**Appendix S1. Impact evaluation methods and output.**

We use propensity score matching (PSM) to pair participants to non-participant observations. PSM defines similarity across observations based on an estimate of the probability of receiving the program (Guo and Fraser 2010). We use logistic regression to estimate the propensity score, i.e., the conditional probability of a participant or non-participant observation enrolling in the forest conservation incentives (FCI) program. Specifically, we estimate:

$Prob\left(P\_{i}=1\right)=F(α+φX\_{i})$,(1)

where $P\_{i}=1$ when a parcel, *i*, is in FCI; $X\_{i}$ are the observable covariates of baseline deforestation, parcel size, and distance to: primary roads, population centers, navigable rivers, and oil wells; and $F$ is the logistic function. Table S1 presents the output from the logistic regression. Baseline deforestation rates are defined in three ways to ensure results are not sensitive to chosen baseline: 2004-2006, 2005-2007, and 2006-2008. Baseline deforestation provides an indirect measure of household-level characteristics associated with past deforestation decisions. Program participants are matched to the control observation with the closest propensity score using 1-to-1 matching without replacement. To improve the quality of matches a caliper equal to 0.25 the standard deviation of the estimated propensity score is used (Rubin 2006).

**Table S1** Determinants of participation in Ecuador-FCI program estimated with logit regression for propensity score matching.

|  |
| --- |
| **Dependent variable: Participation in FCI program (1=FCI, 0=No FCI)** |
| **Variable** | **Marginal effects****(Std Error)** |
| Baseline Deforestation (2004-2006)1 | -0.02(0.01) |
| Size of parcel (sq km) | 0.14\*\*\*(0.05) |
| Distance to major town (km) | 0.01\*\*\*(0.003) |
| Distance to major road (km) | 0.02\*\*\*(0.005) |
| Distance to closest river (km) | -0.01\*(0.004) |
| Distance to closest oil well (km) | 0.002(0.005) |
| *Observations* | *513* |
| *Correctly classified* | *88%* |
| *Wald Chi2* | *47.33\*\*\** |

Significance levels: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01*.* Standard deviations in parentheses.

*1 This shows 2004-2006 baseline deforestation, 2005-2007 and 2006-2008 baseline deforestation result in similar output.*

With the matched sample of participant and non-participant observations, we estimate the impact of the FCI program on deforestation using linear fixed effects panel regression. While a simple t-test or cross-sectional regression can be used following matching to estimate program effects, these methods are susceptible to unobservable bias (Imbens and Wooldridge 2009). As applied to the land cover change setting, fixed effects panel regression uses repeated temporal observations of land cover change on the same parcel of land (Jones and Lewis 2015). Panel techniques use the temporal dynamics of the data – observing the two groups before and after the program – along with cross-sectional variation in program status across parcels to construct the counterfactual outcomes. The key dependent variable in this study indicates forest cover change (FCC) for parcel *i* in time *t*, denoted $FCC\_{it}$. A generic linear fixed effect panel regression equation is constructed as follows:

$FCC\_{it}=α+β\_{1}X\_{it}+β\_{2}G\_{i}+β\_{3}C\_{it}+β\_{4}Y\_{t}+a\_{i}+ε\_{it}$, (2)

where $X\_{it}$ denotes time-varying covariates of forest cover change for parcel *i*, $G\_{i}$ denotes time-invariant covariates of FCC (e.g., parcel size), $C\_{it}$ indicates the time-varying conservation status of parcel *i* (i.e., participation in FCI program), $Y\_{t} $indicates time fixed effects, and $a\_{i}+ε\_{it}$ is the composite unobservable. In panel data analyses, the model unobservable is decomposed into a time-invariant component ($a\_{i}$) and a time-varying component ($ε\_{it}$). The primary goal of estimation is to obtain a consistent estimate of the program effect of conservation, $β\_{3}$. In our study, there are no time-varying covariates, and all time-invariant covariates of forest cover change are consumed by the time-invariant fixed effect ($a\_{i}$), but since we have forest cover change data before and after the conservation program, $β\_{3}$ can be estimated. The years of data used in the PSM equation to define baseline deforestation (i.e., 2004-2006, 2005-2007, and 2006-2008) are not included in the estimation of Equation 2. Output from the linear fixed effects panel model following PSM is presented in Table S2.

Evaluation of program impacts with panel data requires that temporal trends for the two groups are similar – the parallel paths assumption. To check that the parallel paths assumption is valid, we used the fixed effects panel regression model to test that outcomes prior to the program (i.e., before 2011) were not statistically different between the groups. Originally, we included deforestation rates from 2001 to 2013 – all dates that are available from the Hansen et al. (2013) Landsat product. When we conducted the parallel paths test we found statistical differences between the two groups in 2003; thus, we omitted forest cover data from 2001 to 2003, and only used data starting in 2004 to measure pre-FCI forest outcomes.

**Table S2** Impact of Ecuador-FCI program on deforestation in 2011-2013 estimated with linear fixed effects panel regression using the matched1 sample.

|  |
| --- |
| **Dependent variable: Annual deforestation rate**  |
| **Variable** | **Coefficient****(Std Error)** |
| FCI dummy | -0.42\*\*\*(0.14) |
| 2008 Year dummy | 0.26\*(0.14) |
| 2009 Year dummy | -0.04(0.04) |
| 2010 Year dummy | 0.22(0.18) |
| 2011 Year dummy | 0.16(0.13) |
| 2012 Year dummy | 0.46\*\*(0.17) |
| 2013 Year dummy | 0.34\*\*(0.08) |
| *Observations* | *784* |
| *Within R2* | *0.03* |
| *F-test* | *5.11\*\*\** |

Significance levels: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01*.* Standard deviations in parentheses.

*1 This shows result when 2004-2006 is used in PSM as baseline deforestation.*

*Robustness checks*

Quasi-experimental methods can never completely rule out that all remaining bias has been eliminated (Ferraro and Hanauer 2014). Matching rarely eliminates all selection bias (Imbens and Wooldridge 2009), and in our study we do not have household level characteristics that may be important to the decision of enrolling in the FCI program. Fixed effects regression can eliminate time-invariant hidden bias, but not time-varying bias correlated with deforestation. To provide additional confidence in our results we conduct a number of robustness checks: fixed effects regression without matching, falsifying which parcels receive the FCI program, and changing the dates that FCI parcels receive the program to before 2010 – to try and rule out that our results are spurious. The first test helps rule out if matching leads to a spurious outcome. However, using the full sample in fixed effects regression could also lead to a false conclusion if the treatment and control observations are very different from one another. The two falsification tests are attempts to rule out that our results are “random”. If we find statistically significant impacts on lowering deforestation with false assignment of “treatment”, confidence in our presented results is weakened.

Table S3 presents the output from these tests. When we use the full sample in fixed effects panel regression we find a statistically significant impact of FCI on deforestation, with a treatment effect of 0.3%. While this is slightly lower than the treatment effect estimated with matching plus fixed effects regression, this is not too surprising given that we are comparing FCI participants to all control observations, many of which are very different in observable characteristics (see Main Text, Table 1). Our two falsification tests do not result in a statistically significant impact of the “false” FCI on deforestation.

Additionally, we ran alternative specifications of Equation 2 to test the consistency of our results. Specifically, we ran post-matching fixed effects regression that uses a two-year average of baseline deforestation in the match (2004-2005, 2005-2006, and 2006-2007) versus a three-year average. Treatment effects were statistically significant and ranged between 0.4 and 0.6 (not reported). We also estimated Equation 2 defining the dependent variable as 1) changes in hectares, controlling for total forest area, and 2) total forest area. For both of these alternative dependent variable specifications, FCI had a statistically significant effect – negative in the case of changes in hectares and positive in the case of total forest area – on forest cover (not reported).

**Table S3** Robustness checks.

|  |  |
| --- | --- |
|  | **Dependent variable: Annual deforestation rate**  |
|  | **Without matching, only fixed effects regression** | **Correct years of treatment (2011-2013), but random assignment of FCI parcels1** | **Correct FCI parcels, but changed years of “treatment”2**  |
| **Estimated average program effect**  | -0.30\*\*\*(0.11) | 0.25(0.27) | 0.17(0.11) |
| *Total Observations* | *5,130* | *1,586* | *1,120* |

Significance levels: \*p<0.1; \*\*p<0.05; \*\*\*p<0.01*.* Standard deviations in parentheses.

*1 We first dropped the actual 63 parcels enrolled in FCI and then randomly selected 63 parcels to be assigned to “treatment”. These 63 parcels were then matched to control observations and fixed effects panel regression was used to estimate the treatment effect. We repeated this random assignment and estimation 20 times, and each time we found no significant effect. We have presented results from one illustrative sample in the table. If we conducted this enough times we would find a significant effect for some proportion of randomly selected parcels.*

*2 We reassigned the years of FCI to be 2004-2006, 2005-2007, 2006-2008, 2007-2009, and 2008-2010 for the 63 FCI parcels and conducted matching and fixed effects panel regression. We did not find a significant and negative effect of FCI on deforestation in any of these assignments; one illustrative sample presented in the table.*