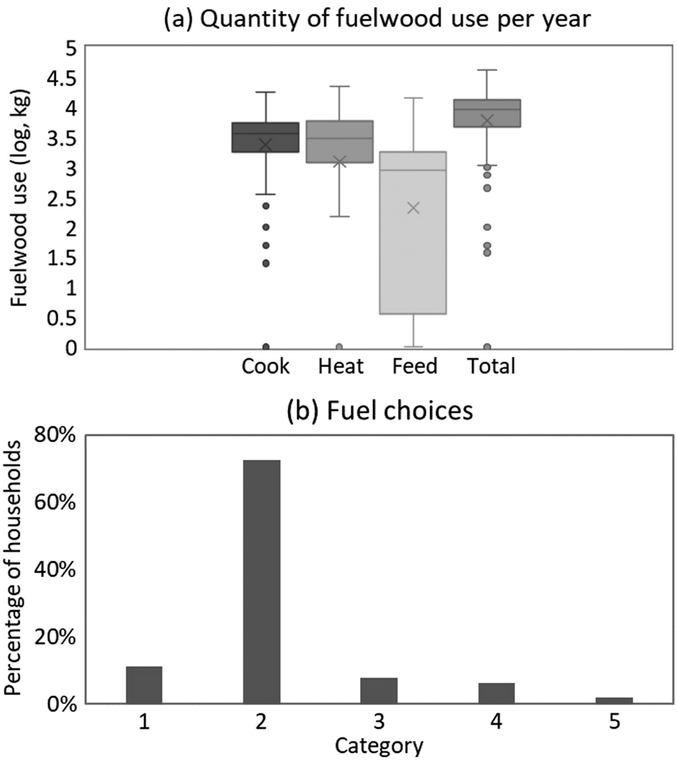

Figure 6.4 The statistical description of fuelwood use and fuel choices. (a) Distributions of fuelwood use amount for cooking, heating, feeding, and all activities; (b) distribution of households with different fuel choices (1: fuelwood or coal as the only energy source; 2: fuelwood or coal as the primary energy source, supplemented with modern fuel; 3: approximately half fuelwood/coal and half gas/electricity for energy; 4: gas/electricity as the primary energy source, supplemented by fuelwood; 5: gas/electricity as the only energy source). The unit is the log-transformed kilogram. Data are derived from the 2014 household survey.

a tree theft phenomenon is an example of a *Policy–Behavior* spillover effect, i.e., the payment from GTGP (Policy 1) may lead to an unintended behavior of tree theft on FEBC land (Behavior 2).

This *Policy–Behavior* spillover effect may arise from a *Behavior–Behavior* spillover effect: migration of the whole family or farm laborers to cities for higher-paying employments (Behavior 1) may lead to a reduction or cessation of monitoring the FEBC forests belonging to the household, giving the perpetrators the chances to steal trees from these forests (Behavior 2). These findings reflect a hidden, negative spillover effect from the GTGP to the FEBC. Given that the GTGP actively promotes out-migration and out-migration increases the probability of tree theft, GTGP may indirectly lead to tree theft, thus degrading

Table 6.4 Results of modeling fuel choices by households in TNNR, China

Variable	*Fuel choice*			*Fuelwood quantity used per capita*
	Score-4	*Score-3*	*Score-2*	*Coef. (std. err.)*
Age of oldest household member	0.977**	1.033***	0.988*	41.2 (16.0)**
Education of household head	1.027	1.022	0.977	−138.3 (58.2)**
Wellness index	1.946***	1.203***	1.152***	−32.9 (41.3)
Household income (natural log)	5.734***	3.698***	2.421***	−386.2 (192)**
Walking time from home to main road (minute)	0.823***	0.957***	0.978***	9.5 (11.6)
Household size	0.938	0.698***	0.61***	−1,146.5 (133.0)***
GTGP area (mu)	0.92	1.022	1.108	120.4 (165.4)
FEBC area (mu)	0.990***	0.974***	0.992***	12.1 (3.6)***
Paddyland under cultivation (mu)	0.757***	0.907**	1.101***	−54.1 (57.2)
Dryland under cultivation (mu)	0.37***	0.558***	0.839***	260.5 (126.6)**

Notes: Fuel score 1 is for households using fuelwood or other solid fuel as the only source of energy. Fuel score 2 is for households using fuelwood or other solid fuel as the primary source of energy with modern fuel as supplementary. Fuel score 3 is for households using half fuelwood or other solid fuel and half modern fuel. Fuel score 4 is for households using modern fuel as the primary or sole source for energy. *$p < 0.1$; **$p < 0.05$; ***$p < 0.01$.

Table 6.5 Statistics of summary explanatory variables for modeling tree theft at TNNR, China[a]

Variable	*Mean*	*Std. dev.*	*Min*	*Max*
Reported tree theft (0 = no,1 = yes)	0.3160	0.4658	0	1
Neighbors' GTGP area (mu)	16.5565	15.9859	0	60.1000
Geographic distance from residence to nearest GTGP land (100 m)	3.4358	2.9849	0.0116	18.6297
Participation in GTGP (0 = no, 1 = yes)	0.5560	0.4979	0	1
FEBC area (mu)	37.7295	46.2826	1	350
FEBC monitoring (0 = no, 1 = yes)	2.0160	0.5806	1	3
Household elevation (100 m)	6.4488	0.9971	4.0500	8.7500
Household head's age	52.4440	9.6159	31	78
Household head's gender (0 = male, 1 = female)	0.0480	0.2142	0	1
Household head's education	6.9560	2.7099	0	14
Household head an out-migrant (0 = no, 1 = yes)	0.2360	0.4255	0	1
Household size	4.5800	1.3752	1	9
Cropland area owned (mu)	5.7128	2.7062	0	16.1000
Livestock ownership (0 = no, 1 = yes)	0.8520	0.3558	0	1
Fuelwood use (1,000 kg)	8.8202	5.9169	0	36.2500
Off-farm income (1,000 yuan)	58.0244	78.8633	0	730

Note: [a] The model is for modeling FEBC tree theft from the 2013 household survey.

Table 6.6 Results of mixed-effects logistic regression of FEBC tree theft at TNNR, China

Variable	*Coefficient*	*Standard error*
Neighbors' GTGP area (mu)	0.0072	0.0136
Geographic distance of household to nearest GTGP land (100 m)	−0.1685**	0.0759
GTGP participation (0 = no, 1 = yes)	−0.5651	0.4180
FEBC area (mu)	−0.0013	0.0040
FEBC monitoring (0 = no, 1 = yes)	0.1924	0.2699
Household elevation (100 m)	−0.2457	0.2170
Household head's age	0.0189	0.0179
Household head's gender (1 = female, 0 = male)	1.1148	0.6995
Household head's education	−0.0432	0.0632
Household head migration status (0 = no, 1 = yes)	0.8855**	0.3796
Household size	−0.0056	0.1190
Cropland owned (mu)	−0.0049	0.0638
Livestock ownership (0 = no, 1 = yes)	−0.1191	0.4537
Fuelwood use (1,000 kg)	−0.0042	0.0306
Off-farm income (1,000 yuan)	0.0019	0.0020
Constant	0.2686	1.9845
Constant variance	0.2577	0.4198

Notes: The model uses data collected from the 2013 survey with a sample size of 250. The dependent variable is the occurrence of tree theft (0 = no, 1 = yes). Neighbors' GTGP area is calculated as the total GTGP area of the resident groups minus the GTGP area of the household of interest in this resident group.

the FEBC forests. Meanwhile, households close to GTGP lands tend to live in areas with a harsh geographic environment and thus depend more on forest resources for livelihoods. In contrast, households that are further away from GTGP lands have better opportunities to engage in alternative livelihoods and diversify income sources, being less dependent on timber and fuelwood from FEBC forests. Moreover, households with more extensive FEBC forests rely more on fuelwood use for energy, further compromising forest conservation effectiveness.

6.5.5 Direct interactions between the GTGP and the FEBC

Based on the combined household sample from 2013 and 2014, we found that households enrolled much more land in the FEBC (50.12 mu ± 62.74) than in the GTGP (2.16 mu ± 1.73) on average, and the distribution by the enrolled area in the GTGP among the enrolled households is more even than that of the FEBC (Figure 6.5). The majority of participating households (81%) enrolled 0.05–3 mu of cropland in the GTGP, whereas nearly three-quarters enrolled less than 50 mu of forestland in the FEBC program. We found both positive and negative hidden

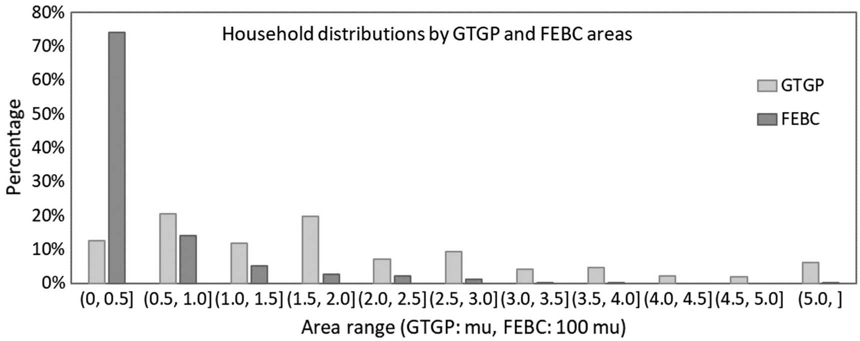

Figure 6.5 Distributions of households by the areas of land enrolled in GTGP and FEBC. Note that the unit of the FEBC area is 100 mu, so the mean FEBC area is generally two magnitudes larger than the mean GTGP area. 1 mu = 1/15 ha. Data are derived from the 2013 and 2014 surveys at the TNNR, China.

spillover effects between the two programs according to the regression model. Cropland area enrolled in the GTGP (dependent variable) is significantly positively associated with FEBC forest area (coefficient = 0.4694, $p = 0.002$; Table 6.7) after controlling for other factors, indicating that every 100 mu of FEBC forestland leads to an additional 0.47 mu of cropland enrolled in the GTGP.

The above positive *Policy–Behavior* spillover effect may come from local farmers' adaptive livelihood strategy. After receiving FEBC payments, the recipient households are required to refrain from timber harvesting and some limited responsibilities in fire prevention and anti-theft patrol. Households with larger FEBC areas (i.e., receiving large FEBC payments) tend to have more cropland parcels located in marginal areas on steep slopes. When compensation comes from FEBC, local households may afford to reduce their farming activities in these marginal areas, enrolling them in GTGP. Despite a relatively low compensation rate of FEBC on the unit area basis (131.25 yuan/ha in 2014 in Tiantangzhai) compared with that of GTGP, the average total compensation received from FEBC was approximately three times that from GTGP due to the large areas of natural forests belonging to households. Some local farmers may afford to buy more food or fodder from the local market, increasing their confidence in food security, making a comfortable living with the income from FEBC alone and/or some local off-farm employment. This situation may make local farmers more willing to enroll marginal (e.g., distant land on steep slopes) cropland parcels in the GTGP. Local farmers may further increase the household income with the freed labor from farming the GTGP land switched to local off-farm employment or migration to cities for higher wages. Unlike the GTGP, the FEBC does not reduce the cropland area from farming, meaning it does not directly free farm

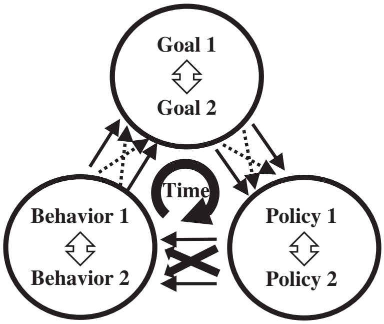

Figure 6.6 Cross-program spillover effects at the TNNR, China. This diagram is modified from Figure 1.3, where the solid one-way arrows stand for internal influences from one element to another within the same initiative, while the dashed one-way arrows and double two-way arrows for potential spillover effects; the circular one-way arrow represents Time–Time spillover effects. The shaded, bold arrow represents the spillover effect with evidence from this section.

Table 6.7 Results of regression of GTGP area against FEBC area at Tianma, China

Variable	*Coefficient*	*Standard Error*	*t*	*p>|t|*
FEBC area (100 mu)	0.4694***	0.1477	3.18	0.002
Household elevation (100 m)	0.0373	0.0899	0.41	0.678
Household size	0.1715***	0.0543	3.16	0.002
Number of out-migrants	0.1691**	0.0675	2.51	0.013
Number of local off-farm labor	−0.1284	0.1155	−1.11	0.267
Cropland under cultivation (mu)	0.0230	0.0256	0.9	0.369
Gross income (1,000 yuan)	−0.0019	0.0017	−1.09	0.277
Constant	0.9244	0.6539	1.41	0.158

Notes: The model uses data collected from both 2013 and 2014 household surveys with a sample size of 408 who participated in both GTGP and FEBC.

labor. Thus, FEBC encourages farmers to stay in their original households, farming the croplands with decent quality and/or good accessibility.

6.6 Summary

This chapter examined two concurrent green efforts in TNNR, China: the GTGP (Policy 1) and the FEBC (Policy 2). We found spillover effects in multiple areas among the two green efforts; some are synergistic, while others were offset. Both the GTGP and the FEBC lead to marginal cropland abandonment. The FEBC tends to make enrolling households continue to rely on fuelwood as the primary energy source, but the GTGP does not seem to substantially affect fuel choice or the amount of fuelwood usage. The FEBC may increase enrollment in GTGP (Behavior 1a), which is a positive *Policy–Behavior* spillover effect (Figure 6.6).

On the other hand, FEBC payments (Policy 2) may lead to lower migration rates, an action that GTGP promotes (Behavior 1), constituting a negative *Policy–Behavior* spillover effect. Furthermore, GTGP payments (Policy 1) may also give rise to a higher likelihood of tree theft in FEBC forests (Behavior 2), a *Policy–Behavior* spillover effect that may arise from a *Behavior–Behavior* spillover effect (Figure 6.6). Explicitly referring to the *Behavior–Behavior* spillover effect, migration of the whole family or farm laborers to cities for higher-paying employments (Behavior 1) may lead to a reduction or cessation of monitoring FEBC forests belonging to the household, increasing the chances of timber theft in these forests (Behavior 2). The concurrent PES programs may not maximize their environmental benefits due to the different spillover mechanisms behind household behavior on land-use and livelihood decisions such as labor migration, use of fuelwood, and illegal tree logging. These hidden spillover effects among concurrent green efforts, such as the two PES programs examined in this chapter, have not been recognized in the previous studies. Therefore, future research on PES program evaluations should consider and account for these spillover effects.

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