ABSTRACT

ARRIAGADA, RODRIGO ANTONIO. Private Provision of Public Goods: Applying Matching Methods to Evaluate Payments for Ecosystem Services in Costa Rica. (Under the direction of Erin O. Sills.)

Payments for environmental services (PES) is a recent policy innovation attracting attention in both developed and developing countries. In developing countries, PES remain poorly tested. Costa Rica was among the first to implement a national PES scheme in which substantial amounts of money have conditionally changed hands, thus representing an excellent laboratory for evaluating the causes and consequences of PES participation.

In this dissertation, I estimate the causal impact of the Costa Rican Program of Payments for Environmental Services (PSA) on forest cover at two scales, using state-of-the-art matching methods. First, I estimate the impact of a PSA forest conservation contract on an individual parcel, during the initial years of PSA in the case study region of Sarapiquí. Second, I estimate the impact of PSA contracting at the census tract level for the entire nation of Costa Rica, considering both binary and continuous measures of contracts signed between 1998 and 2004.

The parcel level analysis is based on a household survey of participants and non-participants in PSA, with the sample drawn from administrative records of PSA and the national land registry, combined with GIS data on biophysical land characteristics and land cover information from aerial photographs and satellite images. The national analysis is based on a combination of administrative data on PSA, census data on socio-economic characteristics, GIS data on biophysical land characteristics from several sources, and various measures of change in forest cover derived from classified satellite images, all organized at the census tract level.

While this dissertation is motivated by the broad policy debate over the effectiveness of PES as a conservation policy tool, it aims to answer a relatively narrow empirical question: what has been the causal impact of PSA contracts on forest cover in Costa Rica? The maintained assumption of this analysis, and of the implementing agency in Costa Rica, is that more forest cover will generate more environmental services. Key hypotheses tested in

this research are that (1) only landowners whose opportunity cost of participation is low have enrolled in PSA, and (2) enrollment in PSA has generated a net increase in the area of forest.

The parcel level analysis suggests that farms that do not have good alternative uses on their land (because of steep slopes or poor soil quality) tend to be enrolled in the program. Matching results provide evidence that during the initial phase of PSA, the program did have a significant but small effect on forest cover, both reducing loss of existing mature forest (gross deforestation as reported by landowners) and increasing total forest cover (net deforestation as determined by remote sensing) on parcels with contracts signed early in the program.

In the national analysis, I also find that participation in PSA is more intense in census tracts with worst soil quality and higher steepness. Using a binary definition of treatment (PSA vs. non-PSA), I find that PSA has a positive and significant impact on forest gain and net deforestation between 1997 and 2005 in the census tracts that contain at least one PSA forest conservation contract signed during the first eight years of the program. However, I cannot conclude that PSA contracting has reduced gross deforestation. Results also indicate that the size and significance of PSA's impact varies by region. Using a continuous definition of treatment, the national analysis suggests that protection intensity matters, even for the direction of PSA's impact on forest gain, forest loss and net deforestation. These results represent the first attempt in the conservation literature to estimate the causal impacts of direct payments for conservation with matching methods that recognize a gradient in intensity of protection.

Private Provision of Public Goods: Applying Matching Methods to Evaluate Payments for Ecosystem Services in Costa Rica

by
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DEDICATION

To the woman that gave me the strength and support to complete this amazing journey……my wife Ana Maria

BIOGRAPHY

Rodrigo Arriagada was born in Santiago in 1972. After finishing high school, he earned a bachelor in forest engineering at the University of Chile. Having completed his bachelor, he founded FORESMAN Consulting Inc., a private consulting firm, devoted to promote sustainable development through Integrated Development Conservation Projects. He also worked for two years as a project analyst for the Chilean Ministry of Education (Improvement of Quality and Equity of Higher Education Program). Prior to join the doctoral program in the Department of Forestry and Environmental Resources at North Carolina State University in 2004, he received a Master of Science in natural resources from North Carolina State University, where he investigated fertilizer demand for rice production around the Palo Verde national park in Guanacaste, Costa Rica. During the doctoral program, he has been part of the National Science Foundation and the Latin American and The Caribbean Environmental Economics Program supported research in Costa Rica. Rodrigo was awarded both a Doctoral Dissertation Improvement Grant by the National Science Foundation and a Latin American and The Caribbean Environmental Economics Program Research Grant in 2007. He has been selected as a Postdoctoral Research Associate at the ecoSERVICES research group in Arizona State University that he begins from August 15, 2008.

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Chapter 1

INTRODUCTION TO PAYMENTS FOR ENVIRONMENTAL SERVICES AND CONCEPTUAL FRAMEWORK

Ecosystem services are the benefits that people derive from the biophysical environment. Following the Millennium Ecosystem Assessment (2005) these are characterized as provisioning services (foods, fuels, fibers, genetic materials, chemical compounds and the like), cultural services (aesthetic, spiritual, moral, recreational, educational, scientific uses) and regulating services (the role of ecosystems in regulating flows of provisioning and cultural services including, for example, water quality regulation, soil erosion reduction, storm damage protection and so on). In particular, forests provide an array of ecosystem services by sequestering carbon, maintaining habitat and biodiversity, stabilizing hydrological flows, mitigating soil erosion, and improving microclimates (Pattanayak and Butry 2005).

The benefits of ecosystem services come in many forms, from the tangible provision of the necessities of life −food, water, medicine, and clean air− to aesthetic inspiration for culture and society. These services are the foundation of daily life, and they are available without people necessarily being conscious of the many and complex processes involved in their production and delivery (Mainka *et al.* 2008). However, human actions (e.g.

deforestation and forest degradation) can irreversibly and substantively impair the provision of ecosystem services.

Paying for the provision of environmental services is a recent policy innovation attracting much attention in both developed and developing countries. This policy mechanism, referred to as Payments for Ecosystem Services (PES), aims to harness market forces to obtain more efficient environmental outcomes (Bulte *et al*. 2008). The concept of PES has emerged in recent years as a potential tool for achieving ecosystem conservation and improving the livelihoods of environmental-service providers and consumers. The emergence of these direct economic incentives for the conservation of environmental services indicates a shift away from the predominant use of command-and-control mechanisms (such as park establishment or logging bans) and a search for more flexible and efficient ecosystem protection (Landell-Mills and Porras 2002).

PES schemes incorporate different services generated from different ecosystems. Important attention has been focused on services produced by forests. First, this is because forests collectively provide innumerable valuable services to humans. Second, high deforestation rates have persisted in the tropics despite many different conservation initiatives over the past couple of decades, thereby focusing attention on the need for innovative tools to preserve environmental services of forest ecosystems. Third, the increased focus on reducing deforestation in developing countries in wake of the agreement on deforestation incorporated into the Bali Action Plan.[1] The markets for ecosystem services seem to fall into categories in a couple of ways. First, ecological commodities follow the popular grouping of: carbon, water, biodiversity, and bundled services. Carbon markets are generally those that reward the stewardship of an ecosystem's atmospheric regulation

[1] After the 2007 United Nations Climate Change Conference on the Bali Island in Indonesia, the participating nations adopted the Bali Roadmap as a two-year process to finalizing a binding agreement in 2009 in Denmark. Over 10,000 politicians, scientists, NGO representatives, and academics met. The goal was to negotiate, lobby, and struggle through the increasingly complex web of international climate change policy. At the end of it, an agreement was reached as part of the "Bali Action Plan" to spend two more years negotiating on a future agreement that should include reducing deforestation in developing countries.

services. Water markets provide payments for nature's hydrological services. Biodiversity markets create an incentive to pay for the management and preservation of biological processes as well as habitat and species. Bundled payments are ones in which a payment secures all or a combination of carbon, water, and biodiversity services. Bundled payments also include those in which the ecosystem service payment is built into the price of the product, such as certified timber or certified produce (Forest Trends and the Ecosystem Marketplace 2008).

Pagiola and Platais (2002) point to several advantages of PES, including more efficient, sustainable and mutually beneficial arrangements between environmental-service providers and users. Similarly, Landell-Mills and Porras (2002) show that, under the right conditions, PES systems can results in both more conservation and improved livelihoods for poor people. However, considerably uncertainty still remains as to what exactly environmental services are, what policies and programs qualify as PES, to what extent they are currently being implemented, and what their prospects for success are (Robertson and Wunder 2005; Bulte *et al.* 2008; Engel *et al.* 2008; Pagiola 2008; Zilberman *et al.* 2008).

In developing countries, PES systems remain poorly tested.[2] There are many incipient PES initiatives (Landell-Mills and Porras 2002; Pagiola and Platais 2002), but for PES schemes with some experience and with money conditionally changing hands, the literature and policy documents typically refer only to Costa Rica and a couple of dozen other pioneer experiences, mostly in Latin America.

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[2] Industrialized nations have used conservation payments for decades to conserve agricultural soil, improve water quality, manage fisheries, and protect wilderness on private lands. Researchers have raised the concern about the actual gains in ecosystem protection from PES and demonstrated its salience for direct conservation payments and other incentives for sustainable agricultural practices and forestry in the U.S. (see Kluender *et al.*1999; Goodwin and Smith 2003; Smith and Wienberg 2004; Wu 2000; Wu *et al.* 2004; Claasen *et al.* 2008). Some older programs in the US like the Conservation Reserve Program (CRP) are being re-conceptualized as PES. While the original CRP focused on enrolling land quickly (Reichelderfer and Boggess 1988), the program has evolved into a multi-objective program that produces environmental benefits beyond the traditional concern for soil erosion and productivity (Feather *et al.* 1999).

This dissertation comprises three essays analyzing the Costa Rican Program of Payments for Environmental Services (*Programa de Pago por Servicios Ambientales*, PSA) in terms of factors that drive program participation and causal impacts associated with PSA. This introductory chapter describes the concept of payments for environmental services with special attention to PSA. Previous evaluations of the program are reviewed, identifying key challenges for future evaluations (e.g. causation analysis under selection bias). This introduction also includes a conceptual framework that draws on the real options literature to identify factors expected to drive participation and to support basic hypothesis about the expected impact of the program on forest cover. The second chapter profiles participants and non-participants landowners in a selected case study region of Costa Rica, describes the process and determinants of enrolling in PSA, and characterizes landowners' experience with the program qualitatively and with descriptive statistics derived from case studies and a survey conducted in 2005-2006. The third chapter analyzes the causal impact of PSA on forest cover at the individual farm level in the selected case study region, comparing results from propensity score matching with simple *t*-tests and OLS regressions. The fourth chapter analyzes the causal effect of PSA nationally applying binary and continuous matching to administrative data on the program, census data on socioeconomic characteristics, biophysical data from various sources, and various measures of change in forest cover derived from satellite images, all organized and analyzed at the level of census tracts.

1.1 PAYMENTS FOR ECOSYSTEM SERVICES

1.1.1 Concepts

Ecosystems can provide a wide variety of services. In specific, the environmental services derived from forest ecosystems, for example typically include (but are not limited to): hydrological benefits, reduced sedimentation, disaster prevention, biodiversity conservation and carbon sequestration (Pagiola and Platais 2002). De Groot *et al*. (2002) recognize four groups of functions: (1) regulating functions that maintain essential ecological processes and life support systems, (2) habitat functions that provide a suitable living space for wild plant and animal species, (3) production functions that provide goods such as timber and non-timber products, and (4) information functions that provide opportunities for cognitive development.[3]

Although forest goods and services benefit both local and global communities not all forest uses generate financial returns commensurate with their “true” economic value. This is because several forest benefits, notably environmental services, are not traded in markets and have no observable price (Landell-Mills and Porras 2002). The lack of payments for these services results in under-investment in the protection, management and establishment of forests. This under-investment results in the depletion of natural vegetation cover and soils, damaged watersheds and species extinction. These effects frequently result in substantial economic and social losses to society (Robertson and Wunder 2005).

As wilderness and natural habitats shrink, environmental services previously provided for free by nature are becoming increasingly threatened. This emerging scarcity makes them potentially subject to trade (Wunder 2005). In an effort to prevent such threat, some analysts and practitioners have called for the incorporation of environmental-service provision into standard economic valuations and, conversely, the use of direct incentives in conservation (Daily and Ellison 2002; Pagiola and Platais 2002). The logic of the argument underlying PES is as follows: when ‘free’ environmental services are made scarce by human exploitation, they obtain an economic value. External service users might want to compensate local resource managers to ensure that the services they need are provided in the future. Consequently, if such compensation is made, the local service providers receive an income for their additional protection efforts (Robertson and Wunder 2005). According to one view, the basic principle of PES is that those who provide environmental services should be compensated for the cost of doing so, whether these are direct costs of specific land use practices or more indirect opportunity costs of avoiding certain activities or types of land use (Grieg-Gran and Bann 2003). Others believe that PES should be a first-best direct-payment

[3] Ecosystem functions refer variously to the habitat, biological or system properties or processes of ecosystems. Ecosystem goods (such as food) and services (such as waste assimilation) represent the benefits human populations derive, directly or indirectly, from ecosystem functions (Costanza *et al.* 1997).

approach, and an incentive mechanism, used to purchase environmental services from local resource managers who otherwise would not provide the services (Ferraro and Simpson 2002; Wunder 2005). Mayrand and Paquin (2004) say that PES are relatively new schemes seeking to support positive environmental externalities through the transfer of financial resources from beneficiaries of certain environmental services to those who provide these services or are fiduciaries of environmental resources.

We can consider payment schemes for environmental services as flexible mechanisms, which can be adapted to different conditions. A number of PES schemes are currently operating around the world involving governments, business, government aid agencies, and non-governmental organizations. Landell-Mills and Porras (2002) review found almost 300 examples of PES schemes worldwide. These schemes involve governments, business, government aid agencies, and non-governmental organizations and most are still in their infancy (WWF 2006).[4] To date, the four main environmental services that have been addressed by PES are watershed services, carbon sequestration, landscape beauty, and biodiversity conservation. These approaches have emerged largely by what is driving the scheme: conservation goals, social goals, market goals, or government goals.

1.1.2 The Costa Rican case

PSA was established in 1996 by Forestry Law No. 7575. This program grew out of an existing institutional structure of payments for reforestation and forest management, but contains several notable changes: (1) most payments are now for conservation of existing mature tropical forest with no harvesting allowed, (2) payments are justified and targeted to produce ecosystem services rather than to support the timber industry per se, and (3) funds come from both earmarked taxes and international donations (Sánchez-Azofeifa *et al.* 2007). Since its inception, PSA has contracted a cumulative total of nearly 600,000 hectares, of which nearly 90% is natural forest that landowners are paid to conserve (with the rest in reforestation, sustainable forest management, agroforestry contracts, among other

[4] http://assets.panda.org/downloads/pes_report_2006.pdf

components).[5] To receive a forest conservation contract, landowners must present a sustainable forest management plan. Once their plans have been approved, they begin to receive the annual payments. Currently conservation contracts pay US$320/ha/year over the five year lifetime of the contract which is renewable for another five years by mutual agreement. The minimum area to be included must be at least 2 hectares and no more than 300 hectares per year.

To implement PSA, several functions need to be fulfilled. The main functions are funding, making land available through farmers' participation, generating awareness and knowledge about land conversion, and compliance control (Miranda *et al.* 2006). The 1996 Forestry Law assigned to the National Fund of Forest Financing (*Fondo Nacional de Financiamiento Forestal*, FONAFIFO), which is a subsidiary organization of the Ministry of the Environment (*Ministerio del Ambiente y Energía*, MINAE).[6] The main objective of FONAFIFO is to get funds for PSA and other necessary activities to develop the natural resources sector (Forestry Law No 7575). FONAFIFO gets funding from different sources. So far, the fossil fuel tax is the main source of funding. According to Law No 8114 from 2001, FONAFIFO annually receives 3.5% of the fossil fuel tax raised by the Costa Rican government. FONAFIFO also receives funds from the sale of carbon bonds by the Costa Rican Office for Joint Implementation (OCIC), another subsidiary body of MINAE on the international market (for instance to Norway, see Miranda *et al.* 2003). Moreover, FONAFIFO has received funding from the GEF to protect territories included in the Mesoamerican Biological Corridor and from private hydropower companies and a beverage company (Florida Ice & Farm), which want to prevent erosion in the catchments in which they are located. These contributions are transferred through PSA to landowners in the watersheds.

[5] According with the Global Forest Resources Assessment published by FAO, in 2005 46.8% of the total land area of Costa Rica was covered by forest which corresponds to 2,391,000 ha.

[6] Since its inception, PSA has passed throughout different administration phases. Between 1997 and 2002, the program was administered by MINAE through its SINAC sub-regional offices, and from 2003, the administration of PSA was completely transferred to FONAFIFO.

1.1.3 Previous evaluations of PSA and key challenges for future evaluations

Reactions to PES in conservation and rural-development circles have been mixed. Advocates of PES stress that innovation in conservation is urgently needed because current approaches provide too little value for money, that PES can provide (especially private sector) conservation funding, and that poor service selling communities can improve their livelihoods (Wunder 2007).

Evaluation of PES causal effect must face several challenges. When buying an environmental service, it is not completely evident what is being paid for. Because the environmental services are provided over time, one always needs to have an idea about what would hypothetically happen without the PES scheme (i.e. construct some counterfactual service baseline). Unfortunately, PES programs usually do not include clear, explicit frameworks for monitoring and evaluation the degree of their own success−a regrettable feature they share with other conservation interventions (Ferraro and Pattanayak 2006; Wunder 2007). Rigorous, empirical evaluation methods are required to establish whether PES schemes have been effective with the key challenge of establishing the counterfactual: what would have happened without the payments?

In the context of the Costa Rican program, estimating the PSA counterfactual is complicated because landowners volunteer to participate in PSA and program administrators often actively target the contracts. When the characteristics that affect who receives a contract (e.g. land use profitability and landowner preferences) also affect land use decisions, any direct comparison of program participants and non-participants would suffer from "selection bias" which can either over-state or under-state the impact of the program (Sills *et al.* forthcoming).

Pagiola (forthcoming) says that PES can suffer from various kinds of inefficiency: (i) offering payments that are insufficient to induce adoption of socially-desirable land uses; (ii) inducing the adoption of socially undesirable land uses that supply environmental services;

(iii) paying for adoption of practices that would have been adopted anyway. The type and size of payments provided by a PES program affect the likelihood of these problems arising. PSA offers a relatively low, undifferentiated, and mostly un-targeted payment. Thus it will only tend to attract participants whose opportunity cost of participation is low. Such a program is very likely to experience the first type of problem, in which socially-desirable land use practices are not adopted because the payment offered is insufficient. Being undifferentiated and untargeted, the program will also attract many land users who would have adopted the desired practices anyway (third problem). The relatively low payments mean, however, that the program is unlikely to induce the adoption of socially inefficient land uses on a significant scale (second problem) (Pagiola 2008).

Counterfactual estimation is also complicated in the context of PSA because when the program was created Costa Rica already had in place a system of payments for reforestation and forest management, and the institutions to manage it. The Forest Law was built on this base, with two major changes. First, it changed the justification for payments from support for the timber industry to the provision of environmental services. Second, it changed the source of financing from the government budget to an earmarked tax and payments from beneficiaries (Pagiola 2008). In other respects, the PSA program was very similar to previous forest sector incentives. Until 2000, the activities financed under the PSA program closely paralleled those financed by previous instruments: timber plantations, sustainable forest management, and forest conservation. Many details of implementation, such as payment amounts and scheduling, were also carried over from earlier programs. Indeed, at first CAF certificates were used to pay PSA program participants (Pagiola 2008).[7] Evaluations of program impact must be able to isolate the causal effect of PSA from the effect of these previous forestry programs.

In an expert evaluation of PSA, Hartshorn *et al.* (2005) identified important accomplishments of the program including maintenance of privately-owned forests in areas of conservation significance; facilitation of private transfers of funds to rural landowners who

[7] The Forest Credit Certificate (*Certificado de Abono Forestal*, CAF) was created in 1986.

agree to protect their forests; encouragement of female landowner and indigenous community participation; direct payments to a relatively greater number of small rural landowners; and, most importantly, broad public recognition that intact forests and their environmental services have value. However, they also noted that it is difficult to determine whether and to what degree the program has contributed to the conservation and expansion of forest cover in Costa Rica, its primary objective. In fact, PSA implementation coincides with an extremely low national rate of gross deforestation (Castro 1998; Sánchez-Azofeifa *et al*. 2001; Kerr *et al.* 2002; Kleinn 2002). Sánchez-Azofeifa *et al*. (2007) conclude that PSA in its initial years (1997-2000) payments were distributed broadly across ecological and socio-economic gradients, but the 1997-2000 deforestation rate was not significantly lower in areas that received payments. These authors also conclude that other successful Costa Rican conservation policies, including those prior to PSA, may explain the current reduction in deforestation rates. Pfaff *et al.* (2008) find a very small impact on deforestation from payments for environmental services in Costa Rica. They also conclude that most PSA participants had negative returns to deforestation, i.e. were not going to clear their land anyway given all of the factors in clearing decisions other than PSA. Sierra and Russman (2006) report that conservation impacts are indirect and realized with considerable lag because they are mostly achieved through land use decisions affecting non-forest land cover. Tattenbach *et al*. (2006) concludes that PSA reduces deforestation.

From above, existing literature does not provide a clear answer about the impact of the program on land use changes in Costa Rica. According with Pagiola (2008), it is difficult to compare results of previous studies on PSA impact as they apply to different areas, different time periods, different dependent variables, and use different methodologies. For example, Sierra and Rusman (2006) only sample parcels that are participants in the program; then their results do not provide any firm evidence on the causal impact of PSA because one does not know if they are cause or effect. Sánchez-Azofeifa *et al*. (2007) do not address the observational dissimilarities between PSA and non-PSA lands. Pfaff *et al.* (2008) apply matching methods to construct a valid counterfactual but using only biophysical land characteristics that affect program participation and outcome without including socio-economic controls and explanatory variables of program targeting.

Measuring avoided deforestation is one way to evaluate the effectiveness of PSA in providing environmental services (assuming that more forest cover implies more provision of services). However, I have explained that measurement is complicated because "avoided deforestation" is a counterfactual event and cannot be observed. The analyst must construct the counterfactual - the deforestation that would have occurred if an area of forest were not protected by PSA - from observations or theory. In this dissertation, I design and interpret rigorous program evaluation of PSA at the property and census tract level using different matching techniques to construct the counterfactual (as advocated by Ferraro and Pattanayak 2006). I apply these methods to data from a survey of landowners in a case study region in order to estimate the impact of participation in the first phase of the PSA program (1997 – 1998) controlling for socio-economic and biophysical observable characteristics that influence program participation, but also may potentially affect program outcome (e.g. deforestation). Then, the impact analysis is extended to the whole country and including forest conservation contracts signed between 1998 and 2004. In this national analysis, biophysical and socio-economic controls are combined with determinants of program targeting using census tracts as the unit of observation.

1.2 OBJECTIVES

This dissertation is motivated by the policy debate over the effectiveness of direct payments for environmental services. This dissertation contributes to that debate by analyzing the causal impact of the Costa Rican Program of Payments for Environmental Services on forest cover, considering different dimensions and different ways of measuring change in forest cover. The two primary objectives are:

1) Estimate the causal effect of participation in PSA on forest cover – as reported by landowners and determined from aerial photographs - at the level of the individual parcel, in the case study region of Sarapiquí.

2) Estimate the causal effect of PSA contracts on forest cover – as determined from satellite images – at the level of the census tract, for the entire nation of Costa Rica.

Three supporting objectives are:

3) Develop a conceptual framework of how land use decisions are affected by the availability of a direct conservation payment, incorporating issues of irreversibility, uncertainty and ability to delay associated with the program participation decision.
4) Describe the process and determinants of participation in PSA, in detail for the case study region of Sarapiquí, and in terms of broad spatial and temporal variation in implementation across different regions of Costa Rica.
5) Demonstrate the feasibility of the application of rigorous program evaluation to payments for ecosystem services, including different methods for sampling, defining treatment and matching.

1.3 DISSERTATION OVERVIEW

This dissertation has a three essay format; each essay stands alone and can be read separately. The first essay (Chapter 2) profiles landowners in the region of Sarapiquí (north eastern Costa Rica), describes the process and determinants of enrolling in PSA and characterizes landowners' experience with the program qualitatively and with descriptive statistics derived from case studies, semi-structured interviews with forest officials and a household survey conducted in 2005-2006. The second essay (Chapter 3) analyzes the causal impact of the first phase of the PSA program on forest cover in Sarapiquí, employing a binary definition of program participation (i.e., properties with at least one PSA forest conservation contract since at least 1999 vs. properties with no PSA contract) and change in mature and total forest determined from self-reports and aerial photographs. The third essay (Chapter 4) analyzes the causal effect of PSA on forest cover across the nation, with both treatment and impacts defined at the census tract level. A binary definition of participation (i.e. at least one PSA forest protection contract issued by 2004 in the tract) is compared with a continuous definition (i.e., percent of census tract under PSA contracts issued between 1998 and 2002). Outcomes considered are forest gain, forest loss, and net deforestation, all derived from satellite images. Both chapters 3 and 4 describe, apply, and compare results from various matching methods to each other and to multivariate OLS. In both cases, participation is defined based on administrative records from the program, and covariates are drawn from various sources including the Costa Rican Atlas, a survey of landowners in Sarapiquí, and the national census.

1.4 CONCEPTUAL FRAMEWORK

For centuries societies have debated the appropriate balance of public and private interest in property in general, and more recently the debate has also addressed the issue of environmental protection, and the extent of the public interest in restricting the conversion of land (Tegene *et al*. 1999).

Forest conservation is an investment in natural capital that yields environmental benefits (e.g. biodiversity protection and tourism benefits), as well as net revenues from the sustainable harvests of non-timber forest products. Governments and land trust secure environmental service flows using several methods, including land use regulation, fee simple ownership, and conservation easements or contracts (Fackler *et al.* 2007). PSA gives us an example of the use of conservation contracts that promote forest conservation through direct payments to forest owners.

Most studies of tropical deforestation employ a deterministic framework that assumes current and future benefits and costs of forest conservation are somehow known. However, and surprisingly little is known about the future environmental benefits of forest conservation (Bulte *et al.* 2002). For virtually all resources, the natural rate of growth of the stock is in fact stochastic and the presence of this ecological uncertainty raises interesting questions about the behavior of renewable resource markets (Pindyck 1984). Major potential benefits of sustainable forestry are related to carbon uptake and biodiversity preservation, but future values of these benefits are uncertain. On the other hand, opportunity costs of forest conservation are the foregone net returns to development. However, future development price is also uncertain. Bulte *et al*. (2002) model uncertainty associated with conservation benefits as a geometric Brownian motion, and provided a numerical application of quasi-option value to the management of tropical forests. Behan *et al.* (2006) explore the dynamics of agricultural producers' decisions in switching land from traditional agriculture to forestry using a real options model and found that increasing the present value of a stream of profits from forestry relative to that of traditional agriculture reduces the optimal transition period to forestry.

When the conditions of irreversibility, uncertainty, and ability to delay are met, a decision is said to entail an implicit option for the value of waiting (Dixit and Pindick 1994). The conceptual framework in this section will explore the forest conservation impact of two scenarios: with and without the introduction of a policy instrument (e.g. PSA) that pays forest landowners to conserve their forest. Time trends, uncertainty about forest conservation and development benefits, and the value of waiting will be included in the analysis. The final objective is to develop a stochastic model that can be used to analyze the impact of PSA on tropical deforestation including uncertainties concerning the benefits of different land use options (e.g. forest conservation vs. agriculture) using a real options framework where it is incorporated the uncertainty about future benefits and benefits of delaying land development.

In order to determine the effect that a conservation contract (i.e. a PSA contract) will have on a landowner that voluntarily agree to keep a parcel of land in less intensive use (e.g. forest conservation) in exchange for a direct payment, we need to understand the decision faced by the owner of land on which multiple uses are possible. Consider a parcel of land with forest in different stage of its transition to become a mature natural forest.[8] The owner of this parcel faces three basic alternatives:

[8] This assumption makes the conceptual framework suitable to be adapted to explain PSA impact on Costa Rican forest transition which will be a key concept to be analyzed in the national-level analysis of program impact.

1. He/she could keep the land forested without conveying a conservation contract, thereby retaining the option to develop the land or convey a conservation contract at some point in the future.
2. He/she could convey a conservation contract and foreclose the option of developing the land during the length of the PSA contract.
3. He/she could develop his/her land (i.e. switch from forest land use to another alternative use) or sell the land for development, making it likely (but not certain) that the land would be developed in the future.

The third alternative represents an irreversible investment decision, at least in the short run in the context of tropical deforestation, since conversion of forest to other land uses constitutes in some respects an irreversible event.

In this analysis, the farmer is a firm facing an investment decision (e.g. deforestation), a firm that has assets (mainly labor and land) and chooses the best use of these assets given its knowledge of product markets and related costs. I will assume that landowners dynamically maximize utility over development[9] and conservation land uses, and that converting to one use precludes use of the other. Landowners are uncertain about future returns to development, and are not obligated to act. For a choice (i.e. develop or conserve) to be optimal, the landowner must receive at least the opportunity cost of the decision, i.e., the minimum willingness to accept a conservation contract. This opportunity cost includes the option values that account for uncertainty (i.e. quasi-option value) and the value of waiting irrespective of uncertainty.

The landowner who decides to enroll in PSA must enter into a $\bar{T}$-year contract. This nature of PSA characterizes the irreversibility effect of the program participation decision which is not in this a case a perpetual effect as it is normally the case with conservation

[9] Development will refer to any other alternative land use beside forest conservation (e.g. agricultural production, cattle production, urban development, etc.)

easements. Land development, which involves conversion of forest to other land uses, also represents in some respects an irreversible decision since deforestation can be considered an irreversible event at least in the short run. In this particular case, irreversibility means that converting today entails not only forfeiting the conservation use of the parcel and reception of a direct conservation payment, but also giving up possible new information in the future- such as changes in government policies, food prices, uncertainty about forest conservation benefits - that might influence the timing and profitability of converting. Hence, in addition to the cost of conversion and the loss of conservation value, there is an additional opportunity cost of converting today instead of waiting and keeping the conversion option alive for future possibilities (Tegene *et al*. 1999).[10]

In sum, the decision to participate in PSA involves uncertainty because the economic and environmental conditions underlying future net returns to conservation and development uses are unknown today. PSA participation decisions are also not a now-or-never proposition and participation decisions can be delayed to take advantage of new information about changing initial conditions.

Following Tegene *et al*. (1999) and Behan *et al.* (2006), let's consider a landowner that owns a piece of land and derives at time t a profit stream worth F (i.e. private net returns obtained from forest). Let net returns to development use be N per acre. For simplicity, I assume that profits from development grow at constant rate μ. The landowner's discount rate is r ($r > \mu$ by assumption).

I assume that the landowner is interested in maximizing net returns in a competitive setting, but the landowner has now the option to sign a $\bar{T}$-year PSA contract now or at some point in the future. First, I consider the value of forest land which cannot be converted to agriculture. The value of this land per acre at time $t = 0$, $V^f(0)$, is as follows:

[10] If conversions were fully reversible, this opportunity cost would be zero.

$$V^f(0) = \int_0^\infty F\, e^{-rt} dt = \frac{F}{r} \tag{1.1}$$

The landowner has the option to switch to development. In this case, the value of land in development use per acre at time t=0, $V^d(0)$, is as follows:

$$V^d(0) = \int_0^\infty N\, e^{-(r-\mu)t} dt = \frac{N}{r-\mu} \tag{1.2}$$

I assume that the landowner owns natural forest, and then this land could or could not be converted to development at some arbitrary future time T. The value of this convertible land per acre at time t = 0, $V^c(0)$, is as follows:

$$\begin{aligned} V^c(0) &= \int_0^T F\, e^{-rt} dt + \int_T^\infty N\, e^{-(r-\mu)t} dt - \int_T^\infty C\, e^{-rt} dt \\ &= \frac{F}{r}(1 - e^{-rT}) + \frac{N}{r-\mu} e^{-(r-\mu)T} - \frac{C}{r} e^{-rT}, \end{aligned} \tag{1.3}$$

where C represents land conversion cost.

The first term on the right-hand side (RHS) of (1.3) is the present value of the stream of forest profits until the date of conversion (i.e. T). The second term is the present value of the stream of development profits from the date of conversion onward. The last term is the present value of the cost of conversion, C, at time T. Results of equation (1.3) can be re-written as:

$$V^c(0) = \frac{F}{r} + e^{-rT}\left(\frac{N}{r-\mu} e^{\mu T} - \frac{F+C}{r}\right) \tag{1.4}$$

The first term on the RHS of (1.4) represent the present value of perpetual forest profits. The second term shows the value of landowner's option to convert the land to development. In this case the value of convertible land is the sum of the present value of perpetual forest value (i.e. private profits) plus an option value. In the context of a direct conservation payment initiative like PSA, the option value, $V^C(0) - F/r$, is the payment that a well-informed landowner would require if the landowner was to give up his right to develop his land. In the context of PSA, the option value would represent the payment that would be necessary to make the landowner to give up his right to deforest.[11]

Given the equations (3) and (4), the landowner will choose the optimal date of conversion T in order to maximize the discounted net returns. If I differentiate (1.3) or (1.4) with respect to T, setting the result equal to 0, and solving for the optimal conversion date (i.e. T^*), gives:

$$T^* = max\left\{\frac{1}{\mu} ln\left(\frac{F+C}{N}\right), 0\right\} \tag{1.5}$$

As one might expect, high forest profits and high conversion costs delay deforestation while high development returns or faster growth of N speed up the conversion process by bringing forward the date of deforestation.

In the scenario with PSA, the landowner has now the option to sign a $\bar{T}$-year PSA contract now or at some point in the future. In this case, the value of land in PSA per acre at time $t = 0$, $V^p(0)$, is as follows:

$$V^p(0) = \int_0^{\bar{\bar{T}}} Pe^{-rt}dt, \tag{1.6}$$

where P is the payment established in the PSA contract. I consider that the land use restrictions imposed in the PSA contract makes the program participation an irreversible decision for the duration of the contract. In the context of PSA, irreversibility means forfeiting the right to receive returns from forest management or to convert the land and receive returns from alternative uses, as well as giving up potentially valuable new information in the future about conservation and development benefits.

Let's consider now the value of convertible land when facing the alternative of signing a $\bar{T}$-year PSA contract. The value of this land per acre at time $t = 0$, $V^{cp}(0)$ is:

[11] Note that $V^C(0) \rightarrow F/r$ as $T \rightarrow \infty$. In this case, the option value decreases as the conversion date become further out in the future; and for forested land with no conversion potential, the option value becomes zero.

$$V^{cp}(0) = \int_0^T F\,e^{-rt}dt + \int_T^{T+\bar{T}} N\,e^{-(r-\mu)t}dt + \int_T^{T+\bar{T}} P\,e^{-rt}dt - \int_{T+\bar{T}}^{\infty} C\,e^{-rt}dt \qquad (1.7)$$

Equation (1.7) tells that the landowner decides to sign a $\bar{T}$-year PSA contract in year T, and then he decides to convert his land after participation at year $T+\bar{T}$.[12] Solving the integration in (8) gives:

$$\begin{aligned} V^{cp}(0) &= \frac{F}{r}(1-e^{-rT}) + \frac{P}{r}\left(e^{-rT} - e^{-r(T+\bar{T})}\right) \\ &\quad + \left(\frac{N}{r-\mu}\right)e^{-(r-\mu)(T+\bar{T})} - \left(\frac{C}{r}\right)e^{-r(T+\bar{T})} \\ &= \frac{F}{r} + \left(\frac{P-F}{r}\right)e^{-rT} + \left(\left(\frac{N}{r-\mu}\right)e^{\mu(T+\bar{T})} - \frac{P-C}{r}\right)e^{-r(T+\bar{T})} \end{aligned} \qquad (1.8)$$

The first term in the RHS of equation (1.8) is the present value of perpetual net forest returns (which is the payoff in the no-PSA and no-deforestation scenario). The second term represents the payoff that a landowner will receive if he decides to sign a $\bar{T}$-year PSA contract at $t = T$. The last term represents again the value of the landowner's option to convert the land to another alternative use. In this case, the option value is equal to $V^{cp}(0) - \frac{F}{r} + \left(\frac{P-F}{r}\right)e^{-rT}$ which represents the compensation value a well-informed landowner would require if the landowner was to give up his right to develop the land (see Tegene *et al.* 1999).

Facing the alternative of participating in PSA, the landowner chooses the optimal date of conversion $T+\bar{T}$ to maximize the value of land given by equation (1.8). Differentiating equation (1.8) with respect to $T+\bar{T}$, setting the results equal to 0, and solving for the optimum conversion date (denoted T^{psa} in this case), gives:

$$T^{psa} = max\left\{\frac{1}{\mu}ln\left(\frac{P+C}{N}\right), 0\right\} \qquad (1.9)$$

[12] T can depend on what stage of the forest transition the forest is. If we start with bare land, more years will be needed to establish a forest suitable to be enrolled in PSA.

The optimum conversion date shown in (1.9) does depend on PSA payments (i.e. P). As one might expect, higher PSA payments and higher conversion costs delay deforestation while higher development returns or faster growth of N speed up the conversion process by bringing forward the deforestation date. In the language of real options, Towe *et al.* (2008) find that the mere existence of an option to preserve farmland delays decisions to convert farmland to developed uses. They conclude that such delays allow local governments to improve infrastructure or implement stricter growth control measures, benefits of a preservation option may be even more long term. This is certainly the case of the introduction of a direct conservation payment. Interpretation of this conceptual framework suggests that one should observe more forest cover in land protected by the program.[13]

The introduction of a direct conservation payment affects the optimum conversion date. The landowner will convert immediately (i.e. $T^{psa} = 0$) only if development returns (N) are equal or exceed N^{*psa}, where:

$$N^{*psa} = P + C \tag{1.10}$$

In sum, landowners facing a decision to convert land use in a scenario with a policy instrument that pays directly forest owners to protect their forest will be affected by the level of these direct conservation payments and also by factors that influence conversion costs, and development returns.

In the analysis of causal effects of PSA, estimation of the missing counterfactual is key to obtain estimates of program impact. However, counterfactual estimation needs to address selection bias especially in cases like PSA where characteristics that affect program

[13] Extensions of this conceptual framework could also include the stochasticity in implementation of PSA across regions and over time. In that case, P could be a function of variables related with program implementation including for example changes in program payments year by year, changes in program priorities to target applicants, application cost and compliance control. F could also vary across regions and by years reflecting different socio-economic and biophysical constraints that could make deforestation more or less appealing across those regions. Cost of conversion, C, could also change representing different costs across different stages of the forest transition (e.g. mature forest is more costly to harvest than young regeneration). Illegal deforestation can be more easily detected when forest is more mature which is also a factor that could make conversion costs change over time. These are factors that future research should address.

participation also can affect program outcome. In that sense, the conceptual framework developed in this section gives important information that can feed the selection of appropriate controls during the estimation of what would have happened had land not protected by PSA. These results will be considered in the rest of this dissertation.

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Chapter 2

COMBINING QUALITATIVE AND QUANTITATIVE METHODS TO EVALUATE PARTICIPATION IN COSTA RICA'S PROGRAM OF PAYMENTS FOR ENVIRONMENTAL SERVICES

2.1 INTRODUCTION

Forests provide multiple services, including conservation of biological diversity, soil and water; supply of wood and non-wood products; provision of recreation opportunities; and storage and sequestration of carbon. Deforestation and forest degradation can irreversibly and substantively impair the ecosystem functions of forests. Examples from situations where this natural degradation has occurred raises the question of why society and governments would allow rapid or excessive deforestation (Pattanayak and Butry 2005). In fact, deforestation, mainly conversion of forests to agricultural land, continues at an alarmingly high rate – about 13 million hectares per year (FAO 2005) despite billions of dollars having been invested in conservation worldwide (James *et al.* 2001; Hardner and Rice 2002).

Economists contend that unreliable information regarding the value of services from these ecosystems is one reason for their loss (Pattanayak 2004). In general, the provision of ecosystem services will be sub-optimal because ecosystem services are public goods, ecosystem management involves externalities, and ecosystems are often the only capital of the poor who have no money or political voice (Pattanayak and Wendland 2007).

In response to the degradation of forest ecosystems, the global area of forest designated principally for the conservation of biological diversity has increased by an estimated 96 million hectares since 1990 and now accounts for 11% of the total world's forest area (FAO, 2005). These forests are mainly, but not exclusively, located inside protected areas. Costa Rica shows the same positive trend in forested area devoted to biodiversity conservation. As shown in Table 2.1, the area designated for biodiversity conservation grew 66% between 1990 and 2005.

According to Table 2.1, 58% of the total forest area in 1990 was of multiple purposes compared with 74% for 2005. Much of these forests under "multiple use" in Costa Rica are privately owned. These lands have the potential to provide services such as biodiversity and watershed protection, landscape beauty, and carbon sequestration if they are managed accordingly. In response, the forestry laws were revised through a long-term process that enabled the establishment of an institutional framework for forest policy with a solid legal, organizational, and social base (Miranda *et al*., 2003; Miranda *et al*., 2006). Within this new legal framework, it was formally recognized the potential of private lands to provide environmental services and launched a system of payments for environmental services called Costa Rican Program of Payments for Environmental Services (*Program de Pagos por Servicios Ambientales*, PSA) which is a formal economic recognition of the owners of natural forests and plantations for the environmental services that their natural areas provide to society (Rodríguez 2001).

Under PSA, the government provides financial compensation to private forest landowners through multi-year renewable contracts paid via the National Fund of Forest Financing (*Fondo Nacional de Financiamiento Forestal*, FONAFIFO). According to FONAFIFO, the most important feature of this Program is that it has changed the traditional concept of a "subsidy" or "incentive" for the forestry sector, replacing it with the idea of "economic compensation" for the environmental services provided by forests, thereby recognizing their ecological, social, and economic value. Table 2.2 shows the amount of land and payments assigned to the different components of PSA.

In order to assess the program's impact on some outcome of interest (e.g. forest cover), it is critical to understand landowner motivations for participating in the program, together with a detailed description of the enrollment process. In fact, the key elements that are critical to the success of incentive-based programs include ensuring effective demand and a thorough understanding of participants' motivations to enroll. Information with regards to these issues can help to ensure the future sustainability of PSA.

A fairly recent evaluation of PSA (Hartshorn *et al*. 2005) identified several important accomplishments including maintenance of privately-owned forests in areas of conservation; facilitation of transfers of private funds to rural landowners who agree to protect their forests; encouragement of female landowner and indigenous community participation in conservation activities; direct payments to a relatively greater number of small rural landowners; and, most importantly, broad public recognition that intact forests and their environmental services have economic value. More previous studies of PSA have also focused on program impacts on specific program outcomes (e.g. poverty alleviation and avoided deforestation) with non-conclusive results. Studies have generally found that the land enrolled in the program has more forest cover that non-enrolled land (e.g. Ortiz *et al.* 2003; Zbinden and Lee 2005; Sierra and Russman 2006), but these results are not conclusive, as they may be due to sample selection bias (Sills *et al.* 2006). Econometric tests of the extent to which PSA has affected forest cover (e.g. Sills *et al*. 2006; Tattenbach *et al.* 2006; Pfaff *et al.* 2008) have generated mixed results because these studies apply to different areas, different time periods, different dependent variables, and use different methodologies (Pagiola 2006). Most other studies of PSA have focused on the program's impact on rural poverty (Miranda *et al*. 2003; Ortiz *et al*. 2003; Zbinden and Lee 2005; Miranda *et al*. 2006). To be able to estimate the causal effect of

PSA, we first need to understand how landowners come to participate in the program, so that we can control for differences between participants and non-participants (Sills *et al.* 2007).

In this paper, I describe the first nation-wide and long-term program of payments for environmental services from tropical forests and describe the factors that drive landowner participation in this program, based on an integrated qualitative and quantitative field research in Costa Rica. Specifically, I describe the main driving forces of enrollment in PSA using an iterative qualitative approach. I consider case studies of landowners in the Sarapiquí Region of Costa Rica combined with semi-structured interviews of forest officials and local professionals in order to gain an understanding of the enrollment process, program administration, and motivations for participation. This qualitative component was then combined with a quantitative survey that interviewed 50 program participants and 150 non-participants in the Sarapiquí Region.

2.2 METHODS

2.2.1 Integrating Qualitative and Quantitative Methods in Program Evaluation

Development economics has a rich tradition of field research. Within this broad tradition, iterative field research methods −in which the collection of data through surveys is combined with detailed observation and conversation to elicit knowledge about an institution− is becoming more common (Udry 2003). When the question of interest is clear (e.g. what are the driving forces in PSA participation?), but the economic environment within which agents live is not well-documented, then iterative field research becomes particularly useful. In the context of program evaluation, qualitative evidence from case studies and interviews can draw out the social and institutional context within which the program operates. For the evaluation of the implementation of PSA in the Sarapiquí region, I use qualitative evidence to develop a detailed understanding of the program (e.g., identifying main actors among government, private, and non-profit sectors) and of how landowners perceive their benefits and costs from the program. These results can complement more quantitative analysis of the participation decision and establish broad patterns showing the factors that influence the enrollment decision. Ultimately, this mixed method approach can generate a contextualized understanding of PSA participation in Costa Rica.

The approach analysis in this study parallels recent calls for participatory econometrics (Rao and Woolcock 2003; Swann 2006), in which the investigator returns to the field to clarify questions and resolve anomalies. Data collection is combined with detailed observation and conversation to elicit knowledge about participant motivations. By using visits to PSA participants and non-PSA participants, we also seek to clarify aspects of the quantitative data (e.g. motivation to participate) to better define the economic environment and to collect complementary data (e.g. data on land characteristics and georeferenced data of property boundaries). Collectively, these lead to better answers to a key research question: *what factors motivate participation in PSA?*

As Rao and Ibáñez (2005) emphasize in their study of the social fund program in Jamaica, in-depth data on participation is traded off with the size and representativeness of the sample. Thus, our findings should not be read as a comprehensive evaluation of PSA that can be applied to the rest of the country.

2.2.2 Case Studies

The main factors that might affect a household's decision to participate in a PES program are grouped into three factors: factors that affect eligibility to participate, factors that affect their desire to participate, and factors that affect their ability to participate (Pagiola *et al.* 2005). In general, opportunity costs, household strategies, and current farming practices are likely to be fundamental determinants of whether an eligible participant in fact wants to participate. However, it is difficult to separate out a priori exactly what factors influence desire and ability. Within this context, the case study is an ideal methodology (Feagin *et al.* 1991 cited by Tellis 1997).

Qualitative interviewing techniques such as the prototypical case-study approach draw on the results of small-sample surveys (Miranda *et al.* 2003; Ortiz *et al.* 2003; Miranda *et al.* 2006) and explore key elements of program participation. In general, case studies are designed to bring out details from the viewpoint of the participants by using multiple sources of data (Tellis 1997). Thomas (2004) suggests that there are three main purposes in conducting a case study: exploratory, explanatory, and theory-testing. Our case studies are exploratory. We use the exploratory case when we know little or nothing about the phenomenon of interest which is the case in explaining driving forces in PSA participation decision. The explanatory case produces grounded theory that can carry more conviction than a theory developed in the abstraction of what happened in the field. Finally, the theory-testing case is used to test a prior theory. In a situation where we have little understanding of the phenomenon of interest, the numbers of mechanisms for research are limited (Swann 2006).

During the summer of 2005 and spring of 2007, a series of in-depth interviews were carried out in the northeast part of Costa Rica. Interviews and field observations were developed with participants and non-participants in PSA with the main purpose of trying to understand the main motivations behind enrollment within the program. I also interviewed government officials, forest professionals, and local authorities and carried out a review of documentation (e.g. titling documents and PSA contracts), observation of properties, which included the collection of GPS points throughout property boundaries in order to follow recommendations from Yin (1994), Rao and Woolcock (2003), Udry (2003), and Berg (2004).

Within the recognized qualitative techniques that use interview methods, the key-informant interview, which is an extended one-on-one exchange with someone who is unique (e.g. PSA participants and non-PSA participants), was selected as the most appropriate approach for use in this study. This participatory econometrics approach tackled a key hypothesis: *"only landowners whose opportunity cost of participation is low will enroll in PSA"*.

The classical, or sequential, approach to participatory econometrics entails three key steps that were followed during the implementation of the case studies:

1. In-depth interviews to obtain a grounded understanding of factors that could help to explain PSA participation/ non-participation. These interviews focused on the process of PSA enrollment. Specifically topics of conversation included:
   - Reasons for personally not participating or why others are not participating, including the benefits and costs of participation in PSA.
   - Beliefs about environmental issues and enforcement of environmental laws. Landowners were directly asked about engaging in activities like illegal logging to assess their perception of environmental and legal impacts of this kind of activities.
   - Determinants of current/past land use on the properties. For each property, we asked landowners to specify the primary and secondary land use and the factors influencing this selection into land uses (e.g. soil quality, slope, road access).
   - Understanding of program administration, including official and *de facto* guidelines for accepting/rejecting/waitlisting applications, canceling contracts, and renewing contracts.
   - Perceptions on program impacts related to quality rather than quantity of forest (e.g., is PSA land exposed to less hunting, better protection from fire, less fuel wood extraction?).

The in-depth interviews also provided an opportunity to visit each property with the landowner or manager, see the forest area under the PSA contract, and observe and discuss forest use and protection. Further, I obtained documentation for each case, including copies of the PSA contract, cadastral maps, payments, and monitoring reports from FONAFIFO and the *Fundación para el Desarrollo de la Cordillera Volcánica Central* (FUNDECOR), which is a very active NGO that operates in the study region and that has helped landowners apply to PSA.

2. Semi-structured, in-depth interviews with forest officials and local professionals to enhance our understanding of the administration of PSA. I focused on application procedures, applicant selection methods, rejection/waitlisting criteria, cancellation of contracts and renewal process. Specifically, topics of conversation included in these interviews included:
    - Details of program administration, including official and de facto guidelines for rejecting/waitlisting applications, canceling contracts, and renewing contracts during 1997-1998 and currently.
    - Official perceptions of landowners' motivations to participate in PSA.
    - Factors affecting land use on properties (e.g. soil quality, slope, titling, and road access).
    - Suggestions for landowners to include in our case studies, including possible sampling frames of representative non-PSA landowners.

3. Development of hypotheses about motivations to participate in PSA, which can then be tested with quantitative (survey) data.

For the case studies, I sought a range of landowners representing various categories, including on-site and absentee landowners with PSA contracts, and landowners who had never applied, been rejected, waitlisted, or not renewed PSA contracts. FONAFIFO records generated a sampling frame of pending, cancelled, rejected, and awarded PSA contracts in 1997-1998 (renewed in 2001 or 2002). Candidates for case studies were classified according to ownership type, hectares owned, biophysical characteristics, and location. FUNDECOR's personnel also helped identify representative or typical PSA participants in the region. To find non-participants in PSA, FONAFIFO's personnel, local forest officials and local forest professionals were asked to nominate representative landowners who did not have PSA contracts but would be willing to participate in the in-depth interviews. Thus, in general, I relied on local informants with good knowledge and contacts with forest landowners to find representative landowners for our case studies.

Caution is needed in interpreting the qualitative evidence because this data draws on interviews with a few landowners in the study region. Since these landowners were not selected on the basis of a probability sample, it is possible that their opinions are not representative. The qualitative evidence should be evaluated in conjunction with the quantitative analysis, which is based on a random sample of participants and non-participants, to get a comprehensive sense of the main determinants of program participation.

2.2.3 Landowner Survey

The ideal database for a rigorous empirical evaluation of PSA would include observations on land use and characteristics of both participant and non-participant landowners and their properties, both before and after the program (Sills *et al.*, 2006). In this case, where the main purpose is to identify driving forces that affect PSA participation, a household survey is the most appropriate methodology given that landowners are the economic agents making decisions about participation, and thus are the most suitable unit of analysis.

In this study, participant and non-participants households in PSA were randomly selected from the cantons of Sarapiquí, Guacimo, Pococí and Oreamuno (see Figure 2.1). This region was selected because it has a sufficient number of PSA contracts, and excellent records on PSA participants maintained by FUNDECOR. We also decided to sample participant properties that had forest protection contracts facilitated by FUNDECOR because government records from the 1997 to 2000 period are difficult to access for this region, due in part to a flood that destroyed records held in the regional offices. 67 and 56 PSA protection contracts assisted by FUNDECOR were signed during 1997 and 1998 respectively. These 123 contracts protected approximately 11,630 hectares in the study region. Out of these 123 contracts, 70 were renewed after completing the stipulated five years contract (i.e. these contracts were in force in 2005 when the survey was implemented).

The quantitative survey included 50 program participants. For the non-PSA properties, the goal was to find a sampling frame that included properties similar to the PSA sample. To the extent possible, we wanted to 'pre-match' the sample, identifying non-PSA properties similar to the PSA properties. For the pre-match, we used a combination of a geographic sampling rule to select 51 immediate neighbors (cf, Zindben and Lee 2005) and 102 from the records of the national land registry (*Catastro Nacional*) selected by district and by buffer zones around the PSA properties in our sample. The national land registry provides the most complete sampling frame of landowners with tenure and therefore eligible for PSA contracts on those years (i.e. 1997 and 1998). In order to obtain the final sample of non-participants, we filtered out properties smaller than 5 hectares (the minimum required by the program is 3 hectares), properties listed in FONAFIFO's records as having PSA protection contracts, and properties owned by the state and large companies. After this process, for each PSA property, we randomly selected one landowner in the same district for a total of 44 and a group of 58 landowners with properties located in buffers around each PSA property. This sampling method, that included non-immediate neighbors of PSA participants, was designed to pre-match landowners for characteristics that are spatially correlated, including biophysical factors and access to markets and public services, but avoid spill-over effects due to communication among neighbors or stricter enforcement of environmental laws near properties with PSA contracts (see the Appendix 1 for a graphical representation of the buffer sampling).

The household survey elicited information about landowner socio-economic characteristics (i.e. age, education, city of origin, marital status, occupation, household composition, etc.), property (land size, soil quality, slope, etc.) and land management (e.g. land titling, previous farming experience, hired and family labor, area under different land uses, etc.). Before beginning an interview, the interviewers verified that the landowner (a) owned or managed the property in the sampling frame since 1996; (b) had at least some natural forest cover on that property in 1996; and (c) had never held a PSA forest protection contract.

2.3 UNDERSTANDING MOTIVATIONS TO PARTICIPATE IN PSA

2.3.1 Determinants of Participation in PSA

In total, seven landowners were included in the in-depth interviews. Most of their properties are located in Sarapiquí, which is the biggest canton in Costa Rica. Although in subsequent years many more landowners applied to the program than could be accepted, in the initial years of 1997 and 1998, very few applications were rejected or waitlisted, and the record keeping on these contracts was poor. In those initial years of the program, it was also rare for private companies and corporations to apply for the program. Thus, no corporations and no waitlisted properties were included in the case studies. We could locate and interview only one landowner who had applied to and been rejected by the program; this property is located in the Central Canton.

Table 2.3 describes the case study landowners. The average property sizes for participants and non-participants were 68.5 and 63.6 ha respectively. Using a Student t-test and assuming equal variances between the groups, I found that these are not statistically different. Table 2.3 also shows the different types of participants found in the study area. Landowner decision to live on their properties depends on factors such as road access, off-farm job, and availability of family labor.

Direct observation of the farms indicates that land characteristics and land use differ between participants and non-participants, although both engage in some form of forest conservation regardless of their participation in PSA. Table 2.3 shows a summary of the main land uses for every landowner included in this study. In general, forest conservation is the most common land use even within properties that are not enrolled in PSA. Note, ‘forest conservation' does not necessarily imply specific conservation activities; instead, it can also suggest lack of any management or 'unmanaged' lands.

The situation is more complex with regards to the main sources of income. In some cases the main sources of income have nothing to do with properties and come from jobs people have external to the farm (i.e. off-farm labor income). Table 2.3 summarizes the different sources of income for the case studies included in this study. As Table 2.3 indicates, in the case of the PSA participant that lives on his property, PSA payments represent a large proportion of the total source of income and in this situation the family does not receive any income not related to their property. For the case of the absentee PSA participant, the main sources of income are not related to the program and part of the income comes from sources not related with the farm. This situation helps to explain why forest conservation (i.e. non-managed forested land) is present in almost all the case studies. Some landowners told that they do not manage their forest simply because they do not have time away from their off-farm jobs. Others expressed that they don't need income from their properties because their off-farm income is enough, and so they prefer to conserve their forest.

In general, off-farm labor income is the main source of income for non-participants: interviewed landowners said that they work on other landowners' land or for the municipality in activities like road maintenance. In fact, only one of the non PSA participants mentioned receiving some income from his land. This was the case for the non-renewed participant, who was a 5-year PSA participant until 2002. He currently grows pepper and rents portions of his land. The forest that was protected by PSA is currently unmanaged, suggesting that he stopped participating simply because he did not want to participate anymore and not because he was planning to manage his forest.

People expressed different reasons for why they decided to participate or not throughout the in-depth interviews. The most frequent answers about reasons to participate include:

- Lack of more profitable land use alternatives due to land characteristics (e.g. poor soil quality, high slope).
- Legal restrictions to manage forest. The Costa Rican Forestry Law 7575 prohibits forest management (e.g. logging) on steep slopes or near water streams and land use changes (e.g. landowners that own a forest can't apply to the Ministry of The Environment (*Ministerio del Ambiente y Energía*, MINAE) for a change in land use to engage in another productive activity like agriculture or cattle ranching).
- Depressed returns to cattle farming (reduced prices of export beef has influenced decisions to abandon cattle ranching activities to plant trees).
- Program payment as an incentive (PSA payment may represent an important source of income).
- Simple application process (suggesting the impact of local NGOs through their assistance with the PSA application process).
- Human biology/productivity limits: at a certain age, PSA represents an attractive alternative because forest protection does not involve a high level of working in the field compared to agriculture or cattle ranching.

Reasons mentioned for not participating include:

- Eligibility problems (e.g. disputes for legal property rights).
- Costs outweigh the benefits (e.g. application and maintenance costs vs. payments).
- Private property rights (e.g. people think that participation implies impossibility to touch the forest which affects their property rights).
- Insufficient payments.
- High cost associated with technical assistance.

Participation in PSA requires the preparation of a forest management plan that must be signed by a forest engineer, who in turn must monitor and certify compliance with these plans. Forest engineers must also prepare annual reports that are submitted to FONAFIFO, which are essential for payments to be made to landowners. In 1997 and 1998, FONAFIFO allowed people to apply even if they did not have property title. In our case studies, the only rejected application was due to a legal fight with another person that was alleging land ownership and had nothing to do with lack of technical assistance to prepare the management plans.

In general, low payments and high maintenance costs are the main motives that make an eligible person decide not to participate. In our cases, all the non-participants receive off-farm income, so they do not depend on income from the farm. For cases where people do not live on the farm, the opportunity cost of participation has a great influence since landowners believe that time is critical for applying and maintaining the forest according to the standards required by PSA. Some of the interviewed people said that they rarely visit their properties due to lack of time.

In the case where people live on their farms but decide not to participate, motives are similar given that they have to spend most of the day outside of their property. In general, it seems that off-farm income is driving the decision to not participate in the program among the group of landowners included in our case studies.

For the case of people that decide to participate, a lack of profitable land use alternatives and program payments have the greatest influence in the decision. Landowners who live on-site and depend largely on farm income are more likely to participate because of cost reasons; that is, their costs of forest management are low because they are already managing their forests and can share some of the costs with other land-related activities, such as cattle farming, because of economies of scale.

The motives for participation by absentee landowners are more complex. Because they are often wealthy farmers and already involved in some forest maintenance and surveillance due to the existence of productive forest areas, the extra costs for participating in the program are minimal. Another important reason was the lack of a better alternative land use (in the case study included in our report, the contracted area was located in a sector of his property not suitable for an alternative land use) and this matches the case of participants that live on their farms. Figure 2.2 shows the data gleaned from the in-depth interviews regarding decisions to participate in PSA during 1997 and 1998.

Government officials can give a more general view of program enrollment process, and can also describe the *de-facto* program implementation in the study region. Interviews with forest officials and local forest professionals included three employees of MINAE, two employees of FONAFIFO, and five employees from FUNDECOR. If we consider their opinions, many of the results derived from the in-depth conversations with landowners about motivations to participate are confirmed.

According to forest officials, before the initial notification of application acceptance during 1997 and 1998, negotiations between the National System of Conservation Areas (*Sistema Nacional de Areas de Conservación*, SINAC) and FONAFIFO decided priority areas based on different criteria (e.g. being close to a particular protected area or to a biological corridor). After defining these priority areas, the first applications to be approved were inside these areas, and after exhausting applications inside priority areas, the approval process continued with the earliest applications submitted to FONAFIFO until they had exhausted the total area assigned to PSA for that region in that year.

During 1997, all applications were accepted. In fact, in 1997 MINAE had to call for applications twice within the annual period as the first call did not generate sufficient applications to exhaust the area assigned for that year. In 1998, the number of applications increased and the selection of applicants was based on priorities defined by MINAE and SINAC and the timing of applications (i.e. priority areas and then early applications were given the highest preference for acceptance) (see Appendix 2 with a graphical representation of the PSA application process followed during 1997 and 1998).

Because land title was not a factor for eligibility in 1997 and 1998, the main reasons for rejecting applications had to do with priority areas defined by MINAE to be included into the program and legal conflicts between landowners (e.g. disputes for land possession). Furthermore, initially MINAE was not directly involved in any kind of program promotion and so the early applications came from people already involved in some way with MINAE (e.g. landowners with forest management plans approved by MINAE) or applications assisted by NGOs (e.g. FUNDECOR). Some promotion external to MINAE did exist during these years as a result of the creation of the *Oficina Costarricense de Implementación Conjunta* (OCIC). OCIC was created as a cooperative effort between the government (MINAE, as the rector entity), a private organization specialized in the attraction of foreign investment CINDE (Costa Rican Trade and Development Board) and two non-governmental organizations, FUNDECOR (forest management) and ACOPE (electricity production).

To sum, the forest professionals and government officials believe that the following factors explain why some landowners are more likely to participate in the program:

- No alternative land use due to topography or poor soil quality. In some cases, PSA became the only feasible and legal alternative (e.g. given legal restrictions to land use changes).
- Land ownership (owners without legal title deeds for their property cannot present forest management plans to MINAE).
- PSA payment was seen as an easy way to earn an income, especially for poor farmers.
- Landowners with higher levels of environmental consciousness tended to enroll in the program, although officials strongly believe that the environmental protectionism was not a key factor that influenced decision to enroll in the program (exceptions were applications from NGOs).
- Collective factor. A kind of “collective fever” to participate and see what will happen (neighbor effect in some cases).

- Absentee landowners tend to have more interest in the forest and consider PSA participation as a convenient land use alternative due to a lack of understanding of agriculture or livestock.
- Owners of big properties are enrolled in PSA “to protect” their land from aggressive land ‘development’ policies by the Costa Rican Institute of Agrarian Development (*Instituto de Desarrollo Agrario*, IDA). IDA believed in those years that forests were “useless lands,” so unmanaged forests were available for seizure by farmers, sub-division and sharing with IDA’s assistance.

2.3.2 Statistical Results

Self-reported land uses in properties included in the household survey are presented in Table 2.4. Self-reports of landowners suggest that PSA properties have significantly more forest cover than non-PSA properties, both prior to and after participation in PSA. As shown in Table 2.4, in 2005 (1996) on average 89.54% (88.25%) of the average PSA property was covered by some kind of forested land (i.e. mature forest, forest regeneration and forest plantation) while 53.37% (53.97%) of the average non-PSA property was covered by some kind of forested land. Table 2.4 also shows that agriculture crops and pasture were more intensive, in terms of hectares, in the non-PSA properties included in the survey, although this difference is not statistically significant before (1996) and after (2005) participation in PSA. These results are consistent with the qualitative results shown in Table 2.3 where forest conservation was identified as the main land use in both participants and non-participants. It is important to treat these results with caution because respondents might not remember or might misreport land use. If non-PSA landowners underreport illegal land clearing, then Table 2.3 provides conservative estimates of the difference in forest cover change on PSA and non-PSA parcels. On the other hand, if landowners with PSA contracts are more aware and concerned about the laws governing land use, they might be less likely to report illegal land clearing, biasing the results in the opposite direction. It is also important not to assign PSA causality to results in Table 2.4 because PSA participants and non-PSA participants may differ in ways other than being participants or not that can also affect both program participation and outcome.

One method for determining what would have happened had the property not enrolled in PSA is to ask the landowners directly what they would have done with the area if it were not under contract with PSA. Table 2.5 shows the responses of the 50 PSA participants in the study region. According to these results, 70% of the interviewed landowners said that they would have engaged in some kind of activity related with keeping the land forested (i.e. wood production, keep unmanaged, forest protection or ecotourism), which indicates that forest management and/or conservation would have been the main land use. This result is again consistent with the qualitative results.

Table 2.5 shows the alternative land use if not under contract assuming that no law could restrict forest use and we allowed multiple responses. This may explain why more of our respondents said that they would put the area into cattle (34%) or timber (36%) production. It is important, again, to be cautious in interpreting these results because of strategic bias in landowner responses. This bias could alter responses in Table 2.5, because landowners do not want to say they would engage deforestation, or because landowners want to say they would maintain forest to ensure the continuation of the program and an increase in payments.

The qualitative research (summarized in the previous sub-section) provides a picture of how landowners come to participate in the program. For a PSA contract to be established, landowners must volunteer to participate in the program and the program administrators must accept their applications. In Sarapiquí, FUNDECOR also played a fundamental role as an intermediary organization. Table 2.6 shows the reasons for enrolling/not enrolling land in PSA. From the household survey, 72% credited their participation to environmental factors, rather than economic factors, which is not consistent with the qualitative evidence that showed that the lack of an alternative use for the contracted land appeared to have the greatest influence on the decision to participate in PSA, but it is consistent with previous studies of PSA participation (e.g. Ortiz *et al.* 2003).

Conversations with forestry professionals and government officials in northeastern Costa Rica indicate that during the years 1997 and 1998 no applications that met all of the requirements were rejected, and contracts processed by FUNDECOR targeted particular zones that had been identified as facing a greater threat of deforestation (Ortiz *et al.* 1992). More contracts were therefore written in these zones (*Guápiles*, *Horquetas*, *Virgen del Socorro*, and *Guácimo*). This description of the administrative selection process is consistent with survey results from non-participant landowners, many of whom say that they do not participate in PSA simply because they lack information about the program (Table 2.6). This is also supported by Zindben and Lee (2005) finding that education, access to extension, and participation in meetings are key determinants of which landowners enroll in PSA. However, this finding on 'information effects' contradicts the qualitative findings (which suggest that low payments and participation costs were the main factors). It is possible that because our case-study sample was based on recommendations by forest officials, we might have ended up with non-PSPA landowners who had some knowledge about the program and therefore there is no information effect from this sub-sample. Table 2.6 also shows the level of payments, application process, and technical assistance cost (main cost involved in the application process) that were also mentioned in the qualitative section.

To evaluate the impact that participation in PSA could have on areas not protected by the program, we can ask how participants spend their additional cash income due to the PSA payments. Table 2.7 shows the use of PSA payments as reported by landowners. 32% of respondents said that they simply added the PSA payments to the household budget for general consumption. However, 30% made investments in the farm that could indicate displacement of agricultural activities to areas not protected by PSA which is consistent with previous studies (e.g. Miranda *et al.* 2003; Ortiz *et al.* 2003). PSA participation could also affect future participation of parcels currently not under contract. In Sarapiquí, 28% of landowners not currently in the program indicated that they plan to apply in the future and 52% of PSA participants have talked with their neighbors or other landowners about the program (56% of respondents that had heard about PSA said that they knew about the program through a friend and 86% of the PSA participants included in this study have specifically recommended to another landowner to participate in PSA).

Qualitative results mentioned that lack of technical assistance and costs associated with PSA participation as some of the main reasons to not participate in the program. When asked about technical assistance, 30% of PSA participants' responses indicated that cleaning of property boundaries was the main assistance received by either FUNDECOR or FONAFIFO. Regarding participation costs, 86% of program participants engaged in cleaning property boundaries, 48% in land surveillance and 16% in fence maintenance. Future program expansions could take into consideration these activities in order to attract more participants (e.g. by giving technical assistance on maintenance of border property).

Participants report high levels of satisfaction with PSA. 70% of respondents reported that they are satisfied or very satisfied with the program, and only 4% said they were very unsatisfied with PSA. When asked about PSA impact on improvement of quality of life, 90% of respondents said the program has had at least some positive impact on their quality of life. This result is consistent with previous studies of program participation (for example, 73% of respondents to Ortiz *et al.* (2003) and 100% of respondents to Muñoz (2004) reported that PSA had improved their quality of life). This is important for the long-term impact of the program, as it will influence decisions about whether to renew contracts. When asked about changes or improvements that PSA would need, 73% of the respondents mentioned either an increase in payments (43%) or an improvement in the timing of the payments (30%).

2.4 CONCLUSIONS

In general, program participation determinants will depend on the socio-economic situation of the applicant. Participation factors can be grouped as follow:

1. People that are leaving their forests unmanaged tend to participate in the program. Given that almost none of the landowners included in this case study depend on their farms to survive, it seems that this could explain participation in many cases.
2. Legal issues also influence program participation. The only rejected application found from the period between 1997 and 1998 failed to participate due to a legal fight with another party that was also claiming ownership of the same property.
3. Property protection is also an important factor, especially for big farms. Land under PSA is automatically protected by MINAE which means that the property cannot be occupied by anyone.
4. Farms in possession without a legal title cannot be managed. According with the Costa Rican law, a title is the main requisite for MINAE to approve a forest management plan. This conclusion mainly comes from conversations with government officials and forest professionals. None of the case studies included in this survey said that this factor influenced their decision (given that all of them already had titles).
5. Farms that do not have good alternative uses on their land (because of steep slopes or poor soil quality) tend to be enrolled in the program. However, several people included in this study did not participate even when they did not have good alternative land uses. This finding may be confounded by the influence of the opportunity cost of participation and income source. Those with high opportunity costs of participation and significant off-farm sources are less likely to participate.
6. Finally and less clear, government officials and local foresters believe that people with high environmental awareness should be more inclined to participate, but they do not believe that this is an important factor that influences participation. None of the people included in our case studies mentioned that they were influenced by such considerations; however, quantitative results show that environmental preferences are important when deciding about program enrollment.

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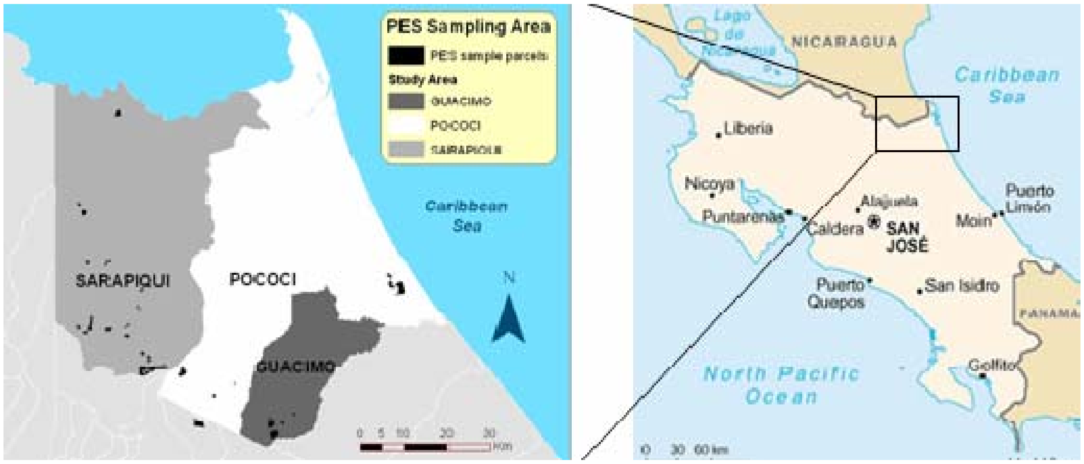


FIGURE 2.1: Study area of household survey (source: Sills *et al.* 2006 and CIA 2007)

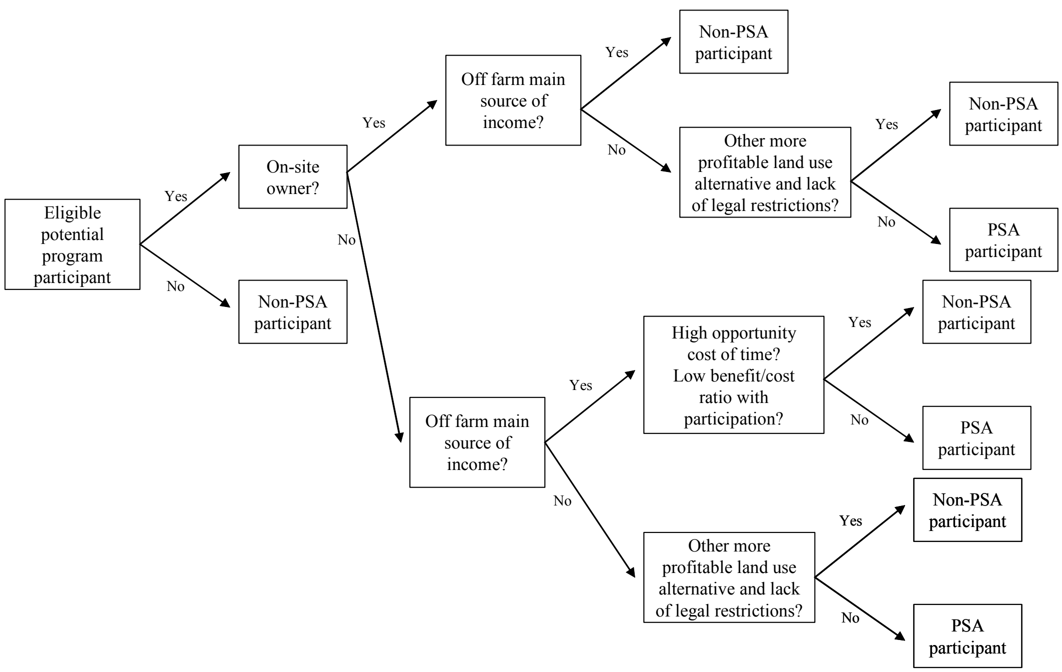


FIGURE 2.2: Description of the process involved in participation in the Costa Rican PES program

Table 2.1: Costa Rica: designated functions of forest and other wooded land

FRA 2005 categories/designated function	*Area (1000 hectares) Primary function* 1990	2000	2005
Production	-	3	3
Protection of soil and water	52	45	45
Conservation of biodiversity	328	582	586
Social services	-	-	-
Multiple purpose	1,476	1,746	1,757
No or unknown function	708	-	-
Total forest	**2,564**	**2,376**	**2,391**

Source: FAO (2005).

Table 2.2: Distribution of hectares and payments among PSA components between 1997 and 2006*

	Forest Protection**		Forest Management		Reforestation		Forest Plantation		
Year	Hectares	Payment*** (Colones/ha)	Hectares	Payment (Colones/ha)	Hectares	Payment (Colones/ha)	Hectares	Payment (Colones/ha)	Total (ha)
1997	88,830	50,000	9,325	80,225	4,629	120,000	—	—	102,784
1998	47,804	60,000	7,620	94,000	4,173	154,000	319	60,000	59,916
1999	55,776	60,000	5,125	94,000	3,156	154,000	724	60,000	64,781
2000	26,583	66,000	—	—	2,457	169,000	—	—	29,040
2001	20, 629	72,600	3,997	113,300	3,281	185,900	—	—	27,907
2002	21,819	79,160	1,999	123,540	1,086	202,700	—	—	24,904
2003	65,405	87,100	—	—	3,155	223,000	205	87,100	68,765
2004	71,081	95,800	—	—	1,557	245,000	—	—	72,638
2005	53,493	29,880	—	—	3,602	380,990	—	—	57,095
2006	19,972	31,840	—	—	4,866	405,960	—	—	24,838
Total	**471,392**	—	**28,066**	—	**31,962**	—	**1,248**	—	**532,668**

*PSA components also include agroforestry systems (1,404,021 trees were planted between 1997 and 2006).
** PSA forest protection contracts are signed for five years and may be renewed.
*** One US Dollar = 528 Costa Rica Colones (June, 16 2008). Inflation rates are: 11.20(1997), 12.36(1998), 10.11(1999), 10.25(2000), 10.96(2001), 9.68(2002), 9.87(2003), 13.13(2004), 14.07(2005), 9.43(2006), 10.81(2007). Source: www.inec.go.cr.
Source: FONAFIFO (2007).

Table 2.3: Type of landowners included in qualitative interview case studies

*Type of PSA participant**	*Property size (ha)*	*Location*	*Main land use*	*Others land uses*	*Main source of income*	*Others sources of income*
Participant landowner on site	29	La Virgen District, Sarapiquí Canton	Forest conservation	Pepper crop	Pepper crop, PES payment	n/a
Participant absentee landowner	108	La Virgen District, Sarapiquí Canton	Cattle	Plantain crop, forest conservation	Cattle, off-farm job	PES payment
Non-participant absentee landowner	50	Horquetas District, Sarapiquí Canton	Forest conservation	n/a	Off-farm job	n/a
Non-participant absentee landowner	126	Horquetas District, Sarapiquí Canton	Forest conservation	Cattle	Off-farm job	n/a
Non-participant landowner on-site	20	La Virgen District, Sarapiquí Canton	Forest conservation	Vegetables and cattle	Off-farm job	n/a
Non-renewed landowner on-site	29	La Virgen District, Sarapiquí Canton	Forest management, forest conservation	Cattle and pepper crop	Off-farm job	Pepper crop, land renting
Rejected absentee landowner	93	Vara Blanca District, Central Canton	Forest conservation	Abandoned prairies	Off-farm job	n/a

*Absentee landowner refers to people that own the property but do not live in their farms

Table 2.4: Land use as reported by landowners in detailed interviews

Variable Description[a,b,d,e]	*Non-PSA*		*PSA*		*P-value*
	Non-PSA Mean (SD)	*%* [c]	*PSA Mean (SD)*	*%* [c]	
Self-reported land use 2005					
Mature native forest (ha)	29.77 (53.16)	35.7	139.19 (315.53)	82.3	0.000
Forest regeneration (ha)	5.63 (23.04)	7.0	5.20 (13.09)	5.3	0.901
Forest plantation (ha)	3.03 (13.93)	5.2	3.44 (15.55)	2.9	0.863
Agricultural crops (ha)	6.64 (28.64)	8.9	0.15 (0.54)	0.3	0.111
Pasture (ha)	26.15 (59.17)	45.5	18.71 (56.58)	11.3	0.438
Self-reported land use 1996					
Mature native forest (ha)	32.89 (62.57)	37.3	138.25 (314.98)	83.0	0.000
Forest regeneration (ha)	4.57 (19.76)	7.1	4.44 (12.63)	4.0	0.964
Forest plantation (ha)	1.40 (5.94)	4.8	3.03 (13.69)	2.9	0.247
Agricultural crops (ha)	5.34 (23.47)	8.5	0.09 (0.35)	0.1	0.116
Pasture (ha)	26.83 (61.09)	43.8	18.84 (51.91)	11.6	0.408

The *p*-values are from standard t-tests of the difference in means.

[a] Self-reported data include 50 PSA and 148 Non-PSA. The mean parcel size is 165.11 ha and 72 ha for PSA and Non-PSA respectively.

[b] Mature native forest includes intervened and non-intervened primary (>20 years) natural forest, and forest regeneration includes intervened and non-intervened secondary (<20 years) natural forest.

[c] It corresponds to the average percent of total property area.

[d] The average percent of total property area in some kind of forestry (i.e. mature native forest, forest regeneration and forest plantation) in 2005(1996) is 89.54.5% (88.25%) and 53.37% (53.97%) for PSA and non-PSA respectively.

[e] The average percent of total property area in pasture and crops in 2005 (1996) is 44.68% (45.54%) and 11.46% (11.42%) for non-PSA and PSA respectively.

Table 2.5: Alternative land use if not under contract

Alternative use	*Percent of respondents*[a]
Crop cultivation	6
Pasture/Cattle ranching	34
Wood Production	36
Would not have used	26
Protection of the forest/conservation	6
Make fenceposts (potreros)	2
Ecotourism	2

[a] Sum of percentages is greater than 100 because some landowners chose more than one alternative landuse.

Table 2.6: Reasons for enrolling/not enrolling land in PSA

Reason for enrolling[a]	*Percent of respondents*[b]
Economic	38
Environmental	72
Reason for not enrolling	***Percent of respondents*[b]**
Lack of information	66
Payment too low	9
Distrust system	2
Too complicated	15
Cannot pay for application	2

[a] 8% of respondents mentioned that were attracted to the program due to the motivation inspired by program promoters (i.e. mainly FUNDECOR personnel).
[b] Sum of percentages is greater than 100 because some landowners chose more than one alternative landuse.

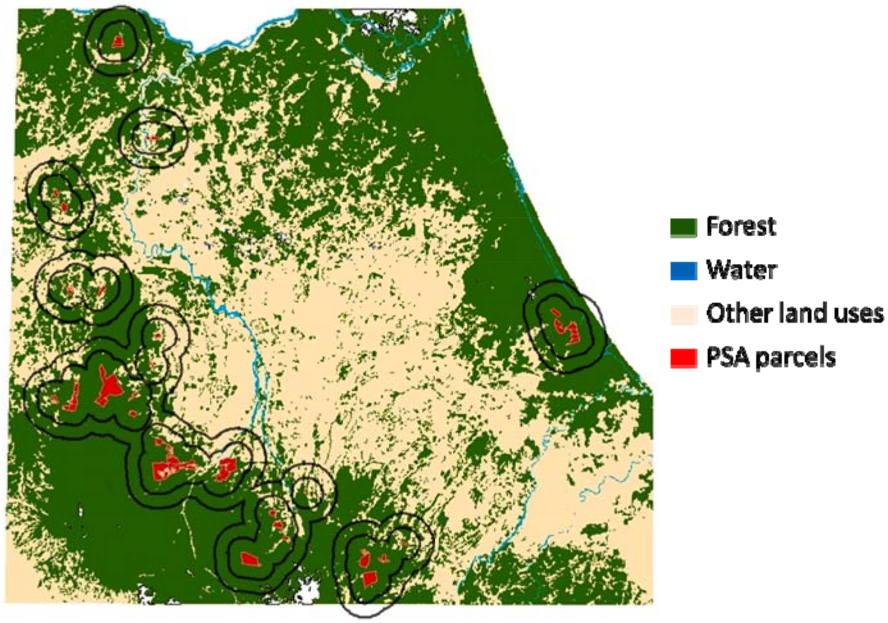
Table 2.7: Use of PSA payments, as reported by landowners)

	Percent of respondents[a]
Consumption (general household budget, food)	32
Investment in farm	30
Other investment	24
Education	8
Savings	12
Pay debts	2

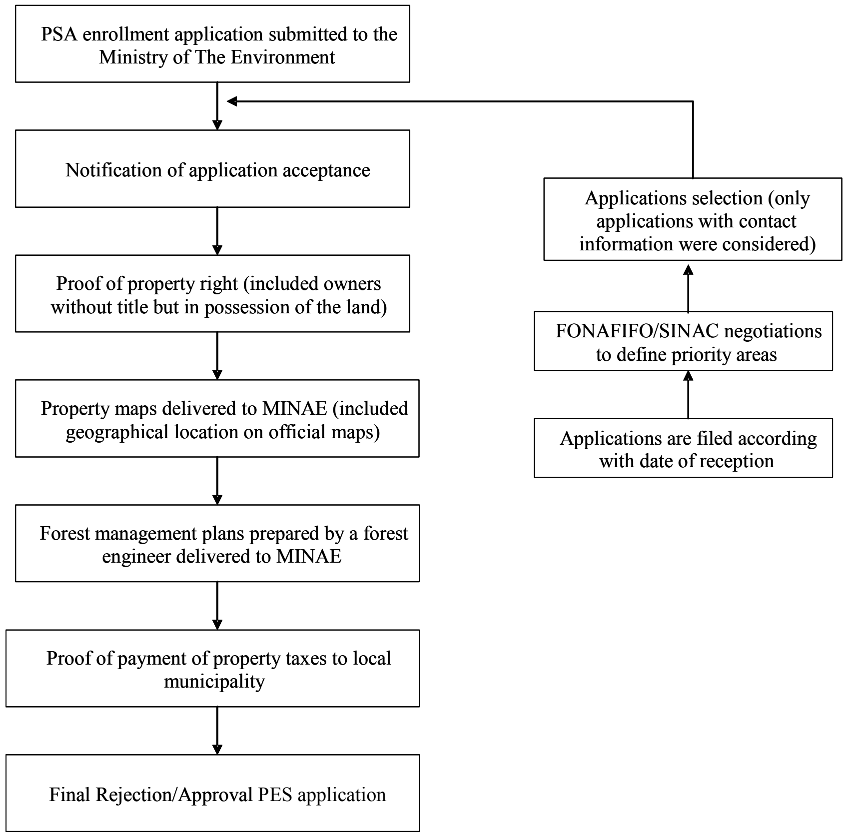
[a] Sum of percentages is greater than 100 because some landowners chose more than one alternative landuse.

APPENDICES

Appendix 1: PSA properties and regions of proximity (buffer) sampling



Appendix 2: application process to enroll in the Costa Rican Program of Payments for Environmental Services during 1997-1998



Chapter 3

ECONOMETRIC ANALYSIS OF THE COSTA RICAN PROGRAM OF PAYMENTS FOR ENVIRONMENTAL SERVICES USING HOUSEHOLD DATA FROM THE SARAPIQUI REGION

3.1 INTRODUCTION

A new paradigm is emerging in the world of environmental conservation. Conservationists have traditionally spoken of conserving the building blocks of nature−genes, species, and ecosystems, along with the air, water, and land with which these interact. But this approach has not captured the interest of those who influence the activities that degrade these building blocks (Mainka *et al.* 2008). In an effort to fill this gap, conservationists have been seeking language that will make the importance of a healthy environment more obvious and relevant to all stakeholders who make decisions upon which nature's future depends (e.g. politicians, economists, business people, and development specialists). One such concept is embodied in the idea of ecosystem services as the benefits that nature provides to people.

Ecosystem services are the benefits of natural ecosystems to households, communities, and economies. More formally, ecosystem functions refer variously to the habitat, biological or system properties or processes of ecosystems. Ecosystem goods (such as food) and services (such as waste assimilation) represent the benefits human populations derive, directly or indirectly, from ecosystem functions (Costanza *et al.* 1997).

Humanity's relationship with nature is rapidly changing. Human actors, operating at scales that are local, regional, and increasingly, global, have a substantial influence on the availability and quality of ecosystem services. In fact, human action is changing the climate, land cover, oceans, and the biogeochemistry of the fundamental cycles that sustain life, and the diversity of life itself, and although people are buffered from the natural environment by culture and technology, ultimately our livelihoods, health, and even survival are completely dependent on ecosystem services (Carpenter *et al*. 2006). More than ever before, human actions have remote effects, including on other people who are effectively invisible, far by distance, culture, and socioeconomic position (Butler and Olouch-Kosura 2006). As a consequence, loss of biodiversity, degradation of ecosystems and subsequent reduction in ecosystem goods and services are seen as major barriers to the achievement of the United Nations' Millennium Development Goals (Mertz *et al*. 2007).

Aligned with the new paradigm in environmental conservation and the evolving human relationship with nature, efforts to support the long-term sustainable supply of ecosystem services are as important to human well-being and survival as they are for nature itself. This has created a new and renovated influx of concerns about forest conservation and deforestation because forests provide an array of ecosystem services by sequestering carbon, maintaining habitat and biodiversity, stabilizing hydrological flows, mitigating soil erosion, and improving microclimates (Pattanayak and Butry 2005). More specifically, some of these ecosystem services (e.g. biodiversity conservation) have been associated primarily with mature natural and undisturbed forest given that once cleared, forests tend not to revert to mature forest (Lawrence *et al*. 2007) leading to new concerns about "gross deforestation". Other ecosystem services (e.g. carbon sequestration) have been associated with any kind of forest cover leading to new concerns about "net deforestation".

In recognition of the connectivity between forest resources and provision of ecosystem services, the responsibility for the provision of environmental services has relied on a combination of regulation and market-based approaches, though the latter have become more prominent in recent years (Landel-Mills and Porras 2002). Incentives for maintaining the provision of ecosystem services (Pagiola *et al.* 2004, Newburn *et al.* 2005) include many components. Among them are regulatory systems of payments for ecosystem services (PES), such as those currently operating in countries such as Australia, Costa Rica, and Mexico (Sánchez-Azofeifa *et al*. 2007). These payment schemes differ from traditional approaches (e.g. Integrated Conservation and Development Projects and Community-Based Natural Resource Management) in three critical ways: emphasis on human-dominated landscapes, focus on ecosystem services, and use of innovative finance mechanisms (Sánchez-Azofeifa *et al*. 2007).

However, PES programs are being implemented globally in much the same way previous conservation interventions were implemented: with an unwavering faith in the connection between interventions and outcomes and without a plan to judge the effectiveness of such interventions (Ferraro and Pattanayak 2007). If we want to ensure that our limited budgets make a difference, we must accept that testing hypotheses about what policies secure the provision of ecosystem services requires the same scientific rigor and state-of-the-art methods that we invest in testing ecological hypotheses.

This paper quantifies the impact of the first generation of contracts signed during the first phase (1997-1998) of the first long-term, large-scale payment for ecosystem services initiative for tropical forests, Costa Rica's *Programa de Pago por Servicios Ambientales* (PSA). To evaluate the impact of PSA at the landowner level, I selected a case study region in northeastern Costa Rica. The region called *Sarapiquí* consists of the cantons of *Sarapiquí*, *Guacimo*, *Pococí* and *Oreamuno*, is part of the province of Heredia, and includes two conservation areas: *Cordillera Volcánica* Central (ACCVC) and *Tortuguero* (ACTO). This region was selected because it has a sufficient number of PSA contracts to analyze quantitatively, and excellent records on PSA participants maintained by a local NGO that played a key role during this phase of PSA, targeting areas believed to have a higher deforestation risk. Because of this, PSA is most likely to have a causal impact in the Sarapiquí region.

I estimated the causal effect of PSA on net and gross deforestation using matching techniques where program outcomes of observationally similar participants and non-participants were compared. The key difference of this study with previous assessments of PSA is the careful construction of controls or comparison groups at the relevant scale (i.e. properties as opposed to regions or census districts used in previous studies) through a careful sampling design that results in a group of non-participants observationally similar to participants that can be used during the matching process. I found that evaluation of PSA causal effect is difficult because of the non-random nature of the contract allocations, and because program administrators and its partners did not implement PSA with the intention of empirically evaluating its effectiveness. Nevertheless, there is some evidence that during the initial years of PSA, the program did have a statistically significant positive effect on gross and net deforestation.

3.2 IMPLEMENTATION OF PSA

Costa Rica is one of the few countries that have tested direct payments for conservation as a policy tool on a national scale and long-term basis. According to the Costa Rican government, PSA constitutes a financial recognition by the State granted to forest and plantation owners for the environmental services rendered by them, which directly affect the protection and improvement of the environment.[1] The basic principle of PSA is that forestry is no longer valued by the public sector as such, but rather it is the services forestry provides that are rewarded by the State (Miranda *et al.* 2006).

[1] More information on PSA can be found at: http://www.fonafifo.com/paginas_english/environmental_services

PSA was not developed from scratch but is the result of a steady history of reforestation and forest protection efforts, dating from at least 1969 when timber plantation expenditures were considered deductible from the income tax according with the forestry law of 1969 (Ortiz 2002). Since that year and after the establishment of this first forestry law and the launching of the General Forest Direction (*Dirección General Forestal*, DGF), Costa Rica has been channeling a process of protection and management of forest, recovery of forest cover, control of illegal logging, and institutional development to support the forest sector (Rodríguez 2002). In 1984, the Ministry of Agriculture released a study (Junkov 1984) that found only 26.1% of the national territory was covered by forest in comparison to estimated original forest cover of 67% during the 1940s (Sader and Joyce 1998). The government reacted by creating a program of low interest loans for reforestation and soil conservation called Conservation of Natural Resources (*Conservación de Recursos Naturales*, CORENA) using funds from the United States Agency of International Development (USAID). The system of credits was progressively modified by the second and third forestry laws of 1986 and 1990 respectively (No. 7032 and No. 7174). Both pieces of legislation changed radically the rules in the forestry sector, reflecting the greater participation of small producers in the policy-making decision process. This new generation of incentives included *Certificado de Abono Forestal* (CAF) created in 1986, the *Certificado de Abono Forestal por Adelantado para Pequeños Reforestadores* (CAFA) created in 1988, the *Certificado de Abono Forestal para el Manejo del Bosque* (CAFMA) created in 1992, and the *Certificado para la Protección del Bosque* (CPB) created in 1995. The creation of the CPB program was a success from its beginning among the rest of the incentives of this kind in Costa Rica. During the first year of its application, 22,000 hectares were enrolled (the average annual enrollment of CAF and CAFA was 3,000 hectares per year, and 6,000 hectares per year for the case of CAFMA). According with an official report (FONAFIFO 2005), CPB owns its success due to the fact that landowners started to receive payments only because they were protecting the forest without the need of doing anything else. The CPB program paved the way for the implementation of PSA in 1997.

The Forestry Law 7575 from 1996 prepared the ground for the implementation of PSA, subsequently; the first payments for environmental services were made in 1997. It explicitly recognizes four environmental services provided by forest ecosystems: (i) mitigation of greenhouse gas emissions; (ii) water protection for urban, rural or hydroelectric uses; (iii) protection of biodiversity for its conservation, sustainable, scientific and pharmaceutical uses; research and genetic improvement; protection of ecosystems and life forms; and (iv) provision of natural scenic beauty for tourism and scientific purposes. The law provides the regulatory basis to contract landowners for the services provided by their forests, and established the National Fund for Forest Financing (*Fondo Nacional de Financiamiento Forestal,* FONAFIFO) which is the governmental agency in charge of administering the program (Pagiola 2006). However, during the period from 1997 to 2000, there was no attempt to measure all four environmental services (i.e. mitigation of greenhouse gas emissions, watershed protection, biodiversity conservation and landscape beauty) on a given parcel at once; rather the assumption was that an identically valued bundle of these services was provided by each hectare of enrolled parcel (Sánchez-Azofeifa *et al.* 2007).

In order to participate in the program, applications should include: a proof of identity or statutes of an organization, a legal authentication of representatives, proof of an official legal title on the land[2], of payment of local taxes, and of no-indebtedness to the National Health System (CCSS), an official cadastral map, and a copy of a cartographic map to indicate the location of the parcel. Moreover, a professional topographer should determine the size of the land and a forest engineer had to prepare a professional Forest Management Plan to be approved by SINAC. If applications are accepted, after the initial screening process described above, contracts are established for the forest area under consideration and

[2] For the period between 1997 and 1998, applicants without legal titles could show proof of possession of the land at least throughout a sworn statement signed by two witnesses. Between 1999 and 2002, possession of land should be demonstrated with at least a judicial certification proving the existence of a sentence ruling the land ownership. From 2003 and so on, landowners without a legal title that meet the requisites, in terms of being forests located in priority areas, established in the Decree No 30761-MINAE will be considered for participation in the program.

government makes annual payments on a per hectare basis[3]. Landowners are required both to maintain the land under contract in forest and to protect that forest, e.g., by establishing fire breaks where relevant, excluding livestock, and refusing access to hunters. The relevant government agencies and intermediary organizations may visit the property with the contract to ensure compliance with the agreement. In addition to the direct payments, participation in the PSA Program may give landowners access to education and technical assistance provided by intermediary organizations, and it may provide greater tenure security to the landowners against potential squatters (Miranda *et al.* 2003, Porras and Hope 2005, Arriagada forthcoming). Table 3.1 describes the different types of PSA contracts issued and payments established for the first phase of the program.

Since its inception, PSA has passed throughout different administration phases. Between 1997 and 2002, the program was administered by the Ministry of The Environment (*Ministerio del Ambiente y Energía,* MINAE) through its SINAC sub-regional offices, and from 2003, the administration of PSA was completely transferred to FONAFIFO. In terms of its functioning, PSA has also evolved considerably. Initially, the program recognized three forest activities: protection of natural forest, sustainable management of natural forest and reforestation (establishment of forest plantations). Also different types of landowners have been accepted in PSA as explained in the footnote No 2. Currently (2008), the program recognizes four activities: reforestation, natural forest regeneration, protection of natural forest, and agroforestry systems. Between 1997 and 2003, payments were also made for sustainable timber management of natural forests, although this option was always controversial and was eliminated in the re-organization of the program in 2003. Agroforestry systems were included into the program in 2003 and natural forest regeneration in 2006. In 2005, the program also experienced a substantial increase of payments levels. They were raised by approximately 50% and were established in dollars with the expectation that this

[3] In principle, all landowners could apply to the program with the exception of those who have gotten their lands through the Agrarian Development Institute (*Instituto de Desarrollo Agropuecario,* IDA). The fact that their land was transferred to them for free with the special duty to turn it into agricultural land motivates this exclusion plan (Miranda *et al.* 2006). From 2003 and so on, landowners can participate in PSA with written permission from IDA.

would reduce the rate of devaluation of the fixed payments that had previously been denominated in *colones* (i.e. Costa Rica local currency) as before.[4]

During the first phase of the program, enrollment was not based on parcel size[5], and the policy was "first come, first served". Factors such as farm size, human capital, and household economic level influenced participation in the program, and large landowners were disproportionately represented among participants at the national and regional levels in the sense that participants were shown to have considerably larger farms than non-participants (Miranda *et al.* 2003, Zbinden and Lee 2005 cited by Sánchez-Azofeifa *et al.* 2007).

As to one of the other crucial functions − technical assistance and compliance control −FONAFIFO and SINAC are officially responsible for the monitoring of the accomplishment of the contracted goals. Specifically, and according with the Decree No 30761-MINAE, contract compliance is done by SINAC and application and payments are responsibility of FONAFIFO. Technical assistance is normally done by some non-governmental organizations (NGOs) like the Foundation for the Central Volcanic Range (*Fundación para el Desarrollo de la Cordillera Volcánica Central*, FUNDECOR). FUNDECOR is the first Central American organization certified by the Forest Stewardship Council. The organization is empowered to evaluate forestry projects and to include or exclude them from the national list of certified forests and plantations (Miranda *et al.* 2006). FUNDECOR concentrates its activities around *Sarapiquí*.

In 1992, FUNDECOR in conjunction with MINAE and USAID developed a strategy of conservation and development for the Central Volcanic Range with the objective of contributing to the social and economic development through the conservation and

[4] The evolution of PSA payments between 1997 and 2007 can be obtained from the FONAFIFO webpage at: http://www.fonafifo.com/text_files/servicios_ambientales/montos.pdf
[5] Applicants should have properties no smaller than two hectares and no bigger than 300 hectares, but any property within this range could have the same priority to participate in PSA.

sustainable use of the natural resources of this region (Ortiz *et al.* 1992). As a result of this strategy, FUNDECOR acting as an intermediary organization focused the promotion of its activities on specific areas helping landowners to obtain other types of forest credits previous to PSA. [6] During the first phase of PSA, FUNDECOR focused on transitioning those initial FUNDECOR's clients over to PSA.

According with Miranda *et al.* (2006), NGOs such as FUNDECOR play a key role in PSA, assisting not only with all the paperwork required by the regional offices of MINAE and FONAFIFO, but also in organizing communications in and with the communities.[7]

3.3 DEFORESTATION IN COSTA RICA

From the arrival of the Spanish until the end of 1950s and the beginning of the 1960s, Costa Ricans cleared thousands of hectares of forest for agriculture and for cattle production (Sader and Joyce 1998, Sánchez-Azofeifa 2001 cited by Sánchez-Azofeifa *et al.* 2007). Costa Rica's deforestation rate between 1976 and 1980 had been estimated at 3.19% per year (FAO 1993). This high deforestation rate ranked the country as fifth in the world (in terms of percentage). According with Barbier and Burgess (2001) and Barbier (2001), over the last fifteen years in most tropical areas dominated by developing economies, the decline in forest and woodlands is mainly the result of land conversion, in particular agricultural expansion. They also suggest that the land expansion occurring in tropical regions could be related to structural features of the agricultural sectors of developing economies, such as low irrigation and fertilizer use as well as poor crop yields. Increasing agricultural productivity and input use reflect greater agricultural intensification and development, which in turn mean less

[6] In selecting areas in this region to promote its activities, FUNDECOR guides its decisions based on biophysical variables: land use capacity; location of recharge zones of streams, rivers, and wells; current land use, mainly location of forests, crops and pastures; and MINAE proposal to expand protected areas (Ortiz *et al.* 1992).

[7] Miranda *et al.* 2006 also say that the success of PSA depends on the NGO's because Costa Rican municipalities so far have had no responsibility for land-use planning. More information about FUNDECOR can be obtained in its webpage: http://www.fundecor.org.

pressure is put on conversion of forests and other marginal lands for use in agriculture (Barbier 1997).

However, important land use changes have occurred in Costa Rica in the last two decades. Among these new trends in land use, the slowing of deforestation due in part to falling output prices inducing, for instance, significant abandonment of cattle across the Guanacaste Peninsula has been documented as one the major new trends (Sánchez-Azofeifa 2000).A study (TSC-CIEDES-CI-FONAFIFO 1998) using Landsat satellite data acquired during 1986/87 and 1996/97 for most of the country showed the average annual alteration of existing forest to be 16,400 ha per year. However, the same study showed an increase of 126,772 ha due to the establishment of secondary forest and regeneration. Consequently, the net loss of forest was estimated to be about 3,800 ha per year during this 10-year period. According with Sánchez-Azofeifa (1996) Costa Rican deforestation rates may have been reduced as a results of several element factors: (1) an increase in the cost of wood, (2) the increase in the efficiency of harvest, (3) increased efficiency at the industrial level (4) a greater desire to protect forest by the organized rural population, (5) the increase of private reserve areas, (6) the development of financial incentives by the central government for the preservation of forest, and (7) the presence of several joint implementation initiatives.
Changes in the use of land in the Sarapiquí region have been historically influenced by three factors: (1) the population growth and the immigration of peasants in the region; (2) the expansion of the cattle-raising frontier as a result of credits/incentives aimed at meat production; and (3) the peasant migration into areas near protected zones, as a result of land-granting policies (Batterfield 1994 cited by Sánchez-Azofeifa and Quesada-Mateo 1995).

According to Sánchez-Azofeifa and Quesada-Mateo (1995), the area around Puerto Viejo de Sarapiquí (the main town in the Sarapiquí region) lost 1,023 primary forest hectares between 1986 and 1991, for an annual deforestation rate of 4.28%. A study of land use change conducted by Read et al. (2002) and cited by Joyce (2006) in a 1,440 square km area in the vicinity of Puerto Viejo de Sarapiquí using data acquired by satellite-borne sensors in

1986 and again in 1996 showed the establishment of the Chiquita banana plantations and the conversion of forest to cropland and pasture, but with some selectivity cut forest remaining outside protected forest areas. Joyce (2006), using data from March 2003, showed that other land use changes, especially with respect to palmito and pineapple plantations, had taken place in Sarapiquí.

3.4 ISOLATING PSA CAUSAL EFFECT

Deforestation rates in Costa Rica have been falling for the last two decades (Kerr *et al.* 2002) and while forest cover has increased since 1997, it is unclear to what extent this is due to PSA. According with FONAFIFO, between 1997 and 2006, 471,392 hectares have been protected by PSA (almost 10% of the national territory). Hartshorn *et al.* (2005) identify several important accomplishments including maintenance of privately-owned forests in areas of conservation significance; facilitation of private transfers of funds to rural landowners who agree to protect their forests; encouragement of female landowner and indigenous community participation in conservation activities; direct payments to a relatively greater number of small rural landowners; and, most importantly, broad public recognition that intact forests and their environmental services have value. However, they note that it is difficult to determine whether and to what degree the program contributed to the changes in land use that have been happening in Costa Rica after the implementation of PSA.

National level evaluations of PSA using methods widely recognized as best for determining causal impact have concluded that there has been effectively no impact on forest cover. For example, Sánchez-Azofeifa *et al.* (2007) examine the effect of PSA between 1997 and 2000 using ordinary least square (OLS) regressions.[8] They show that PSA coincided with a significant drop in the national rate of deforestation (1997-2000), relative to the 1986-1997 time period and the high forest rates of forest clearing between the 1960s and 1980s mentioned in the previous section. They conclude that given the very low deforestation during the study period (0.06% per year and 0.03% per year during 1986-1997 and 1997-

[8] Sánchez-Azofeifa *et al.* (2007) explain the differences in deforestation rates across space and time based on PSA density, life zones, slopes, aspect, and distances to major locations.

2000 respectively), only 7.7% of PSA payments were located close to deforestation fronts, and that the PSA contracts signed between 1997 and 2000 did not reduce deforestation rates or total deforestation in Costa Rica. Pfaff *et al.* (2008) analyze forest protection contracts for 1997-1999 using spatially-varying pixel-level deforestation rates and employing a matching approach to select a more appropriate base of comparison than all non-PSA pixels.[9] They find that PSA is likely to have had a minimal impact on deforestation during the period 1997-1999.

More regional evaluations using a variety of empirical methods have reached more optimistic conclusions about the impact of PSA. For example, the study by Tattenbach *et al.* (2006) defines the scenario that maximizes efficacy and efficiency of PSA. They develop an econometric model of gross deforestation during the period 1996-2000 using data from the the *Cordillera Volcánica Central* conservation area (ACCVC) and conclude that PSA reduces deforestation saying that primary forest cover nationwide in 2005 was about 10% greater than it would have been without PSA. Sierra and Russman (2006) evaluate the efficiency of PSA in the Osa Peninsula. In this study, the role of PSA, relative to other factors, was examined using a sample of participants and non-participants farms and a set of OLS regression models that explain variations in land cover as a function of PSA incentives and proxy measures for regional and local costs of agricultural production.[10] They conclude that payments have limited immediate effects on forest conservation and that conservation impacts are indirect and realized with considerable lag because they are mostly achieved through land use decisions affecting non-forest land cover.

[9] Pfaff *et al.* (2008) choose the control group using a probit regression to determine the effects of a location's observed characteristic on its probability of being treated. They used in the regression forest cover for 1986 and 1997, vegetation type, slope of the terrain, planning region, and distances to cities, ports, schools, sawmills, rivers, national parks, and both local and national roads.

[10] Sierra and Russman (2006) use an estimate of the relative transportation costs from each farm to the main regional transportation hub and a relative measure of each farm's terrain characteristic for the regression of the land cover characteristic of each farm.

Other studies of the Costa Rican PES program have focused on the program's impact on rural poverty and determinants of program participation (Ortiz *et al*. 2003, Miranda *et al*. 2003, Miranda *et al*. 2004, Zbinden and Lee 2005, Miranda *et al.* 2006).

Given this PSA evaluation scenario with different estimations of program impact, Pagiola (2006) emphasizes that disentangling the effect of PSA (and its predecessors) from that of other policy measures and broader economic trends is difficult, and that formal tests of the extent to which PSA program has affected forest cover have given mixed results although it is difficult to compare these results as they apply to different areas, different time periods, different dependent variables, and use different methodologies.

Previous evaluations of PSA also have additional shortcomings. National-level analysis cannot really control for selection into PSA because these studies lack data on landowner characteristics, and previous studies on determinants of participation in PSA (e.g. Ortiz *et al*. 2003, Zbinden and Lee 2005, Sierra and Rusman 2006) have generally found that PSA recipients are not observationally similar to non-participants in important aspects that can affect program outcome and participation. Some of these studies have also used state-of-the art evaluation methods (e.g. matching) but they have not tested the main identifying assumptions of their estimates (i.e. that program outcome and selection into the program can be explained using observable controls, ruling out the existence of unobservables characteristics that can affect deforestation and PSA participation). Regional level analyses have not applied most state-of-the-art evaluation methods (e.g. matching methods using household-level data) and have not evaluated the spatial dispersion of program impacts (e.g. in the context of PSA, neighbors deforestation actions could affect individuals deforestation decisions) (see Robalino and Pfaff 2005).

In this scenario with national-level analyses of PSA concluding that PSA has almost no impact on deforestation and with regional-level analysis often hampered by the cost of data collection, this paper focuses on a specific region where PSA is most likely to have an effect (due to FUNDECOR targeting of critical areas) and where quality data are available from FUNDECOR records.

3.5 RESEARCH METHODS

3.5.1 Roy-Rubin model of causal effect

In the context of a conservation initiative that pays landowners to conserve their forest resources (e.g. PES), we can observe the conservation outcome (e.g. forest cover) of those who participated and who did not participate in PES. In the prototypical model of the microeconometric evaluation literature, we can say that the landowner faces two states of the world: participation in PES or nonparticipation in PES. There is a hypothetical (potential) forest cover outcome for both states of the world. The "causal effect" is defined then as the difference between these two potential outcomes. This approach to evaluation was developed by Rubin (1974, 1977, and 1978) and now is known as the Roy (1951) and Rubin (1974) model (RRM). In this literature, the term *treatment* is used interchangeably with *cause*. It refers to any variable whose impact on some outcome is the object of the study. In the environmental economics field, examples of treatment-outcome pairs include protected areas and species conservation (e.g. Greenstone and Gayer 2007, Ferraro *et al*. 2007), forest reserves and income of local people (e.g. Blessings *et al.* 2006), and pollution regulation (Greenstone 2004).

To truly know the effect of PSA, we should compare the forest cover of participants with the forest cover that would have resulted had they not participated in the program. The impossibility of observing this so-called *counterfactual outcome* creates the evaluation problem. Within the framework of a *potential outcome model* (POM), which assumes that every element of the target population is potentially exposed to the treatment, the triple (Y_{1i}, Y_{0i}, D_i, i=1,..,N), forms the basis of treatment evaluation. In the context of PSA, the categorical variable D takes the values 1 when property is enrolled in PSA and 0 otherwise; Y_{1i} measures the forest cover for property i in the program and Y_{0i} measures forest cover when not in the program. In addition, each property has a vector of characteristics, referred to as covariates, pretreatment variables or exogenous variables, and denoted by X_i. Given that each property is either a participant in PSA or a non-participant, we observe for each property the triple (Y_i, X_i, D_i), where Y_i is the *realized outcome*:

$$Y_i \equiv Y_i(D_i) = \begin{cases} Y_i(0)\ if\ D_i = 0, \\ Y_i(1)\ if\ D_i = 1. \end{cases} \tag{3.1}$$

In the context of PSA, after the landowner has decided to enroll in the program and some time enough to see some effects on forest cover has passed, we can calculate the individual gain from PSA which is measured by $\tau_i = (Y_{1i} - Y_{0i})$. In this *ex-post* evaluation of program impact scenario, the fundamental evaluation problem arises because only one of the potential outcomes is observed for each property i (i.e. either forest cover after PSA participation or forest cover after non-participation).

Certainly, due to the inherent problems of observability mentioned above, there will be never be an opportunity to estimate individual program impacts upon forest cover with confidence. Yet, one might still hope to be able to assess the population average of gains from PSA, since we know that the population averages E[·] of the frequency distributions of Y_{1i} and Y_{0i} can be estimated for participants and non-participants, respectively (Frondel and Schmidt 2005). The average causal effect of D_i = 1, relative to D_i = 0, is measured by the population average treatment effect (ATE):

$$\tau_{ATE} = E[Y_i(1) - Y_i(0)], \tag{3.2}$$

where the short hand notation E[·|D=1] denotes the mean in the population of all properties that participate in PSA (D=1) and these expectations are with respect to the probability distribution over this population of PSA participants.[11]The average treatment effect on the treated (ATT) is defined as follows:

$$\tau_{ATT} = E[Y_i(1) - Y_i(0) \mid D = 1]. \tag{3.3}$$

[11] Distributions of (D_i, Y_i, X_i) refer to the distribution induced by the random sampling from the population.

The most commonly-used evaluation parameters are means like the ones defined in (3.2) and (3.3) (see Heckman *et al.* 1997; Heckman *et al.* 1998a; Heckman *et al.* 1998b; Frondel and Schmidt 2005; Ravallion 2008). Heckman and Robb (1984) and Heckman, Ichimura, and Todd (1997) argue that the subpopulation of treated units is often of more interest than the overall population in the context of narrowly targeted programs. ATT will be the focus of this paper (i.e. the average effect of PSA on participants).

In the use of observational data generated under nonrandom treatment assignment, the consistent estimation of ATT will be threatened by several complications that include, for example, possible correlation between the outcomes and treatment, omitted variables, and endogeneity of the treatment variable (Cameron and Trivedi 2005). In particular, the counterfactual mean for those PSA participants − $E[Y(0)|D=1]$ − is not observed, then one has to choose a proper substitute for it in order to estimate ATT. In an *ex-post* evaluation of PSA, we can use the mean forest cover of non-participants properties $E[Y(0)|D=0]$, however in non-experimental studies this is usually not a good idea, because it is most likely that components which determine PSA participation also determine forest cover. Moreover, in a voluntary initiative like PSA, we might anticipate that those who volunteer differ from the wider eligible population of landowners in terms of their expected gains from the program (endogenous selection). Landowners in some regions may perceive greater benefits from participation in the program and for that reason they decide to participate. In the study region, FUNDECOR played an active role during the first phase of PSA targeting critical areas believed to be under greater deforestation threat. Thus, the forest cover of properties from PSA and non-PSA groups will differ even in the absence of PSA leading to a *self-selection bias*. This bias is not likely to be zero for most environmental applications (Bennear 2006).

In observational studies where assignment to treatment is not random one has to invoke a set of *identifying assumptions* (i.e. assumptions that allow you to identify the true causal effect). In fact RRM clarifies that the average causal treatment effect is generally not identified. Identification is obtained by untestable assumptions, and their plausibility depends on the substance of the economic problem analyzed and the data available (Lechner 2002).

Assumption 1 (*Unconfoundedness or Conditional Independence Assumption*)

Under this assumption, we can say that given the set of observable covariates *X* which are not affected by treatment, potential outcomes are independent of treatment assignment:

$$(Y_i(0),\ Y_i(1)) \perp D_i |\ X_i. \tag{3.4}$$

This implies that selection is solely based on observable characteristics and that all variables that influence treatment assignment and potential outcomes simultaneously are observed by the researcher (Caliendo and Kopeinig 2005). Under this assumption, we say that there is *selection on observables*.

Assumption 2 (*Overlap or Common Support*)

This assumption rules out the phenomenon of perfect predictability of *D* given *X*:

$$0 < P(D=1|X) < 1 \tag{3.5}$$

It ensures that people with the same *X* values have a positive probability of being both participants and non-participants (Heckman, LaLonde and Smith 1999). We shall say that treatment assignment is strongly ignorable given a vector of covariates by combining both the unconfoundedness and overlap assumptions (Rosenbaum and Rubin, 1983). Heckman *et al*. (1998b) discovery of the empirical importance of imposing a common support condition in reducing bias as conventionally measured demonstrates the benefit of a nonparametric approach to econometrics. Rigorous application of nonparametric methods entails careful specification of the domain over which estimators can be identified.

There has been some controversy about the plausibility of assumptions 1 and 2 in economic settings. Imbens (2007) offer three arguments for considering these assumptions. First, a natural starting point in the evaluation of any program is a comparison of average outcomes for treated and control units, and then an adjustment of any difference in average outcomes for differences in exogenous background characteristics. Second, almost any evaluation of a treatment involves comparisons of units who received the treatment with units who did not, and where the key is to identify which units best represent the treated units had they not been treated. Third, even when agents optimally choose their treatment, two agents with the same values for observed characteristics may differ in their treatment choices without invalidating the unconfoundedness assumption if the difference in their choices is driven by differences in unobserved characteristics that are themselves unrelated to the outcome of interest.

Given strongly ignorable treatment assignment one can identify the population average treatment effect τ by first estimating the average treatment effect for a subpopulation with covariates $X = x$, and then we can show:

$$\begin{aligned} \tau(x) &\equiv E\,[Y_i(1) - Y_i(0)|X_i = x\,] = [E\,[Y_i(1)|X_i = x] - E\,[Y_i(0)|X_i = x] \\ &= E\,[Y_i(1)|X_i = x\,, D_i = 1] - [E\,[Y_i(0)|X_i = x, D_i = 0] \\ &= E\,[Y_i|X_i = x, D_i = 1] - E\,[Y_i|X_i = x, D_i = 0] \end{aligned} \tag{3.6}$$

The second line in equation (3.6) holds because of the ignorability of treatment conditional on *X*. Now, to make the last line feasible, one needs to be able to estimate the expectations $E\,[Y_i|X_i = x, D_i = d]$ for all values of *d* and *x* in the support of these variables. This is where the overlap assumption enters. If this assumption is violated at $X = x$, it would be infeasible to estimate both $E\,[Y_i|X_i = x, D_i = 1]$ and $E\,[Y_i|X_i = x, D_i = 0]$ because at those values of *x* there would be either only treated or only control units.

One can weaken the unconfoundedness in a different direction if one is only interested in the average effect for the treated (see, for example, Heckman, Ichimura and Todd, 1997; Imbens 2004; Abadie and Imbens 2006a). In the case one need only assume[12]:

[12] Assumption 3 and 4 are sufficient for identification of ATT because the moments of the distribution of $Y_i(1)$ for the treated are directly estimable (Imbens, 2004).

Assumption 3 (*Unconfoundedness for Controls*)

$$Y_i(0) \perp D_i \mid X_i. \tag{3.7}$$

and the weaker overlap assumption

Assumption 4 (*Weak Overlap*)

$$P(D=1|X) < 1 \tag{3.8}$$

Finally, to make the model's representation of outcomes adequate for causal analysis, the *stable-unit-treatment-value assumption* (SUTVA) has to be satisfied for all members of the population (Rubin 1986). In economics, this is sometime referred to as no-macro-effect or partial equilibrium assumption. SUTVA, as implied by its name, is a basic assumption of causal effect stability that requires that the potential outcomes of individuals be unaffected by potential changes in the treatment exposures of other individuals (Morgan and Winship 2007). In the words of Rubin (1986:961), who developed the term,

> SUTVA is simply the a priory assumption that the value of *Y* for unit *u* when exposed to treatment *t* will be the same no matter what mechanism is used to assign treatment *t* to unit *u* and no matter what treatments the other units receive.

Rather than consider SUTVA as overly restrictive, researchers should always reflect on the plausibility of SUTVA in each application and use such reflection to motivate a clear discussion of the meaning and scope of a causal effect estimate (Morgan and Winship 2007). This will be discussed in the results section of this paper.

3.5.2 Multivariate matching

Matching estimators impute the missing potential outcomes, but do so using only the outcomes of the most similar observations not in the treatment group. This method is based on the unconfoundedness identifying assumption. This assumption produces a comparison group that resembles the control group of an experiment in one key respect: conditional on *X*, the distribution of potential outcomes given treatment assignment is the same. In the absence of experimental data, which is largely the case of conservation initiatives like PSA where contracting assignment is not random, the popularity of matching is due to its intuitively appealing technique of mimicking an experiment *ex post* (Kluve *et al.* 2007).

In a typical matching setting, covariate data are available for a large sample of potential control subjects but only a relatively small treated sample, and the goal of matching is to select a subset of the control sample that has covariate values similar to those in the treated sample (Rubin and Thomas 2000). Traditional matching methods pair nonparticipants with participants that are "close" in terms of X using different metrics, and given these matching metrics, the researcher only has to choose the number of matches. Within the class of matching estimators, using only a single match leads to the most credible inference with the least bias, at most sacrificing some precision (Imbens 2007). Adapting Heckman *et al.* (1998a), for each observation i in the participant sample, a weighted average of comparison sample observations is formed to estimate the average treatment effect on i:

$$Y_{1i} - \sum_{j \in \{D=0\}} W_{N_0 N_1}(i,j) Y_{0j}, \tag{3.9}$$

where $\sum_{j \in \{D=0\}} W_{N_0 N_1}(i,j) = 1$ for all i.

Matching estimators differ in the weights attached to members of the comparison group. Following Heckman *et al.* (1998a), let's define a neighborhood $C(X_i)$ for each participant i. The persons matched to i are in A_i where $A_i = \{j \in \{D = 0\} | X_j \in C(X_i)\}$. Different matching methods use different neighborhoods. Nearest neighbor matching sets $C(X_i) = \{X_i | X_i = \min_i \|X_i - X_j\|, j \in \{D=0\}\}$ where $\| \ \|$ is a norm, $W_{N_0 N_1}(i,j)=1, j \in A_i$, and $W_{N_0 N_1}(i,j)=0$ otherwise. When there are several covariates, multivariate matching methods generally utilize dimension reduction techniques, which involve matching on a distance measure or (often one-dimensional) summary of the covariates. The most popular metrics are the Mahalanobis metric. Mahalanobis metric matching is an example of a full-rank matching method, where full-rank refers to the fact that the distance between two units is 0 if and only if the distance between each of the covariates is 0. The Mahalanobis distance on covariates *X* between units *i* and *j* is:

$$d_M(x_i, x_j) = (x_i - x_j)' \Sigma^{-1} (x_i - x_j), \tag{3.10}$$

where Σ is the covariance matrix of the covariates, and the inverse variance diagonal version of that is (see Abadie and Imbens 2006a):

$$d_{AI}(x_i, x_j) = (x_i - x_j)' diag(\Sigma^{-1}) (x_i - x_j), \tag{3.11}$$

I will call in this paper the estimator that uses the distance defined in (3.10) as the *Mahalanobis Multivariate Matching Estimator*, and the estimator that uses the distance defined in (3.9) as the *Inverse-Variance Multivariate Matching Estimator*. In these formulas, Σ is the control group variance-covariance matrix given my interest in estimating the effect of PSA on participant properties, and thus in predicting the potential forest cover outcome under non-participation for the PSA participants.

According with Imbens (2003), matching estimators have been most often applied in settings with the following characteristics: (i) the interest is in the average treatment effect for the treated, (ii) there is a large reservoir of potential controls. Now, two major challenges when moving to matching in a multivariate setting are (1) difficulty in defining and finding close matches in a multidimensional space, and (2) generalizing the theoretical results to determine settings where the matching is guaranteed to not be increasing bias in the outcome. When interest is in estimating the treatment effect for the full treated group, Rosenbaum and Rubin (1985) caution against multivariate methods that require exact matches on covariate categories (either categorical covariates or categories defined by ranges of continuous covariates), because it can greatly limit the number of matches obtained.

3.5.3 Matching on the propensity score

Use of propensity score has become a common tool for reducing bias in observational studies. Since the work by Rosenbaum and Rubin (1983) there has been considerable interest in methods that avoid adjusting directly all covariates, and instead focus on adjusting for differences in the propensity score, the conditional probability of receiving the treatment. According with the unconfoundedness, conditioning on all relevant covariates is very limiting in case of a high dimensional vector X. For instance, if X contains s covariates which are all dichotomous, the number of possible matches will be 2^s. To deal with this dimensionality problem, Rosenbaum and Rubin (1983) suggest using the so-called *balancing score, b(X).* They show that if potential outcomes are independent of treatment conditional on covariates X, they are also independent of treatment conditional on a balancing score. The propensity score $Pr(D = 1|X) = e(X)$, i.e. the probability for an individual to participate in a treatment given his observed covariates X, is one possible balancing score.[13]

Given that unconfoundedness assumption holds and assuming that there is overlap between both groups (i.e. we have strong ignorability), the propensity score matching estimator for ATT can be written in general as:

$$\tau_{PSM}^{ATT} = E_{P(X)|D=1}\{E[Y(1)|D = 1, e(X)] - E[Y(0)|D = 0, e(X)]\}. \tag{3.12}$$

To put it in words, the propensity score matching estimator is simply the mean difference in outcomes over the common support, appropriately weighted by the propensity score distribution of participants.

As the case with multivariate matching, the most straightforward matching estimator is nearest neighbor matching (NN) where the individual from the control group is chosen as a matching partner for a treated individual that is closest in terms of propensity score. Several variants of NN matching are proposed, e.g. NN matching 'with replacement' and 'without replacement'. In the former case, an untreated individual can be used more than once as a match, whereas in the latter case it is considered only once.

[13] Rosenbaum and Rubin (1983) show that the propensity score, $e(X)$, is a balancing score and that any score that is 'finer' than the propensity score is a balancing score; moreover, X is the finest balancing score and the propensity score is the coarsest.

NN matching faces the risk of bad matches, if the closest neighbor is far away. This can be avoided by imposing a tolerance level on the maximum propensity score distance (caliper). Imposing a caliper works in the same direction as allowing for replacement. Bad matches are avoided and hence the matching quality rises (Caliendo and Kopeinig 2005). Dehejia and Wahba (2002) suggest a variant of caliper matching which is called radius matching (RM). The basic idea of this variant is to use not only the nearest neighbor within each caliper but all of the comparison members within the caliper.

NN uses only the nearest neighbor of the treated observation and RM uses a few observations from the comparison group that are within the defined caliper. Kernel matching (KM) is a non-parametric matching estimator that uses a different definition of neighborhood by using all individuals in the control group to construct the counterfactual outcome (similar to the specification in (3.7) for the case of multivariate matching). Thus, one major advantage of this approach is the lower variance which is achieved because more information is used. A drawback of this method is that possibly observations are used that are bad matches. Hence, the proper imposition of the common support condition is of major importance for KM.

In the context of multivariate matching discussed in the previous section and matching on the propensity score, matching with replacement involves a trade-off between bias and variance. If we allow replacement, the average quality of matching will increase and the bias will decrease (Caliendo and Kopeinig 2005). This is of particular interest in cases where we don't have a significant overlap in the propensity scores between treatment and control groups. This can be overcome by allowing replacement, which in turn reduces the number of distinct non-participants used to construct the counterfactual outcome and thereby increases the variance of the estimator (Smith and Todd 2005).

3.6 DATA

3.6.1 Study Region

The *Heredia* province is located in the north-central part of Costa Rica. To the north it borders Nicaragua, to the east is the province of *Limón*, to the south the province of *San José*, and to the west *Alajuela*. The capital is the city of Heredia. The province covers an area of 2,657 km², and has a population of 368,334 according to the 2000 Census.

While Heredia province is perhaps best known as a northern suburban area of the capital city of San José, its great majority lies in the much less populated northern lowlands and rainforests of the Sarapiquí region, bordering Nicaragua and the San Juan River Basin. Some of the most famous travel destinations in this province are the Barva Volcano and Braulio Carrillo National Park. The Sarapiquí River is born on the slopes of the Barva and Poas Volcanoes, and quickly becomes much larger, offering some of Costa Rica's finest locations for whitewater rafting and kayaking. In the highlands areas of Heredia, tourism includes coffee plantation tours and Spanish language schools combined with adventure and nature tours. Many of these include bed and breakfasts, small hotels, and home stay with Costa Rican families.[14]

The geographical variation contained within this province (the smallest of Costa Rica's seven) gives it a wide range of climatic conditions, from warm and humid lowlands, to cool and damp highlands, to the mild but seasonally wet and dry Central Valley. The ACCVC cover almost all the Central Valley and due to its climatic and topographic variation there is a great variation of ecosystems. 9 out of the 12 Holdridge life zones defined for Costa Rica are contained in this conservation area. In recognition to its biological diversity and socio-economic characteristics, in 1998 UNESCO designated ACCVC as Biosphere Reserve.

[14] http://www.costaricaroadmaps.com/Heredia-Province.html

ACTO is known for containing the greatest area of humid tropical forest. Birds' species are abundant (309 known species)[15]. Figure 1 shows the study region.

3.6.2 Household Survey

The objective of this study is to evaluate the impact of the first phase of PSA contracts (i.e. PSA contracts signed between 1997 and 1998). The sample contains only forest conservation contracts assisted by FUNDECOR that had been renewed and were currently in force during the implementation of the survey in 2005 (i.e. indicating continued participation in PSA). Remote sensing data combined with self-reported land use allowed me to consider impacts on forest cover. The final database will consist of the survey data, program records for PSA participants, forest cover before and after the program derived from classified Landsat TM images (Atlas Digital de Costa Rica 2004) and from self-reports, and other spatially referenced data on markets and biophysical characteristics.

During the first phase of PSA, 67 and 56 PSA protection contracts assisted by FUNDECOR were signed during 1997 and 1998 respectively. These 123 contracts protected approximately 11,630 hectares in the study region. Out of these 123 contracts, 70 were assisted by FUNDECOR and then renewed after completing the stipulated five years (i.e. these contracts were in force in 2005 when the survey was implemented). FUNDECOR's records for current contracts include data from the time of application, such as ownership type, hectares owned, biophysical characteristics, and location. From these 70 contracts, 50 participants were randomly selected to be included in the survey. For the case of non-participants, we used a combination of a geographic sampling rule to select 51 immediate neighbors (cf, Zindben and Lee 2005) and 102 from the records of the national land registry (*Catastro Nacional*) selected by district and by buffer zones around the PSA properties in our sample. The national land registry provides the most complete sampling frame of landowners with tenure and therefore eligible for PSA contracts on those years (i.e. 1997 and 1998). In

[15] Information on ACCVC and ACTO was obtained from the official webpage of SINAC http://www.sinaccr.net/

order to obtain the final sample of non-participants, we filtered out properties smaller than 5 hectares (the minimum required by the program is 3 hectares), properties listed in FONAFIFO's records as having PSA protection contracts, and properties owned by the state and large companies. After this process, for each PSA property, we randomly selected one landowner in the same district for a total of 44 and a group of 58 landowners with properties located in buffers around each PSA property. This sampling method, that included non-immediate neighbors of PSA participants, was designed to pre-match landowners for characteristics that are spatially correlated, including biophysical factors and access to markets and public services, but avoid spill-over effects due to communication among neighbors or stricter enforcement of environmental laws near properties with PSA contracts. Figure 3.2 shows the buffer zone drawn around PSA participants in the study region.

The household survey elicited information about landowner socio-economic characteristics (i.e. age, education, city of origin, marital status, occupation, household composition, etc.), property (land size, soil quality, slope, etc.) and land management (e.g. land titling, previous farming experience, hired and family labor, area under different land uses, etc.). Before beginning an interview, the interviewers verified that the landowner (a) owned or managed the property in the sampling frame since 1996; (b) had at least some natural forest cover on that property in 1996; and (c) had never held a PSA forest protection contract.

3.6.3 Case studies

For this study, we integrate qualitative interviews with the quantitative survey. First, through careful observations, conversations, and review of records at FUNDECOR, FONAFIFO, and SINAC, we developed a detailed description of program administration. Within an iterative field research framework, information was gathered through (a) semi-structured interviews with government officials and forestry professionals, and (b) case studies of participant and non-participant forest landowners based on in-depth interviews, field visits, and review of records. The main objective of these case studies and semistructure interviews was the identification of the main driving forces that determine participation in PSA, especially for the years included in this analysis.

3.6.4 Self-reports vs. aerial photographs

The household survey elicited information on property characteristics including self-reported land cover. Landowners were directly asked about land uses in 1996 (i.e. recollection of land use one year before the PSA implementation) and 2005 (i.e. the date when the survey was implemented).

Specifically the survey elicited information on number of hectares with mature native forest (i.e. forest with trees older than 20 years old), regeneration (i.e. forest with trees younger than 20 years old), plantations, crops and pastures. Changes in mature native forest cover between 1996 and 2005 will be used as a proxy for gross deforestation given that it would take more than 9 years to consider areas with natural regeneration as areas with mature forest (i.e. we can expect that areas with regeneration in 1996 would still be considered regeneration in 2005). Therefore any change in mature forest cover will be a direct cause of the area covered by mature forest in 1996 and won't be affected by new transitions into mature forest from other classes (e.g. regeneration, crops or pastures).

GPS readings on the farm were also taken, and when possible linked to maps from the national land registry to create a GIS layer with property polygons. Land use changes in 1986, 1992 and 2005 were then estimated for those properties in the GIS layer using aerial photos. Specifically, aerial photos provided information on number of hectares with total native forest cover (i.e. it includes mature native forest and regeneration). Changes in total native forest cover will be used as a proxy for net deforestation (i.e. gross deforestation minus all area transitions into native forest classes from all other classes). These estimates of land use changes will also allow comparing them with changes reported by landowners during the survey, and check the consistencies of the estimated land use changes using both sources of information.

3.7 EMPIRICAL STRATEGY

The causal effect of PSA on forest cover changes was estimated using PSA forest conservation contracts signed between 1997 and 1998 in the study region. PSA and Non-PSA groups were compared after controlling for pre-PSA (i.e. predetermined) observable socio-economic and biophysical characteristics which determined selection into the program and are likely to have affected outcomes (i.e. changes in forest cover). First, I generate estimates of program impact using simple OLS regression. Second, I employed multivariate matching and propensity score matching to improve covariate balance and relax functional form assumptions.

3.7.1 Ordinary least squares

I first estimate the effect of PSA conservation contracts, signed between 1997 and 1998 in the study region, using a dummy that indicate program participation and a full set of exogenous (i.e. pre-determined before PSA) socio-economic and biophysical controls, self-reported land use for 1996 and land use for 1992 obtained from aerial photos. The model can be written as:

$$y_i = PSA_i + \alpha' X_i + \gamma' Z_i + \theta' W_i + \delta'(HistUse_i) + \varepsilon_i \qquad (3.13)$$

where y_i can be defined as the change (1996-2005) in mature native forest cover (i.e. intervened and non-intervened primary (>20 years) natural forest) obtained from self-reports or as the change (1992-2005) in total native forest cover (i.e. intervened and non-intervened primary (>20 years) natural forest and secondary (<20 years) natural forest) obtained from aerial photos (separate regressions will be estimated in both cases) for parcel i. PSA_i is a dummy that indicates participation in the program (i.e. PSA_i = 1 if parcel i has a PSA conservation contract signed between 1997 and 1998, and PSA_i = 0 otherwise), X_i is a vector of socio-economic household characteristics (i.e. years of education of respondent, age, household labor force in 1996, place of origin), Z_i is a vector of land management controls (i.e. experience with forest plantations before 1996, forest management plan before 1996, previous participation in other forest programs, resident on parcel in 1996), W_i is a vector of biophysical land characteristics (distance to forestry office, parcel size, % of parcel with steep slope and poor soil) , $HistUse_i$ is a vector with self-reported land uses for 1996 or with land use from 1992 obtained from aerial photos, and ε_i is the error term.

3.7.2 Multivariate matching

In selecting covariates, by the usual rule for avoiding omitted variables bias, one should include all variables that affect both the treatment assignment and, controlling for the treatment, the dependent variable. To avoid post-treatment bias, we should also exclude variables affected by the treatment (Ho *et al*. 2007). The theoretical literature emphasizes that including variables only weakly related to treatment assignment usually reduces bias more than it will increase variance (Rubin and Thomas 1996, Heckman *et al*. 1998), and so most believe that all available control variables should always be included. However, the theoretical literature has focused on the case where the pool of potential controls is considerably larger than the set of treated units. According with Ho *et al*. (2007) if, as is often the case, the pool of potential control units is not much larger than the pool of treated units, then always including all available control variables is bad advice. Instead, the familiar econometric rules apply about the tradeoff between the bias of excluding relevant variables and the inefficiency of including irrelevant ones. In general, economic theory, a sound knowledge of previous research and also information about the institutional settings should guide the researcher in building up the model (see e.g. Smith and Todd 2005 or Sianesi 2004). Heckman *et al*. (1998b), in their evaluation of a social program, also show the value of having good data. They show that access to a geographically-matched comparison group administered the same questionnaire as program participants is essential in constructing comparison groups that have outcomes close to those of an experimental control group.

According with Abadie and Imbens (2006a) the number of discrete covariates that are used in the matching process does not affect the asymptotic properties of the estimators. In small samples, however, matches along discrete covariates may not be exact, so discrete covariates may create the same type of biases as continuous covariates. For our case, I will follow recommendations from previous studies, and from the case studies and household survey.

In the context of PSA, we need to control for variables that affect program participation and land use. Our case studies, interviews with local forest officials, representatives of government agencies and intermediary organizations serve this purpose. For a PSA contract to be put in place, the landowner must volunteer to participate in the program, and the program administrators must accept his or her application. In Sarapiquí, FUNDECOR also plays a fundamental role as an intermediary organization, especially in first phase of the program (Sills *et al*. forthcoming) when 'critical areas' were defined based on population, logging activities, proximity to IDA settlements, slope and road infrastructure, and these areas were given priority to be introduced in PSA (see Ortiz *et al.* 1992). Arriagada *et al*. (forthcoming) report on the reasons that case study landowners gave for their decisions on participating in PSA. While these motivations are not mutually exclusive, the lack of an alternative use for the farm appeared to have the greatest influence on the decision to participate in PSA. Ortiz *et al*. (2003) find that often PSA translates into an economic incentive that halts deforestation in exchange of a short-term income, especially on marginal lands. Neither the case study landowners nor governmental officials indicated that environmental beliefs are a major factor. During the first phase of PSA, MINAE did not promote the program, with the result that there were initially almost only applications from people who for various reasons were familiar with the MINAE regional offices (for example, because they submitted forest management plans for MINAE's approval) (Sills *et al*. forthcoming). In the case of contracts processed by FUNDECOR in Sarapiquí, the first contracts were written with landowners in critical areas defined mainly on being subject to a higher deforestation risk as explained in Ortiz *et al.* (1992). Zindben and Lee (2005) report that education, access to extension, and participation in meetings are key determinants of which landowners enroll in PSA.

Matching is done with replacement which allows reducing bias, since it produces matches of higher quality than matching without replacement.[16] For estimating the conditional variance we use the estimator proposed by Abadie and Imbens (2006a) which does not require consistent nonparametric estimation of $\sigma_d^2(x)$ (i.e. the conditional outcome variance). This is particularly relevant because there is evidence that the bootstrap is not valid with non-smooth nearest-neighbor estimators.[17] If the conditional outcome variance differs by treatment status and covariates, one needs to estimate it for all sample points (Abadie *et al*. 2004), then I used the robust version of the formula to allow for heteroskedasticity using two neighbors in the second-stage matching, which allows the treatment effect to be non-constant.[18,19]

Abadie and Imbens (2006a) show that with k continuous covariate the estimator will have a term corresponding to the matching discrepancies (i.e. the difference in covariates between matched units and their matches) that will be of the order $O_p(N^{-1/k})$. In practice one may therefore attempt to remove some of this bias term that remains after the matching; then I used a post-matching bias-correction procedure that asymptotically removes the conditional bias term in finite samples (i.e. the bias-corrected matching estimator adjusts the difference within the matches for the differences in their covariate values).

[16] Multivariate matching was done using "Multivariate and Propensity Score Matching Software with Automated Balance Optimization: the Matching Package for *R*" developed in Sekhon (Forthcoming) and using the estimators of average treatment effects developed in Abadie *et al.* (2004).
[17] Abadie and Imbens (2006a) show that when the set of matching variables contains at most one continuously distribution variable (e.g. propensity to participate in PSA), the conditional bias term is $o_p(N^{-1/2})$, so that matching estimators are $N^{1/2}$-consistent in this case.
[18] I specified two matches in estimating the conditional variance functions given that in the data this number seems to include sufficient information without matching unlike individuals which was confirmed using t- tests for the balancing between the treatment and control groups of the covariates used in the matching.
[19] The *R* package Matching implements a variety of algorithms for multivariate matching including propensity score, Mahalanobis, inverse variance and Genetic Matching (GenMatch). The last of these is a genetic search algorithm which automatically finds the set of matches which minimize the discrepancy between the distribution of potential confounders in the treated and control groups—i.e., covariate balance is maximized. This stage is the so-called first-stage matching. During the second-stage matching, you have to run the Match command in order to obtain causal effect estimators, standard errors and balance statistics.

3.7.3 Matching on the propensity score

In the context of PSA, the propensity score is the probability of being a program participant, conditional on a number of control variables: *Pr(D=1/X)*. In that sense, the propensity score is a function of the control variables. Let's imagine a formula where you plug in the values of the covariates (e.g. landowner age, education, parcel size, etc.) and you get out the probability that the parcel will be in PSA. Now, as was the case with multivariate matching, because participation in PSA requires allocation of land to forest, the characteristics of landowners and parcels that determine participation in PSA are also likely to determine land use, including changes in forest cover, which is the program outcome being analyzed in this study. Therefore, in the estimation of propensity scores, it is most important to include variables that influence simultaneously the participation decision and the outcome variable. When estimating the propensity score two choices have to be made. The first one concerns the model to be used for the estimation, and the second one the variables to be included in this model.

Regarding the model choice, little advice is available regarding which functional form to use for the estimation of the propensity score. In principle any discrete choice model can be used. Preference for logit or probit models (compared to linear probability models) derives from the well-known shortcomings of the linear probability model, especially the unlikeness of the functional form when the response variable is highly skewed and predictions that are outside the [0, 1] bounds of probabilities. For the binary treatment case, where we estimate the probability of participation vs. non-participation (e.g. PSA vs. Non-PSA), logit and probit models usually yield similar results. Hence, the choice is not too critical (Caliendo and Kopeinig 2005). I use a maximum likelihood logit model to estimate the probabilities. In the general framework of probability model we have: *Prob*(PSA participation) = *Prob*(D=1) = *F*[relevant effects, parameters]. In this case, the probability of participation in PSA is a cumulative distribution function F evaluated as a function of a set (X) of explanatory variables that include household socio-economic and land biophysical characteristics, and a vector β of unknown parameters. The probability of participation model can be written as:

$$Prob(D_i = j) = \frac{e^{\beta' x_{ij}}}{e^{\beta' x_{i0}} + e^{\beta' x_{i1}}} \; for \; j = 0, 1. \tag{3.14}$$

For the decision about which variables to include in the model, there is more available advice regarding the inclusion (or exclusion) of covariates in the propensity score model (Caliendo and Kopeinig 2005). As for the case of multivariate matching, the matching on the propensity score strategy builds on the conditional independence assumption, requiring that the outcome variable (i.e. forest cover change) must be independent of treatment (i.e. PSA) conditional on the probability of PSA participation (i.e. the propensity score). Heckman, Ichimura and Todd (1997) show that omitting important variables can seriously increase bias in resulting estimates.

It is important to note that there is a trade-off in finite samples between the plausibility of the CIA and the variance of the estimates. When using a full specification, bias arises from selecting a wide bandwidth in response to the weakness of the common support. In contrast to that, when matching on the minimal specification, common support is not a problem but the plausibility of the CIA is.

I selected explanatory variables departing with a parsimonious specification of the propensity score, and from there I started adding more controls. For the case of the estimation of propensity score it is important to obtain a good predictive power without sacrificing the unconfoundedness and overlap assumptions, and then the balance between common support and CIA will also be considered in selecting variables. Following Ho *et al*. (2007), I also recognize the value of the *propensity score tautology* which is the main justification for using this technique: the estimated propensity score is a balancing score when we have a consistent estimate of the true propensity score, and we know we have a consistent estimate of the propensity score when the propensity score method balances the raw covariates.[20]

For nearest neighbor propensity score matching, I present results with bootstrap standard errors using 999 repetitions and Abadie-Imbens bias corrected standard errors. For radius and kernel matching, I only use bootstrap standard errors using 999 repetitions.[21]

3.8 RESULTS

3.8.1 Program participants vs. non-participants

The landowners who we interviewed are characterized in Table 3.3, which reports descriptive statistics for socioeconomic characteristics of their households, historical and current management of their properties, and biophysical land characteristics using available cases. The table compares landowners who do not participate in PSA (column 1) to landowners with PSA forest protection contracts signed between 1997 and 1998 (column 2), reports the p-value for standard t-tests for the difference in means (column 3) and the initial standardized difference in percentage (column 4). It is important to emphasize that these statistics are descriptive and not inferential, in the sense that they do not purport to estimate relevant population parameters, but rather simply describe the two samples and their differences. According with Table 3.3, landowners with PSA contracts are similar on average to our pre-matched comparison sample of non-PSA landowners on many counts, including family structure (i.e. fraction of family are women and men), landowner age and education, management of the parcel (e.g. family members working on parcel, experience with plantations before 1996, years of experience with agriculture, etc.), and basic biophysical characteristics of the property (distance to nearest agricultural and forestry office, percent of

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[20] Propensity score was done is Stata v.9 using PSMATCH2: Stata module to perform full Mahalanobis and propensity score matching, common support graphing, and covariate imbalance testing by Leuven and Sianesi (2003).

[21] Abadie and Imbens (2006b) prove that the bootstrap is not valid for the standard nearest-neighbor matching estimator with replacement although empirical applications of the method still use it (see, for example, Ferraro *et al.*2007). However, if the number of neighbors increases (as it is the case for RM and KM) the matching estimator does become asymptotically linear and sufficiently regular for the bootstrap to be valid.

land with steep slope and poor soils, etc.). However, as can be seen from Table 3.3, there exists considerable initial bias between the PSA and non-PSA groups. For instance, PSA participants are more likely to be from the Central Valley near San José (that is, not born in the region where they now own a parcel) and less likely to have been resident in the parcel in 1996 and 2005. They are also less likely to have fenced their forest in 1996. PSA participants are also more likely to have prepared forest management plans before 1996 and participated in other forest programs before 1996. Finally, they own significantly larger properties on average, with steeper slopes. In terms of initial standardized differences, twelve of the sixteen continuous covariates have initial standardized differences larger than 10%. Clearly, pre-matching using immediate and non-immediate neighbors of program participants did not eliminate differences in these variables, suggesting that they are related to some self-selection or administrative targeting process for PSA.

Another diagnostic assessment compares the pairwise available-case correlation between the 16 continuous variables in Table 3.3. Suppose that we plotted the 120=16×15/2 pairwise correlations in the PSA group against the pairwise correlations for the non-PSA group. If the groups had similar distributions of their pairwise correlations, then they would have approximately the same means and variances, and we would see a roughly linear relationship (D'Agostino and Rubin 2000). The mean correlation is 0.029 in the PSA group and 0.058 in the non-PSA group, and the corresponding variances are 0.034 and 0.030, indicating larger and less variable correlations for the non-PSA group. Moreover, the R^2 value of 0.42 is not particularly high. These results just show another way to summarize aspects of the observed data for comparison across treatment groups.

The initial PSA versus Non-PSA group differences summarized in Table 3.3 and the R^2 value indicate the possible extent of biased comparisons of outcomes due to different distributions of observed covariates in the PSA and Non-PSA groups. Ideally all descriptive statistics presented in Table 3.3 should suggest the same distribution of observable characteristics in the PSA and non-PSA groups, as they would be in expectation if the participation indicator (i.e. PSA vs. non-PSA) had been randomly assigned. These results already suggest that a direct comparison between participants and non-participants in PSA would produce biased estimates of program impact.

3.8.2 Land use changes from self-reports and from aerial photos

Table 3.4 shows the number of hectares on different land uses obtained from self-reports collected during the household survey, and also the number of hectares on these same land uses but obtained from aerial photos. For the case of self-reported land uses, Table 3.4 shows land uses for 2005 and 1996, and for the case of aerial photos it reports land uses for 2005 and 1992. Aerial photographs from 1992 and 2005 were orthorectified and used along with a geo-referenced satellite image of 1992 to estimate land use in 1992 and 2005.[22,23] An orthorectified satellite image of Landsat 5 from 1986 was used to estimate land use in that year. By using aerial photos, the 50 PSA parcels were classified, and because of cloud cover and problems with geo-referentiation of non-PSA properties, only 87 Non-PSA parcels could be classified (i.e. 32 properties located in buffers, 39 from districts, and 16 neighbors). With all this information (i.e. land use from self-reports and aerial photos) was possible to calculate land use changes for the 1986-1992, 1992-2005, and 1996-2005 periods for both groups (i.e. PSA participants and non-participants) which will be used later during the analysis of the causal effect of PSA.

According with Table 3.4, both self-report of landowners and aerial photos suggest that PSA parcels have significantly higher proportion of forest cover than non-PSA parcels in 2005 (i.e. after participation in PSA). For the same year, self-reported number of hectares in crops and pasture do not suggest statistically significant differences between PSA and Non-PSA. However, data from aerial photos suggest that Non-PSA parcels have significantly more crops and pasture. For 1996 and 1992, both self-reported area of natural forest and the

[22] Parcels not covered by the 1992 aerial photographs were classified using a geo-referenced Landsat 5 satellite image.

[23] Aerial photographs from 1997 were tested to be used to estimate land use in that year, but given the poor coverage of the study region (mainly due to cloud cover) the 1992 photos were used instead.

one obtained from aerial photos suggest that PSA parcels had significantly more native forest (i.e. before the establishment of the program in 1997). These results can be a consequence of the FUNDECOR's effect in targeting areas with highest deforestation risk in the study region (as explained in previous sections), selecting then parcels of land with significant portions covered by forest.

In terms of land use changes for the study region, Table 3.5 shows the changes in land use as obtained from self-reports and aerial photos. If we focus only on total native forest cover changes (i.e. proxy for net deforestation), which will be used as an outcome during the PSA impact analysis, self-reports and aerial photos suggest that there is a statistically significant difference between groups (differences are statistically significant at 10% and 5% for the case of self-reports and aerial photos respectively) indicating a significant impact of PSA on net deforestation. Difference of self-reported mature native forest cover change (i.e. proxy for gross deforestation) between participants and non-participants was not found to be statistically significant which would indicate no significant PSA-impact on gross deforestation. On average, PSA parcels report a positive forest cover change (i.e. more forest cover is sustained in 2005 compared with 1992 and 1996) while Non-PSA parcels show a negative change. Initial standardized differences for forest cover changes, from self-reports and aerial photos, are greater than 25%. However and as explained before, these comparisons of outcomes does not provide any firm evidence on the causal impact of PSA on land cover, because we do not know if it is a result of the causal effect of this program or it is a result of the different distributions of observed covariates in the PSA and Non-PSA groups that could be affecting program participation and deforestation. This naïve approach can then be compared with estimates of program impacts that aim to control for observable factors that can bias the estimates of PSA causal effect.

Both sources of land use information, self-reports and aerial photos, contain measurement errors that are difficult to avoid (e.g. recollection of past land uses and photo interpretation of aerial photos). For the case of self reports, one could argue that strategic bias could affect survey responses because landowners could have incentives to not reveal the truth (e.g. not reveal illegal logging and avoid problems). The appendix 1 shows the correlations between the differences in area of total native forest cover as reported by landowners and obtained from aerial photos. All of the highly significant correlations are expected and probably do not indicate strategic bias in the responses: parcel size and self-reported area of forest in 1996.

3.8.3 Estimates of program impact

3.8.3.1 OLS Regression estimates

The conventional method for estimating the impact of participation in a program is OLS regression with participation as a binary explanatory variable. These OLS regression estimates are shown in Tables 3.6 and 3.7, with the last column in both tables corresponding to the preferred specification indicated in equation (3.13). For sake of comparison with a naïve approach, the first column in Tables 3.6 and 3.7 show the association between forest cover change and participation in PSA. According with Table 3.6, in a model without any covariates, I found that parcels with PSA protection contracts signed between 1997 and 1998 do have significantly more self-reported mature native forest (4.062 ha) compared with non-PSA parcels (i.e., the counterfactual of 0 hectares more of self-reported mature native forest). For the case of native forest from aerial photos, Table 3.7 also shows that PSA contracts do have significantly more native forest (11.975 ha) compared with non-PSA parcels. Both estimates of program impact represent the marginal effect of PSA on native forest (mature and total) cover change for a linear regression with PSA participation as the only explanatory variable.

We know from Table 3.3 that PSA participants differ from non-PSA. If I want to control for these observable differences, then I can estimate the PSA impact using linear regression. The second column of Tables 3.6 and 3.7 select explanatory variables informed by social science theory as to what are hypothesized to affect the deforestation decision (e.g., in a von Thünen model, accessibility is hypothesized to affect choice; in a Ricardian model, land quality; in a Chayanovian model, labor supply) (Geoghegan *et al.* 2001). The remaining columns in Tables 3.6 and 3.7 show the stepwise inclusion of controls: canton fixed effects, biophysical land characteristics, land management controls and household socio-economic characteristics. For the case of outcome data obtained from aerial photos, biophysical controls included distance to markets, elevation and soil quality obtained from the Costa Rica Atlas using ArcMap®. These variables replace self-reported biophysical controls to make the model of land-use change use information strictly available from remotely sensed imagery, with the addition of other readily available self-reported data (i.e. land management and socio-economic controls) and then compare this modeling approach with results obtained using only self-reported data (see Geoghegan *et al.* 2001).

In Table 3.6, all the specifications show a positive and significant impact of PSA. The final column suggests that after accounting for all the covariates that affect program participation and outcome (i.e. change in mature native forest cover), forest cover is still higher in parcels with PSA contracts. The estimated impact of PSA is 7.707 ha more of mature native forest cover in PSA parcels. Although the impact is positive and significant, it represents only 4.7% the size of the average PSA parcel as reported in Table 3.3. For the case of aerial photos, Table 3.7 shows a positive (2.969 hectares) but not significant impact of PSA on total native forest cover. Although, the number of observation used in the full specification is smaller than the observations used for self-reports, these results indicate that PSA could have at best a statistically significant but even smaller effect on forest conservation that the estimate using self-reported data.

However, OLS is problematic in this case because it conflates the selection and outcome equations, and thus assumes that the determinants and coefficients are the same for these two processes. OLS also assumes that data generating process is linear in the parameters and uses control units for estimating the counterfactual regardless of whether they are on a common support with treated units (Ferraro *et al*. 2007). Unless there is a substantial overlap on the covariates distributions, with regression modeling, one relies heavily on model specification (i.e., on extrapolation) for the estimations of treatment effects. This could be especially problematic in this case given the small sample size and the big number of dropped observations for the case of the analysis using aerial photos.

Table 3.8 provides robustness checks for the OLS estimates. Specifications include: (1) including controls for 1986 forest cover from Landsat satellite images; (2) including controls for the percent of land parcel in native forest for 1986 from Landsat satellite images; (3) including locality level fixed effects to control for additional locality-level unobservables; (4) changing the outcome variable by looking at % of natural forest cover in each parcel for 2005 (i.e. after participation in PSA for the case of program participants). In general, the estimates of PSA impact are robust across the checks. OLS estimates suggest positive and significant impacts for self-reported outcome and positive and non-significant impacts for outcome from aerial photos.

3.8.3.2 Multivariate matching

Table 3.9 shows the estimates of PSA effect by using multivariate matching. Selected matching covariates included the same controls used in the OLS parsimonious specification that included main determinants of tropical deforestation as recognized in the literature. Although these covariates are suggested by social science theory, these covariates are also directly related with program participation and land use based on the evidence provided by the household survey, case studies, and also previous studies of PSA participation. Measurement of steepness is directly related with land opportunity costs, a key factor that influences participation decision in the context of PSA. Parcel size and distance to forestry office have been identified in previous studies as important elements that also affect program participation (e.g. Zbinden and Lee 2005). Land use in 1996 is obviously a significant determinant of future land uses changes and PSA participation. Also following Rosenbaum and Rubin (1985a) recommendation, the covariates included in the matching represent continuous variables in order to avoid limiting the number of matches obtained. Because of missing data on the covariates, 6 observations in the treatment group were dropped from the original group of 50 participants during the matching process and no treated observations were judged to be off support by looking at the estimated distance between treated observations and their matches based on the values of the covariates and the selected weight matrix (i.e. inverse variance and Mahalanobis metric) (see Abadie *et al*. 2004). Figures 3.3-3.6 show the number and kind of controls used during the multivariate matching.

The first row of Table 3.9 shows the estimates of PSA impact on self-reported changes in mature native forest cover (i.e. older than 20 years). Inverse variance-multivariate matching using 1, 2 and 3 matches shows systematically a positive and significant PSA impact between 5.303 and 7.705 ha (i.e. on average PSA participants have between 5.303 and 7.705 more ha of mature native forest older than 20 years). Mahalanobis matching using 1, 2 and 3 matches reports a positive but not significant PSA impact. Results are similar for the case of changes in total native forest cover from aerial photos which show a positive and significant PSA impact between 6.730 and 8.186 ha using inverse variance-multivariate matching. [24] Mahalanobis matching using three matches was the only ATT estimator that found positive and significant estimates of PSA impact in order of magnitude similar to the estimates using inverse variance-multivariate matching (i.e. 4.583 ha).

For the case of changes in self-reported total native forest cover, only inverse variance-multivariate matching using nearest neighbor (i.e. one match) found a positive and significant PSA impact (i.e. 4.818 ha). In the first phase of PSA implementation and given the FUNDECOR's targeting in the study region, PSA contracts were focused on areas with more mature forest (in fact only in 2006 FONAFIFO introduced natural forest regeneration contracts). Moreover, although self-reported outcome data and data from aerial photos contain measurement errors (e.g. recollection of past land uses by landowners or scanning resolution of aerial photos), for the case of self-reported land use changes, it could be argued

[24] Multivariate matching used self-reported biophysical controls (i.e. parcel size, soil quality and steepness). Matching with biophysical controls from remote sensing imagery was tested, but the resulting covariate balance did not support the selection of these as good controls to obtain a proper covariate balancing between participants and non-participants in PSA.

that landowners may remember better, among the area cover by forests, the land area covered by more mature native forest and in some cases regeneration area could be mistakenly assigned to pastures. This situation may explain why PSA impact on changes in total native forest was found not significant in most of the cases using both matching estimators (i.e. Mahalanobis and inverse variance multivariate matching).[25]

The main purpose of multivariate matching is to identify a comparison group that is “very similar” to the treatment group with only one key difference: the comparison group did not participate in PSA. This way, we can calculate unbiased estimates of ATT. To judge covariates balancing between PSA and non-PSA, Tables 3.10 and 3.11 show the *p*-values from standard t-tests of the differences in mean between participants and non-participants. For the case of self-reported household data, only self-reported 1996 total native forest cover remained unbalance at the 90% confidence level after the matching when using inverse variance-multivariate matching with three closest matches and Mahalanobis multivariate matching with two and three closest matches. For the case of data from aerial photos, percent of parcel with steep slope and self-reported 1996 total native forest cover remained unbalanced for some of the matching estimators (i.e. both covariates remained unbalanced at the 90% confidence level when using inverse-variance multivariate matching with three closest matches and Mahalanobis multivariate matching with three closest matches, and % of parcel with steep slope remained unbalanced at the 90% confidence level when Mahalanobis multivariate matching with one closest match).

By using a restraint group of covariates during the matching, we make a trade-off between the plausibility of the CIA and the variance of the estimates. In this case a parsimonious specification gives less bias in response to the good balancing shown in Tables 3.10 and 3.11. However when matching on this minimal specification, common support is not a problem but the plausibility of the CIA is. Tables 3.10 and 3.11 also present the

[25] Estimates of ATT were calculated for the outcome that included only self-reported changes in regeneration and only one of the estimates were statistically significant at the 10% indicating a negative impact of PSA (on average PSA participants have 2.902 hectares less of forest regeneration younger than 20 years).

covariate balancing for controls not used in the matching process but that are important in explaining program participation and forest cover.[26] In some cases (e.g. dummy for Central Valley), the balance remained after matching and differences are highly significant (i.e. 99% confidence level). In this scenario, it is more difficult to conclude about PSA impact because the estimated PSA causal effect presented in Table 3.9 could be a consequence of the remaining covariates unbalance. In order to check consistency of the results by increasing the number of covariates using during the matching (making CIA more plausible), the next section will estimate program impacts using propensity score matching.

3.8.3.3 Propensity Score matching

The first step in the matching on the propensity score is the estimation of the probability of being a PSA participant. Tables 3.12 and 3.13 report the estimated marginal effects on propensity of a landowner to have a PSA contract. In order to directly compare the results obtained using multivariate matching, a parsimonious logit specification was included first (Model 1 in Tables 3.12 and 3.13), and then full logit specifications including all the pre-determined covariates judged to be important in predicting program participation that also affect program outcome (Model 2 in Table 3.12 and Models 2 and 3 in Table 3.13). For the case of self-reported data, Table 3.12 show that for the full logit specification, % of parcel with steep slope, self-reported 1996 native forest, previous participation in other forest programs, and dummy for Central Valley were found to be positively associated with PSA participation. These results are consistent with conclusions from case studies (see Arriagada *et al*. forthcoming) and previous studies of PSA participation (see Zbinden and Lee 2005). Dummy for residency on parcel in 1996 was found to be negatively correlated with PSA participation which is also consistent with previous studies (e.g. Zbinden and Lee (2005) found that availability of family labor was found to be negatively associated with participation)[27]. Years of education of respondent was also found to be negatively correlated

[26] The covariates not used in the matching and presented in Tables 3.10 and 3.11 represents the controls used in the full OLS specification presented in Tables 3.6 and 3.7.
[27] Table 3.12 shows that household labor force in 1996, which is a proxy for labor because we do not have data on number of household members in 1996, is positively but not significantly related with PSA participation.

with PSA participation. This is an unexpected result and may reflect some peculiarity of the sample or some interacting effect with some of the controls included in the logit specification.[28]

For the case of data from aerial photos, two full logit specifications were included: Model 2 using self-reported biophysical controls (i.e. distance to forestry office, parcel size, % of parcel with steep slope and % of parcel with poor soil) and Model 3 using biophysical controls obtained using remote sensing imagery (i.e. distance to city, parcel size from aerial photos, hectares in high elevation and hectares with poor soil). In the logit specification using self-reported biophysical controls (i.e. Model 2 in Table 3.13), significant covariates included the same ones obtained using self-reported data including also forest management plans pre-1996 and native forest in 1992 from aerial photos (both were found to be positively related with PSA participation). These new significant determinants of program participation are consistent with the story of PSA application during the first phase of PSA when first applications came from landowners that had a previous relationship with MINAE personnel and FUNDECOR targeting of critical areas. The logit specification with biophysical controls from remote sensing imagery, also included household labor force in 1996, distance to city, and parcel size from aerial photos as significant variables that explain PSA participation. This is a counterintuitive result given that the analogous self-reported controls (i.e. distance to forestry office and parcel size) were not found to be related with program participation. Appendix 2 shows the pairwise correlation between self-reported biophysical controls and the ones obtained from remote sensing imagery.

Once you have estimated the propensity score, matching can be completed using the treatment effect estimators described in section 3.5.3. Table 3.14 shows the estimates of program impact using propensity score matching. Because of missing data on program outcome and covariates the sample size differs across the different logit specifications

[28] A model of PSA participation that only include years of education as explanatory variable found that is positively related with PSA participation, however this relationship was found to be not statistically significant.

models. Results using a parsimonious specification of the propensity score (i.e. Model 1) found comparable results with the ones obtained using multivariate matching and OLS. For the case of self-reported changes in mature native forest PSA impact is between 3.092 and 8.381 ha using NN and RM respectively. For the outcome obtained from aerial photos only NN found a positive and significant impact of PSA (i.e. 6.522 ha).

If we control for other covariates that affect PSA participation and land use (i.e. using Models 2 and 3 in Table 3.14), the impact of participation in PSA on self-reported changes in mature native forest ranges between 4.852 and 16.425 ha using RM and NN respectively. For the case of aerial photos using self-reported biophysical controls, significant estimates of PSA impact range between 10.170 and 12.686 ha using KM and NN respectively. If biophysical controls from remote sensing imagery are included, then significant estimates of PSA impact range between 11.177, 13.648 and 15.398 ha using RM, KM and NN respectively.[29]

In general, PSA impact estimates on changes in mature native forest cover and total native forest cover show a clear trend in the sense of suggesting a positive but small and significant impact of PSA on deforestation.

Unconfoundedness, a term coined by Rubin (1990), refers to the case where (non-parametrically) adjusting for differences in a fixed set of covariates removes biases in comparisons between treated and control units, thus allowing for a causal interpretation of those adjusted differences. Parsimonious specification of propensity score implies less bias in the estimation of casual effect, but sacrifice plausibility of unconfoundedness in the treatment assignment. Full specifications of propensity score makes the CIA more plausible, but increase bias given the remaining covariate imbalance shown in Tables 3.15 and 3.16.

[29] In order to address concerns on the proper imposition of the common support condition for KM, the PSMATCH2 options 'common' and 'trim' were used. In fact, the trimming was set at 5% which is the highest recommended to use in PSMATCH2.

According with these tables, NN achieved balance on all covariates used in Model 1 for both self-reported data and data from aerial photos, and these estimates are consistent with estimates from OLS and multivariate matching. For Model 2, NN using self-reported data achieve balance on all covariates used during the matching except for distance to forestry office. For the case of aerial photos, Model 2 NN did not achieve balance on four covariates (i.e. distance to forestry office, native forest in 1992 from aerial photos, years of education of respondent and dummy for Central Valley). For Model 3 NN, five covariates remained unbalanced (i.e. household labor force in 1996, experience with forest plantations before 1996, forest management plan pre-1996, previous participation in other forest programs, and hectares in high elevation). Then, estimates of program impact in these cases must be considered with caution although they are similar in magnitude to the estimate of PSA impact using NN in model 2 with self-reported data.

For the case of RM, Model 1 did not balance all covariates in both cases with self-reported data and data from aerial photos (interestingly, these estimates were not consistent with estimates from inverse-variance multivariate matching). For Model 2 using self-reported data, RM achieved balance on all variables except for % of parcel with steep slope and dummy for Central Valley. For data from aerial photos, RM achieved balance on Model 2 for all covariates except for % of parcel with steep slope and Model 3 RM did not balance three covariates (native forest in 1992 from aerial photos, parcel size from aerial photos and hectares in high elevation).

For the case of KM and self-reported data, Models 1 and 2 achieved balance on all covariates used during the matching. The impact of PSA obtained from KM in this case were in the same order of magnitude with OLS and inverse-variance multivariate matching, but none of these estimates were found to be statistically significant. In the case of data from aerial photos, four covariates remained unbalance in Models 2 and 3 (i.e. distance to forestry office, native forest in 1992 from aerial photos, years of education of respondent and dummy for Central Valley in Model 2, and experience with forest plantations before 1996, previous participation in other forest programs, parcel size from aerial photos and hectares with high elevation in Model 3). These estimates were consistent with the ones obtained using inverse-variance multivariate matching

Asymptotically all the propensity score matching estimators presented in Table 3.14 should yield the same results, because with growing sample size they all become closer to comparing only exact matches (Smith 2000). However, the selection of the matching algorithm (e.g. nearest neighbor vs. kernel propensity score matching) in small samples can be important (see Heckman, Ichimura and Todd 1997), where usually a trade-off between bias and variance arises. However the similarity in the results shown in Table 3.13 suggests that the algorithm choice may not be critical although the results must treated with cautious given the remaining unbalance detected in Tables 3.15 and 3.16.

Table 3.17 reports two robustness checks by dropping the only non-predetermined covariate used during the matching (i.e. proxy for household labor force in 1996) and using multiple imputation. [30] Results without using proxy for labor force are comparable with results reported in Table 3.14. However, results with multiple imputation do not look very consistent with previous results of program impact. Statisticians have become increasingly aware of the inadequacy of "complete-case" analysis of datasets with missing observation. Results using imputation and provided in Table 3.17 not only differs in terms of the matching algorithm being used to estimate PSA causal effect, but also on the number of observation used during the matching. The basic idea of multiple imputations by chained equations (MICE) is to create a small number of copies of the data, each of which has the missing values suitably imputed, and analyze each complete dataset independently. Estimates of parameters of interest are averaged across the copies to give a single estimate.[31] Given the parametric assumptions used during the imputation process, these results must be considered

[30] Imputation was done in Stata v.9 using the "switching regression" method of multiple multivariate imputation described by van Buuren, Boshuizen, and Knook (1999) and implemented by Royston (2004).
[31] MICE implemented in Stata v.9 estimated parameters of the logistic regression using five copies of each complete dataset.

with more confidence to judge direction and significance of PSA impact, but not to judge magnitude of program impact.

The outcome of interest − changes in mature and non-mature native forest cover − would ideally be measured objectively – such as through remote sensing before and after establishment of the PSA Program. Satellite images can potentially provide such a historical record, but comparisons across time periods are only valid if the same processing and classification methods are used, and I do not have access to such land cover classifications. Thus, in this case study, measures of forest cover were obtained by asking the landowners directly to report current and retrospective land use. The advantages of this self-reported measure are that it is not affected by miss-alignment of parcel maps and the satellite image, it is not subject to errors in interpretation of the satellite image, and it measures land use rather than land cover (for example, an area with scrubby land cover could be cattle pasture or regenerating forest). The disadvantages are that respondents might not remember or might misreport land use. However, the bias is unknown; that is, it could be that PSA participants are less likely to report loss in forest cover because of their contractual obligations, or if only non-PSA participants lose forest cover, they might not report this due to other legal restrictions.

It is also important to emphasize that these results were obtained from a case study in the Sarapiquí region that only included 50 program participants and 150 non-participants, and that sample size was reduce even further because of missing data on the covariates and outcome and because of problems classifying land use using data from aerial photos. Propensity score matching is 'data hungry' not only in terms of the number of variables required to estimate participation and outcomes, but also in terms of the number of non-participants required for the matching process. Then, our results based on a relatively small sample of non-participants should be treated with caution. Figure 3.7 shows the overlap of the distribution of propensity scores between PSA participants and non-participants. As expected, most participants have a high propensity to participate, and most non-participants have a low propensity to participate. There is common support at most levels of the propensity score, but this is based on relatively few non-participants[32].

3.8.4 Assessing spillover effects and unconfoundedness

PSA can influence land use decisions on unregulated lands. Such spillovers (also called "leakage") can be negative or positive. On the positive side, there could be spillover conservation benefits, with neighbors of PSA participants more likely to conserve forest. The mechanism for these spillovers could be the option value of a future PSA contract, shifts in preferences or increased knowledge about the value of standing forest, or increased enforcement activity (Sills *et al.* forthcoming). Depending on how the program is presented and perceived by landowners, there could also be negative effects, as suggested by Cardenas *et al.* (2000: 1720): "a monetary reward to motivate socially desirable behavior may actually do the opposite because it may crowd out an individual's sense of public-spiritedness." Program benefits may also be reduced by leakages, with recipients of PSA payments investing these in expansion of agriculture or pasture on other properties. In the presence of spillovers, the use of surrounding unprotected lands as controls biases estimates of the effect of PSA. For example, if PSA reduces deforestation on nearby unprotected forests, a comparison of deforestation rates on protected and unprotected lands would underestimate the avoided deforestation from PSA. Tables 3.18 and 3.19 show tests for spatial spillover effects using matching and OLS. Table 3.18 shows weak evidence of the presence of spillover effects (only NN and RM show significant effects of being an immediate neighbor to a PSA participants on changes in self-reported mature native forest cover and Table 3.19 shows that distance to nearest participant is a significant predictor of forest cover changes in the case of changes in total native forest cover from aerial photos.

Now, matching to be credible needs a rich dataset since the evaluator needs to be confident that all the variables affecting both participation and outcome are observed. That is,

[32] In the case of NN using self-reported data only 21 non-participants were used as controls during the matching process. For the case of data from aerial photos, NN used only 16 non-participants as controls during the matching process.

it is assumed that any selection on unobservables is trivial in that these unobservables do not affect outcomes in the absence of the treatment. However, the unconfoundedness use throughout this study is not directly testable. Nevertheless, there are often indirect ways of assessing this, a number of which are developed in Heckman and Hotz (1989) and Rosenbaum (1987). These methods typically rely on estimating a causal effect that is known to be equal to zero. If based on the test we reject the null hypothesis that this causal effect varies from zero, the unconfoundedness assumption is considered less plausible (Imbens 2007).

One set of tests of unconfoundedness focuses on estimating the causal effect of the treatment variables on a variable known to be unaffected by it, typically because its value is determined prior to the treatment itself. Such a variable can be time-invariant, but the most interesting case is in considering the treatment effect on a lagged outcome. Table 3.20 shows the results of the OLS regression using 1986 and 1992 native forest cover from aerial photos as outcomes. Given that PSA started in 1997, I would expect a zero effect of PSA. The parameter coefficients associated to PSA were -6.810 hectares and 13.865 and both were not statistically significant which confirms the expected result. Table 3.21 shows the results using propensity score matching and results are similar (only NN using Model 3 and total native forest cover 1986 from aerial photos as outcome shows a significant impact of PSA). Given that the estimated PSA effect is zero, this implies that the treated observations are not different from the controls in terms of this particular variable given the other covariates used in the regression and matching reported in Tables 3.20 and 3.21. Figure 3.8 shows the deforestation trend between participants and non-participants in PSA. This graph could be also used a simple test of the identifying assumption needed to use other program evaluation methods based on selection on unobservables (e.g. differences-in-differences). Figure 3.8 shows that PSA participants consistently have more forest cover than the control group even in the absence of PSA. In this case, I could say that in the absence of PSA the trend (or change) in forest cover is the same for the two groups. This conclusion also helps to rule out the possibility of bias in the estimates of program effects due to unobservable differences between groups.

3.9 CONCLUSIONS

PSA is currently the longest running program of payments for ecosystem services in the Tropics. During the first phase of PSA (i.e. 1997 and 1998), PSA contracts (i.e. forest management, forest conservation and reforestation contracts) were not assigned in a systematic fashion. Program administrators also did not design the program implementation with the intention of empirically evaluating its effectiveness by testing and measuring against a clear baseline or "control" case. Moreover forest cover has apparently been increasing even before the establishment of PSA. To evaluate the effect of PSA on forest cover changes, the analyst must disentangle the effects of PSA from the effects of the elimination of government subsidies that promoted deforestation, incorporate the non-random assignment of contracts, and the economy-wide changes that have made deforestation less appealing. This makes difficult the evaluation of PSA impact.

Even more, there are many reasons to expect that PSA did not have a significant effect in its first phase: FONAFIFO sought to minimize transactions costs and program delays by not differentiating or targeting payments, and results of household survey and case studies suggest that landowners responded by enrolling forest that they would not have converted in any case (mainly due to low returns to alternative uses). In fact, I did find that regions with less productive land, fewer roads, and lower population density are more likely to have PSA contracts. In Sarapiquí, absentee landowners with larger parcels that have more steep slopes and that are not used for commercial agriculture are more likely to have enrolled in PSA, as compared to other landowners who were also eligible but did not enroll. These conclusions are consistent with previous studies of program impact (e.g. Hartshorn *et al.* 2005 found that much of the land under PSA forest protection contracts might not have been converted to other uses in the absence of payments).

However, there are also reasons to believe that PSA could have a significant effect on the study region given the active role of FUNDECOR during the first phase of PSA targeting program participation in ‘critical areas’ associated with high deforestation risks.

I applied matching methods to evaluate the impact on forest cover of PSA forest protection contracts implemented in the first phase of the program. Several studies have shown that farms with PSA contracts have more forest cover. I considered changes in that forest cover, as self-reported by landowners in the Sarapiquí region for 1996 and 2005 and as obtained from aerial photos for 1992 and 2005. This study shows evidence that during the initial phase of PSA the program did have a statistically significant but small positive effect on gross and net deforestation. However, it is also clear from this case study that the credibility of these impact evaluation strategies to identify the causal effect of PSA depends crucially on the quality and amount of observable pre-PSA socio-economic and biophysical household characteristics. This is why, in this study, data collection is an important component of the overall evaluation framework.

While the estimated effects of PSA on forest cover are statistically significant, they are also very small (for example, approximately 8.4 ha, or 5.1% increase in self-reported mature native forest cover on the average parcel enrolled in PSA in Sarapiquí using nearest neighbor propensity score matching). This result significantly extends previous suggestions of relatively low impact from PSA (e.g. Hartshorn *et al.* 2005, Sierra and Russman 2006, Sánchez-Azofeifa *et al.* 2007, Pfaff *et al.* 2008).

Different matching estimators gave similar results in terms of impact of the program on mature native forest cover change. However, and given the small sample size, these results must be considered with caution. In the case of multivariate matching and propensity score matching estimators, PSA and non-PSA group members should be balanced during the matching process in terms of their covariates values and propensity scores respectively. In our case, few untreated observations could be found to be compared with treated ones especially for propensity scores close to 1. This means that a small group of non-participants were used to be compared with PSA participants throughout the different matching estimators, so it is not surprising the lack of sensitivity in the estimates of program impact when changing the matching algorithm. This framework analysis can be used for future evaluations of direct conservation payments such as PSA. By making the proper adjustments of sample size necessary to apply matching algorithms, this methodology can provide very rigorous analysis of causal effects.

Finally, results of this study, although applied to PSA forest conservation contracts signed in the first phase of the program, already suggest some implications about program design. If program administrators want to either raise forest conservation benefits and/or save funds, targeting of payments in areas with higher deforestation risks seems more appropriate than protecting forest that would be conserved with or without PSA. Future evaluations of PSA should also concentrate on the impact of the program on provision of environmental services given that payments on land with low opportunity costs could be justified if the environmental benefit is high.

3.10 BIBLIOGRAPHY

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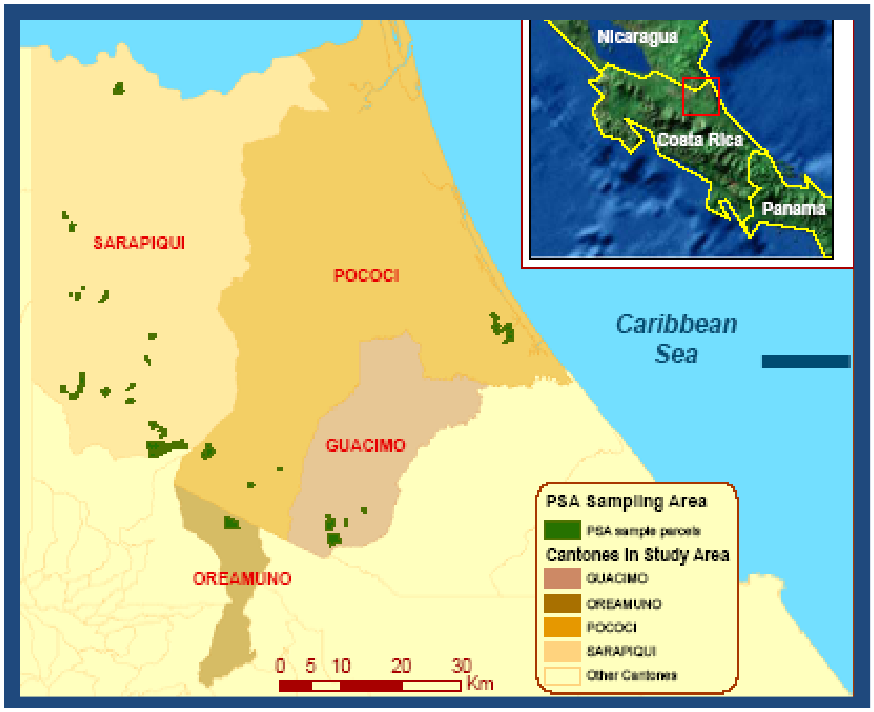

Figure 3.1: Study area

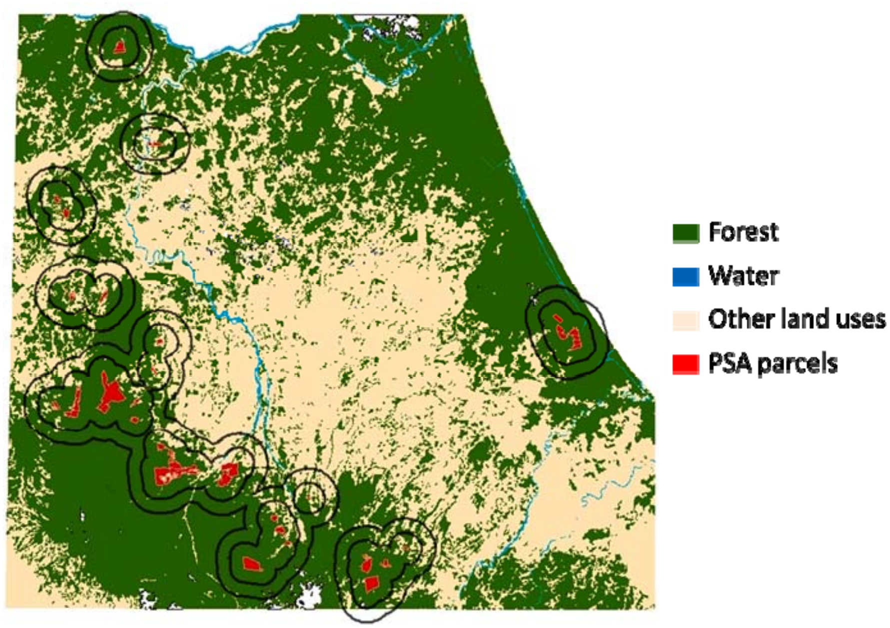

Figure 3.2: PSA Parcels and Non-PSA Sampling Using Buffers

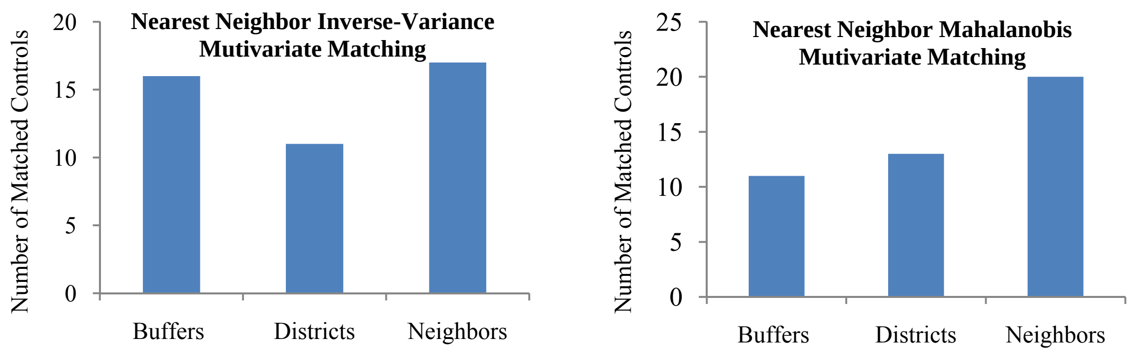

Figure 3.3: Distribution of matched controls for changes in mature native forest cover 1996-2005 from self-reports using nearest neighbor inverse-variance and Mahalanobis multivariate matching

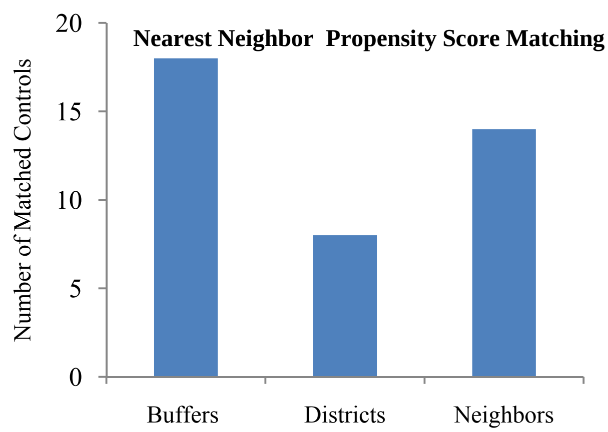

Figure 3.4: Distribution of matched controls for changes in mature native forest cover 1996-2005 from self-reports using nearest neighbor propensity score matching and full logit specification

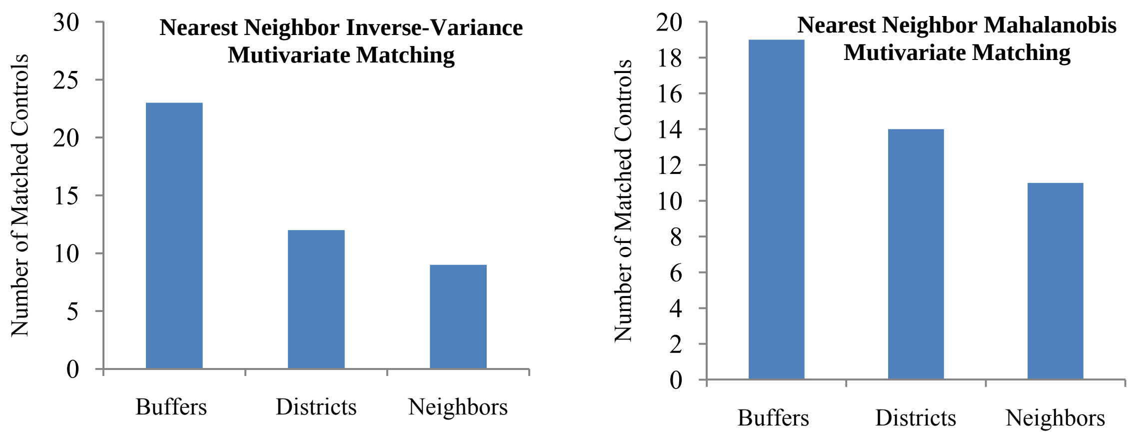

Figure 3.5: Distribution of matched controls for changes in total native forest cover 1992-2005 from aerial photos using nearest neighbor inverse-variance and Mahalanobis multivariate matching

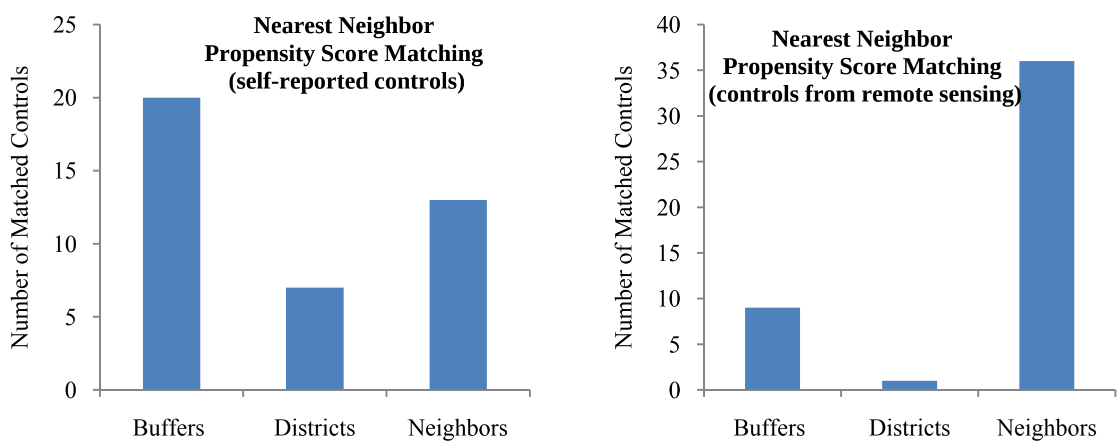

Figure 3.6: Distribution of matched controls for changes in total native forest cover 1992-2005 from aerial photos using nearest neighbor propensity score matching and full logit specification using self-reported and remote sensing imagery biophysical controls

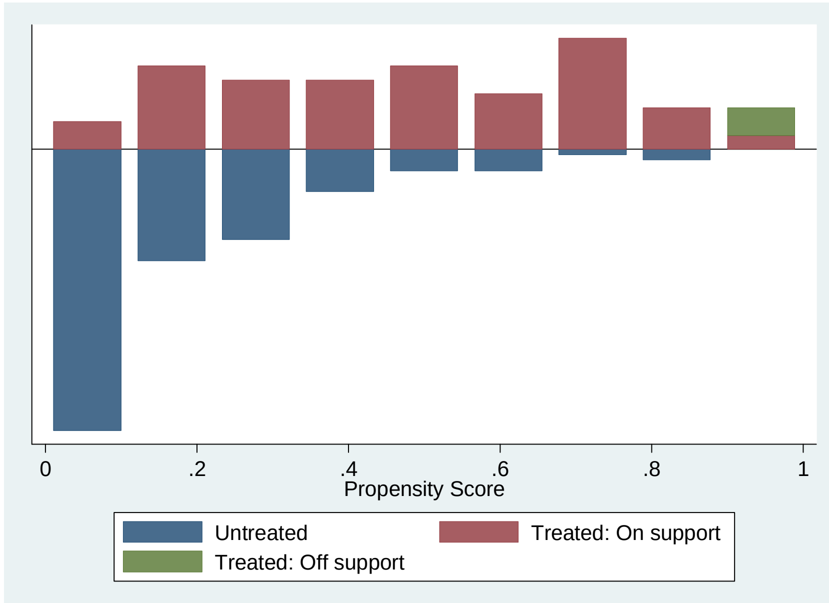

Figure 3.7: Common support graph of propensity scores for PSA participants (treated) and non-participants (untreated)

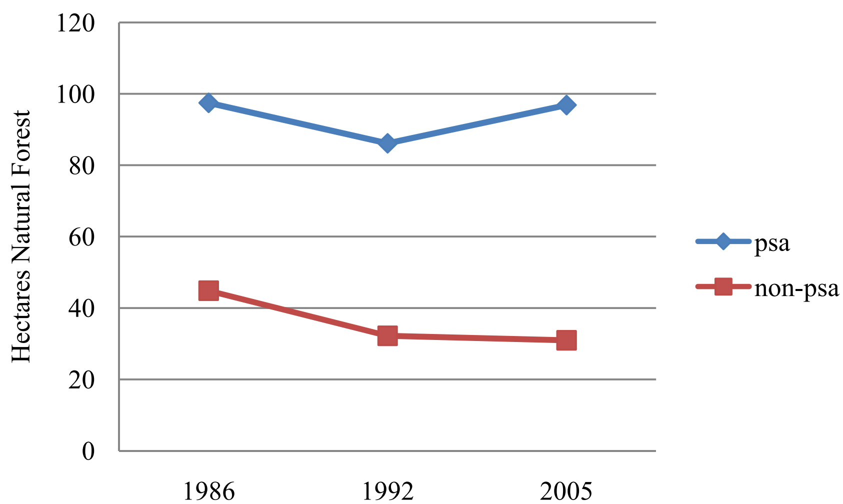

Figure 3.8: Deforestation trend between participants and non-participants in PSA

Table 3.1: Description of PSA modalities during initial years (1997-2000)

Program Option	*Total Payment[a] (Colones)*	*Contract Period (years)*	*Contract Area Min. ha*	*Contract Area Max. ha*	*Disbursement % of payment per year*
Forest Management	80,225 (1997) 94,000 (1998) 94,000 (1999) — (2000)	10	2	300	50%, 20%, 10%, 10%, 10%
Forest Conservation	50,000 (1997) 60,000 (1998) 60,000 (1999) 66,000 (2000)	5	2	300	20%, 20%, 20%, 20%, 20%
Reforestation	120,000 (1997) 154,000 (1998) 154,000 (1999) 169,000 (2000)	Max 15	1	300	50%, 20%, 15%, 10%, 5%

Source: www.fonafifo.com
[a] Payments are in nominal values.

Table 3.2: Hectares protected by PSA contracts signed between 1998 and 2007 in the study region

Canton	*PSA Modality[a]*			
	Protection	*Reforestation*	*Forest Management*	*Agroforestry*
Sarapiquí	28,831 (341)	2,651 (83)	3,703 (52)	9,500 (3)
Pococí	15,376 (134)	499 (31)	1,003 (10)	187,673 trees (71)
Guácimo	4,315 (42)	83 (7)	241 (3)	38,775 trees (13)
Oreamuno	2,392 (9)	—	—	—

Source: www.fonafifo.com
[a] In parenthesis the number of signed PSA contracts.

Table 3.3: Comparison of pre-matched samples of PSA and non-PSA landowners in Sarapiquí

Variable Description[a]	*Non-PSA Mean (SD)*	*PSA Mean (SD)*	*P-value*	*Standardized difference (%)[e]*
D - From Central Valley	0.37 (.49)	0.70 (.46)	0.000	69.4
D - Resident on parcel in 2005[b]	0.49 (.50)	0.22 (.42)	0.001	-58.5
D - Resident on parcel in 1996[b]	0.45 (0.04)	0.26 (0.07)	0.026	-333.3
Years of education of respondent[b]	9.02 (5.16)	9.16 (5.84)	0.875	2.5
Age of respondent (years) [b]	52.86 (12.12)	53.62 (11.21)	0.698	6.5
Adults (>15 years old) in family	3.21 (2.12)	4.24 (2.95)	0.008	40.2
Fraction of family are men[b]	0.45 (0.20)	0.40 (0.23)	0.142	-23.2
Fraction of family are women[b]	0.42 (0.19)	0.43 (0.21)	0.635	5.0
D - Sole owner of parcel[b]	0.69 (0.46)	0.74 (0.44)	0.528	11.1
D - Inherited parcel[b]	0.16 (0.37)	0.24 (0.43)	0.225	19.9
D- Own other parcels	0.26 (0.44)	0.36 (0.48)	0.202	20.6
D - Own other houses	0.39 (0.49)	0.24 (0.43)	0.070	-31.5

Table 3.3 Continued.

Variable Description[a]	*Non-PSA Mean (SD)*	*PSA Mean (SD)*	*P-value*	*Standardized difference (%)*[e]
D - Experience with forest plantations before 1996[b]	0.49 (.50)	0.40 (.49)	0.297	-18.2
D - Participation in voluntary activities	0.45 (0.50)	0.60 (0.50)	0.020	30.0
D - Environmentalism index (1 to 10)[b]	2.78 (0.91)	2.85 (1.37)	0.688	6.02
D - Member of environmental group[b]	0.07 (0.26)	0.20 (0.40)	0.012	38.5
Family members working on parcel[b]	1.20 (1.29)	1.54 (1.79)	0.158	21.8
Household labor force in 1996[b,c]	1.47 (2.17)	1.57 (3.38)	0.826	3.4
D - Children will manage land in future	0.95 (0.22)	0.94 (0.24)	0.779	-4.5
D - Secondary occupation	0.45 (0.50)	0.38 (0.49)	0.383	-14.4
D - Sell crops[b]	0.25 (.44)	0.10 (.30)	0.023	-39.8
Total native forest in 1996 (ha) [b,d]	37.46 (69.67)	142.69 (314.63)	0.000	46.2
Mature native forest in 1996 (ha)[b,d]	29.77 (53.16)	139.19 (315.53)	0.000	48.4
Total native forest in 1992 (ha) [b,d]	32.22 (50.62)	86.13 (146.87)	0.002	49.1
Crops in 1996 (ha)[b]	5.43 (23.64)	0.09 (0.35)	0.113	-31.9
Pasture in 1996 (ha)[b]	26.83 (61.09)	18.84 (51.91)	0.408	-14.1
D - Forest fenced in 1996[b]	0.54 (0.50)	0.22 (0.42)	0.000	-69.3
Years experience with agriculture[b]	18.21 (15.76)	20.15 (17.27)	0.487	11.7
Head of cattle on parcel in 1996[b]	34.42 (61.67)	16.42 (44.31)	0.088	-33.5
D- Hired workers in 1996[b]	0.51 (0.87)	0.54 (0.50)	0.789	4.2
D - Money loans from 1996 to 2005	0.40 (0.49)	0.54 (0.50)	0.090	27.9
D - Financial investment	0.47 (0.50)	0.60 (0.49)	0.101	27.2
D - Forest management plan pre-1996[b]	0.18 (0.38)	0.38 (0.49)	0.003	45.6
D - Previous participation in other forest programs[b]	0.14 (0.35)	0.32(0.47)	0.005	43.4
Percent steep slope[b]	25.24 (24.73)	38.40 (31.48)	0.003	46.5
D - Forest logged in past 50 years[b]	0.45 (0.50)	0.50 (0.51)	0.524	9.9
D - Sell, use, cut or give wood 1996-2005	0.50 (0.50)	0.54 (0.50)	0.660	7.3
D- suffer wood robbery 1996-2005	0.12 (0.33)	0.22 (0.42)	0.081	27.3
Distance to agricultural office (km)[b]	24.74 (14.3)	23.13 (13.14)	0.506	-11.7
Distance to forestry office (km)[b]	25.07 (13.98)	29.15 (14.39)	0.092	28.8
Parcel size (ha) [b]	70.66 (112.25)	165.11 (338.02)	0.003	37.5
Percent poor soil[b]	19.57 (25.38)	27.08 (30.87)	0.100	26.6

The *p*-values are from standard t-tests.
[a] D indicates a "dummy" variable, coded as 1 = statement true for the respondent, and 0 = statement false for respondent; the mean for these variables is therefore a percentage of respondents.
[b] Variable suffers from some missing data.
[c] Labor in 1996 is proxied by interacting number of males and females in 2005 with the dummy that indicated residency in the parcel in 1996.
[d] Mature native forest includes intervened and non-intervened primary (>20 years) natural forest, and total native forest includes intervened and non-intervened primary (>20 years) and secondary (<20 years) natural forest.

[e] The standardized difference is the mean difference as a percentage of the average standard deviation: $[100(\bar{x}_p - \bar{x}_n)]/\sqrt{(s_p^2 + s_n^2)/2}$, where for each covariate $\bar{x}_p$ and $\bar{x}_n$ are the sample means in the PSA and non-PSA groups and s_p^2 and s_n^2 are the corresponding variances.

Table 3.4: Self-reported land uses vs. land uses from aerial photos

Variable Description[a,b,c]	*Non-PSA Mean (SD)*	*PSA Mean (SD)*	*P-value*	*Standardized difference (%)*[e]
Self-reported land use 2005				
Mature native forest (ha)	29.77 (53.16)	139.19 (315.53)	0.000	48.4
Total native forest (ha)	35.40 (66.89)	144.39 (315.21)	0.000	47.8
Crops (ha)	6.64 (28.64)	0.15 (0.54)	0.111	-32.0
Pasture (ha)	26.15 (59.17)	18.71 (56.58)	0.438	-12.9
Self-reported land use 1996				
Mature native forest (ha)	32.89 (62.57)	138.25 (314.98)	0.000	46.4
Total native forest (ha)	37.46 (69.67)	142.69 (314.63)	0.000	46.2
Crops (ha)	5.34 (23.47)	0.09 (0.35)	0.116	-31.6
Pasture (ha)	26.83 (61.09)	18.84 (51.91)	0.408	-14.1
Land use from aerial photos 2005[d]				
Total native forest (ha)	30.98 (52.67)	96.86 (147.84)	0.000	59.4
Crops (ha)	10.65 (31.72)	0.33 (2.26)	0.023	-45.9
Pasture (ha)	20.82 (41.52)	3.44 (9.15)	0.004	-57.8
Land use from aerial photos 1992				
Total native forest (ha)	32.22 (50.62)	86.13 (146.87)	0.002	49.1
Crops (ha)	9.95 (42.37)	0.02 (0.17)	0.101	-33.1
Pasture (ha)	19.00 (33.93)	3.50 (9.42)	0.002	-62.3

The *p*-values are from standard t-tests.

[a] Self-reported data include 50 PSA and 148 Non-PSA, and data from aerial photos include 50 PSA and 87 Non-PSA.

[b] For self-reports the average parcel size is 165.1 and 70.7 hectares for PSA participants and non-participants respectively, and for aerial photos the average parcel size is 102.75.1 and 64.74 hectares for PSA participants and non-participants respectively.

[c] Mature native forest includes intervened and non-intervened primary (>20 years) natural forest, and total native forest includes intervened and non-intervened primary (>20 years) and secondary (<20 years) natural forest.

[d] The standardized difference is the mean difference as a percentage of the average standard deviation: $[100(\bar{x}_p - \bar{x}_n)]/\sqrt{(s_p^2 + s_n^2)/2}$, where for each covariate $\bar{x}_p$ and $\bar{x}_n$ are the sample means in the PSA and non-PSA groups and s_p^2 and s_n^2 are the corresponding variances.

Table 3.5: Change in land use as reported by landowners and obtained from aerial photos

Variable Description[a,b,c]	*Non-PSA Mean (SD)*	*PSA Mean (SD)*	*P-value*	*Standardized difference (%)*[d]
Self-reported land use change 1996-2005				
Mature native forest (ha)	-3.12 (19.13)	0.94 (8.47)	0.148	27.5
Total native forest (ha)	-2.07 (14.45)	1.70 (10.43)	0.091*	28.5
Crops (ha)	1.30 (13.14)	0.06 (0.59)	0.506	-13.3
Pasture (ha)	-0.68 (9.81)	-0.13 (13.18)	0.755	4.7
Land use change from aerial photos 1992-2005				
Total native forest (ha)	-1.24 (22.22)	10.74 (42.79)	0.033**	35.1
Crops (ha)	0.70 (17.74)	0.30 (2.27)	0.874	-3.2
Pasture (ha)	1.82 (19.78)	-0.06 (9.50)	0.529	-12.1
Land use change from aerial photos 1986-1992				
Total native forest (ha)	-12.65 (23.82)	-11.35 (45.17)	0.826	3.6
Crops (ha)	3.72 (14.35)	0.03 (0.17)	0.072*	-36.4
Pasture (ha)	5.53 (17.45)	-1.59 (9.85)	0.009***	-50.2

The *p*-values are from standard t-tests. *** = 99% confidence, ** = 95%, * = 90%.

[a] Self-reported data include 50 PSA and 148 Non-PSA, and data from aerial photos include 50 PSA and 87 Non-PSA.

[b] For self-reports the average parcel size is 165.1 and 70.7 hectares for PSA participants and non-participants respectively, and for aerial photos the average parcel size is 165.1 and 72.2 hectares for PSA participants and non-participants respectively.

[c] Mature native forest includes intervened and non-intervened primary (>20 years) natural forest, and total native forest includes intervened and non-intervened primary (>20 years) and secondary (<20 years) natural forest.

[d] The standardized difference is the mean difference as a percentage of the average standard deviation: $[100(\bar{x}_p - \bar{x}_n)]/\sqrt{(s_p^2 + s_n^2)/2}$, where for each covariate $\bar{x}_p$ and $\bar{x}_n$ are the sample means in the PSA and non-PSA groups and s_p^2 and s_n^2 are the corresponding variances.

Table 3.6: Effect of PSA on self-reported mature native forest cover change using OLS regression

	OLS 1	*OLS 2*	*OLS 3*	*OLS 4*
Dependent Variable	***Change in Self-Reported Mature Native Forest Cover 1996-2005***[b]			
Intercept	-3.122 (1.575)**	0.267 (2.919)	-2.233 (4.435)	-13.1112 (7.011)*
PSA	4.062 (1.976)**	7.320 (2.838)**	8.237 (3.078)***	7.707 (3.143)**
Distance to forestry office		0.120 (0.078)	0.154 (0.085)*	0.168 (0.087)*
Parcel size		-0.007 (0.006)	-0.007 (0.007)	-0.005 (0.007)
Percent of parcel with steep slope		-0.047 (0.041)	-0.052 (0.043)	-0.059 (0.044)
Ln (Self-reported native forest in 1996)		-1.726 (0.838)**	-2.248 (0.898)**	-2.591 (0.922)***
Household labor force in 1996[a]		0.083 (0.483)	0.099 (0.524)	-0.521 (0.826)
Percent of parcel with poor soil			0.022 (0.043)	0.021 (0.044)
D - Experience with forest plantations before 1996			3.661 (2.402)	4.477 (2.386)*
D - Forest management plan pre-1996			3.148 (2.922)	3.693 (2.940)
D - Previous participation in other forest programs			2.770 (3.157)	2.764 (3.125)
D - Resident on parcel in 1996				1.238 (4.060)
Years of education of respondent				-0.395 (0.260)
Age				0.267 (0.101)***
D - From Central Valley				3.995 (2.687)
Canton fixed effects	No	No	Yes	Yes
Observations	198	163	153	151
R-Squared	0.011	0.084	0.136	0.204
Prob > F	0.041	0.031	0.070	0.015

Standard errors in parenthesis, *** = 99% confidence, ** = 95%, * = 90%.

OLS 1 uses program participation as the only explanatory variable to explain mature native forest cover change.

OLS 2 includes a parsimonious specification of mature native forest cover change that includes main determinants of tropical deforestation.

OLS 3 adds land management controls.

OLS 4 adds household socio-economic characteristics.

[a] Labor in 1996 is proxied by interacting number of males and females in 2005 with the dummy that indicated residency in the parcel in 1996.

[b] Mature native forest includes intervened and non-intervened primary (>20 years) natural forest.

Table 3.7: Effect of PSA on total native forest cover change from aerial photos using OLS regression

	OLS 1	*OLS 2*	*OLS 3*	*OLS 4*
Dependent Variable	***Change in Total Native Forest Cover 1992-2005 from Aerial Photos***[f]			
Intercept	-1.239 (2.386)	-93.655 (23.520)***	-80.010 (24.981)***	-81.159 (32.308)**
PSA	11.975 (6.489)*	4.672 (5.349)	3.661 (5.890)	2.969 (6.353)
Ln (Distance to city)[a]		10.555 (3.027)***	7.935 (3.278)**	7.370 (3.603)**
Ln (Parcel size)[b]		17.916 (3.389)***	16.074 (3.583)***	17.281 (3.773)***
Hectares in high elevation[c]		0.316 (0.056)***	0.346 (0.060)***	0.345 (0.062)***
Ln (Native forest in 1992 from aerial photos)		-18.291 (2.835)***	-17.532 (2.961)***	-17.826 (3.132)***
Household labor force in 1996[d]		-0.251 (0.831)	-0.079 (0.867)	-0.254 (1.304)
Percent of parcel with poor soil[e]			0.178 (0.119)	0.155 (0.125)
D - Experience with forest plantations before 1996			0.720 (4.640)	0.503 (4.791)
D - Forest management plan pre-1996			3.509 (6.010)	5.052 (6.520)
D - Previous participation in other forest programs			6.363 (6.445)	5.397 (6.639)
D - Resident on parcel in 1996				0.374 (8.138)
Years of education of respondent				-0.654 (0.529)
Age				0.142 (0.218)
D - From Central Valley				2.309 (5.103)
Canton fixed effects	No	No	Yes	Yes
Observations	137	119	117	115
R-Squared	0.033	0.479	0.521	0.533
Prob > F	0.067	0.000	0.000	0.000

Standard errors in parenthesis, *** = 99% confidence, ** = 95%, * = 90%.
OLS 1 uses program participation as the only explanatory variable to explain mature native forest cover change.
OLS 2 includes a parsimonious specification of mature native forest cover change that includes main determinants of tropical deforestation.
OLS 3 adds land management controls.
OLS 4 adds household socio-economic characteristics.
[a,c,e] Distance to city, hectares in high elevation and hectares with poor soil was calculated in ArcMap using the Atlas Digital de Costa Rica (2004).
[b] Parcel size is the one obtained from aerial photos and not the one self-reported during the household survey.
[d] Labor in 1996 is proxied by interacting number of males and females in 2005 with the dummy that indicated residency in the parcel in 1996.
[f] Total native forest includes intervened and non-intervened primary (>20 years) and secondary (<20 years) natural forest.

Table 3.8: Robustness checks

Dependent Variable[a]	*Change in Self-Reported Mature Native Forest Cover 1996-2005*	*Change in Total Native Forest Cover 1992-2005 from Aerial Photos*
(1) Including controls for 1986 forest cover from Landsat satellite images		
PSA	9.838** (4.123)	3.356 (6.310)
# Observations	104	115
R-Squared	0.368	0.545
Prob > F	0.001	0.000
(2) Including controls for the percent of land parcel in native forest for 1986 from Landsat satellite images		
PSA	11.299** (4.425)	2.232 (6.408)
# Observations	104	115
R-Squared	0.271	0.537
Prob > F	0.030	0.000
(3) Including controls for 1992 forest cover from aerial photos		
PSA	11.616*** (4.190)	na
# Observations	104	na
R-Squared	0.342	na
Prob > F	0.002	na
(4) Including district fixed effects		
PSA	7.302** (3.219)	4.567 (6.529)
# Observations	152	115
R-Squared	0.214	0.542
Prob > F	0.013	0.000
(5) Using outcome from aerial photos combined with self-reported biophysical controls		
PSA	na	6.410 (5.014)†
# Observations	na	104
R-Squared	na	0.305
Prob > F	na	0.005
(6) Using % of 2005 natural forest cover as the outcome of interest		
PSA	31.540* (16.704)	6.398 (18.575)
# Observations	152	115
R-Squared	0.839	0.548
Prob > F	0.000	0.000

Standard errors in parenthesis, *** = 99% confidence, ** = 95%, * = 90%. † In this case, only distance to forestry office was statistically significant.

[a] Mature native forest includes intervened and non-intervened primary (>20 years) natural forest, and total native forest includes intervened and non-intervened primary (>20 years) and secondary (<20 years) natural forest.

Table 3.9: PSA effect estimates using multivariate matching

PSA Outcome[a]	*Multivariate Matching Estimator*[b,c]					
	M1	***M2***	***M3***	***M4***	***M5***	***M6***
Change in Self-Reported Mature Native Forest Cover 1996-2005	7.705*	7.102**	5.303*	5.364	3.250	2.852
	(0.054)	(0.045)	(0.063)	(0.140)	(0.135)	(0.109)
Change in Self-Reported Total Native Forest Cover 1996-2005	4.818**	3.455	3.114	1.500	1.443	1.746
	(0.046)	(0.160)	(0.156)	(0.404)	(0.409)	(0.313)
# Observations	163	163	163	163	163	163
# PSA	44	44	44	44	44	44
# PSA off common support	0	0	0	0	0	0
Change in Total Native Forest Cover 1992-2005 from Aerial Photos	6.730**	7.474***	8.186***	2.318	3.306	4.583*
	(0.011)	(0.002)	(0.000)	(0.628)	(0.343)	(0.091)
# Observations	111	111	111	111	111	111
# PSA	44	44	44	44	44	44
# PSA off common support	0	0	0	0	0	0

P-values in parenthesis using Abadie-Imbens bias corrected robust standard errors. *** = 99% confidence, ** = 95%, * = 90%.

[a] Mature native forest includes intervened and non-intervened primary (>20 years) natural forest, and total native forest includes intervened and non-intervened primary (>20 years) and secondary (<20 years) natural forest.

[b] M1, M2, M3: Multivariate matching - Inverse variance with one, two and three closest matches; M4, M5, M6: Multivariate matching - Mahalanobis with one, two and three closest matches.

[c] For outcomes from self-reports, inverse variance and Mahalanobis multivariate matching included: parcel size, self-reported hectares of native forest in 1996, distance to forestry office, % of parcel with steep slope and a proxy for adults living in parcel in 1996. For outcome from aerial photos, hectares of native forest in 1996 from aerial photos was used instead of the one self-reported.

Table 3.10: Balance-checking criteria for multivariate matching using self-reported household data

Variables	*Multivariate Matching Estimator*[a]					
	M1	***M2***	***M3***	***M4***	***M5***	***M6***
Outcome: Change in Self-Reported Mature Native Forest Cover 1996-2005[b]						
Balancing on covariates used during matching						
Distance to forestry office	0.227	0.217	0.177	0.510	0.686	0.697
Parcel size	0.797	0.486	0.459	0.246	0.173	0.118
Percent of parcel with steep slope	0.888	0.486	0.479	0.885	0.482	0.182
Self-reported 1996 total native forest cover	0.353	0.101	0.091*	0.160	0.078*	0.048*
Household labor force in 1996[c]	0.449	0.696	0.759	0.801	0.726	0.543
Balancing on covariates not used during matching						
Percent of parcel with poor soil	0.475	0.249	0.225	0.203	0.117	0.133
D - Experience with forest plantations before 1996	0.422	0.190	0.141	0.060*	0.118	0.077
D - Forest management plan pre-1996	0.035**	0.030**	0.041**	0.060*	0.071*	0.054*
D - Previous participation in other forest programs	0.117	0.022**	0.018	0.002***	0.005***	0.013**
D - Resident on parcel in 1996	0.578	0.423	0.485	0.943	0.801	0.680
Years of education of respondent	0.738	0.629	0.593	0.924	0.556	0.848
Age	0.298	0.811	0.759	0.585	0.518	0.997
D - From Central Valley	0.013**	0.002***	0.002***	0.013**	0.001***	0.000***
Distance to city[d]	0.007***	0.005***	0.003***	0.011**	0.005***	0.001***
Parcel size from aerial photos[e]	0.903	0.763	0.676	0.752	0.605	0.449
Hectares in high elevation[f]	0.254	0.117	0.107	0.218	0.140	0.093*
Hectares with poor soil[g]	0.138	0.785	0.704	0.050**	0.338	0.186

P-values from standard t-tests in parentheses. *** = 99% confidence, ** = 95%, * = 90%; NN refers to nearest neighbor propensity score matching.

[a] M1, M2, M3: Multivariate matching - Inverse variance with one, two and three closest matches; M4, M5, M6: Multivariate matching - Mahalanobis with one, two and three closest matches.

[b] Mature native forest includes intervened and non-intervened primary (>20 years) natural forest.

[c] Labor in 1996 is proxied by interacting number of males and females in 2005 with the dummy that indicated residency in the parcel in 1996.

[d,f,g] Distance to city, hectares in high elevation and hectares with poor soil was calculated in ArcMap using the Atlas Digital de Costa Rica (2004).

[e] Parcel size is the one obtained from aerial photos and not the one self-reported during the household survey.

Table 3.11: Balance-checking criteria for multivariate matching using data from aerial photos

Variables	*Multivariate Matching Estimator*[a]					
	M1	***M2***	***M3***	***M4***	***M5***	***M6***
Outcome: Change in Total Native Forest Cover 1992-2005 from Aerial Photos[b]						
Balancing on covariates used during matching						
Distance to forestry office	0.635	0.770	0.416	0.493	0.515	0.666
Parcel size	0.511	0.451	0.331	0.748	0.397	0.290
Percent of parcel with steep slope	0.358	0.053	0.020**	0.086*	0.030	0.007***
Self-reported 1996 total native forest cover	0.350	0.131	0.080*	0.296	0.112	0.064*
Household labor force in 1996[c]	0.861	0.715	0.805	0.753	0.975	0.882
Balancing on covariates not used during matching						
Percent of parcel with poor soil	0.073*	0.361	0.477	0.394	0.539	0.599
D - Experience with forest plantations before 1996	0.289	0.361	0.437	0.277	0.335	0.343
D - Forest management plan pre-1996	0.075*	0.063*	0.018**	0.035**	0.025**	0.010***
D - Previous participation in other forest programs	0.389	0.069*	0.043**	0.255	0.024**	0.005***
D - Resident on parcel in 1996	0.789	0.745	0.471	0.578	0.393	0.187
Years of education of respondent	0.855	0.752	0.847	0.967	0.961	0.714
Age	0.607	0.533	0.629	0.682	0.788	0.997
D - From Central Valley	0.005***	0.013	0.002***	0.006***	0.004***	0.002***
Distance to city[d]	0.006***	0.000***	0.000***	0.007***	0.000***	0.000***
Parcel size from aerial photos[e]	0.583	0.799	0.639	0.799	0.682	0.411
Hectares in high elevation[f]	0.179	0.093*	0.065*	0.147	0.071*	0.044**
Hectares with poor soil[g]	0.398	0.223	0.126	0.314	0.170	0.285

P-values from standard t-tests in parentheses. *** = 99% confidence, ** = 95%, * = 90%; NN refers to nearest neighbor propensity score matching.

[a] M1, M2, M3: Multivariate matching - Inverse variance with one, two and three closest matches; M4, M5, M6: Multivariate matching - Mahalanobis with one, two and three closest matches.

[b] Total native forest includes intervened and non-intervened primary (>20 years) and secondary (<20 years) natural forest.

[c] Labor in 1996 is proxied by interacting number of males and females in 2005 with the dummy that indicated residency in the parcel in 1996.

[d,f,g] Distance to city, hectares in high elevation and hectares with poor soil was calculated in ArcMap using the Atlas Digital de Costa Rica (2004).

[e] Parcel size is the one obtained from aerial photos and not the one self-reported during the household survey.

Table 3.12: Marginal effects on the propensity of a parcel to have a PSA contract using self-reported area with natural forest in 1996 land use (dependent variable = 1 if parcel has a PSA contract)

Characteristic[a]	***Marginal Effect***	
	Model 1[b]	***Model 2***[c]
Intercept	-1.950 (0.497)***	-1.052 (1.303)
Distance to forestry office	0.010 (0.013)	0.002 (0.016)
Parcel size	-0.011 (0.007)*	-0.006 (0.005)
Percent of parcel with steep slope	0.015 (0.007)**	0.016 (0.008)*
Self-reported 1996 native forest	0.020 (0.008)**	0.015 (0.007)**
Household labor force in 1996[d]	-0.006 (0.086)	0.240 (0.177)
Percent of parcel with poor soil		0.000 (0.009)
D - Experience with forest plantations before 1996		-0.332 (0.482)
D - Forest management plan pre-1996		0.541 (0.534)
D - Previous participation in other forest programs		0.998 (0.563)*
D - Resident on parcel in 1996		-1.692 (0.957)*
Years of education of respondent		-0.117 (0.057)**
Age		-0.020 (0.019)
D - From Central Valley		1.961 (0.564)***
Observations	163	152
Pseudo R-square	0.132	0.280
Log-likelihood	-82.500	-64.481

Standard errors in parenthesis. *** = 99% confidence, ** = 95%, * = 90%.

[a] D indicates a "dummy" variables, coded as 1 = statement true for the respondent, and 0 = statement false for respondent.

[b] Model 1 is a parsimonious logit specification that includes the determinants of tropical deforestation used in OLS 2 of Table 3.6.

[c] Model 2 adds land management controls and household socio-economic characteristics as used in OLS 3 of Table 3.6.

[d] Labor in 1996 is proxied by interacting number of males and females in 2005 with the dummy that indicates residency in the parcel in 1996.

Table 3.13: Marginal effects on the propensity of a parcel to have a PSA contract using area with native forest in 1992 and other controls from aerial photos (dependent variable = 1 if parcel has a PSA contract)

Characteristic [a]	***Marginal Effect***		
	Model 1 [b]	***Model 2*** [c]	***Model 3*** [d]
Intercept	-1.810 (0.530)***	-0.864 (1.586)	-2.601 (1.975)
Distance to forestry office	0.012 (0.014)	0.004 (0.019)	na
Parcel size	0.001 (0.001)	0.000 (0.002)	na
Percent of parcel with steep slope	0.023 (0.008)***	0.023 (0.012)*	na
Native forest in 1992 from aerial photos	0.007 (0.005)	0.011 (0.005)**	0.087 (0.027)***
Household labor force in 1996 [e]	-0.021 (0.090)	0.281 (0.232)	0.491 (0.273)*
Percent of parcel with poor soil		-0.005 (0.011)	na
D - Experience with forest plantations before 1996		-0.095 (0.562)	-0.101 (0.672)
D - Forest management plan pre-1996		1.379 (0.676)**	1.628 (0.786)**
D - Previous participation in other forest programs		1.854 (0.675)***	4.070 (1.226)***
D - Resident on parcel in 1996		-1.776 (1.243)	-2.053 (1.449)
Years of education of respondent		-0.140 (0.071)**	-0.021 (0.082)
Age		-0.028 (0.024)	-0.029 (0.032)
D - From Central Valley		2.405 (0.707)***	2.211 (0.833)***
Distance to city [f]		na	0.000 (0.000)*
Parcel size from aerial photos [g]		na	-0.057 (0.019)***
Hectares in high elevation [h]		na	0.302 (0.323)
Hectares with poor soil [i]		na	-0.022 (0.014)
Observations	111	104	115
Pseudo R-square	0.128	0.338	0.574
Log-likelihood	-64.997	-46.434	-32.978

Standard errors in parenthesis. *** = 99% confidence, ** = 95%, * = 90%.

[a] D indicates a "dummy" variables, coded as 1 = statement true for the respondent, and 0 = statement false for respondent.

[b] Model 1 is a parsimonious logit specification that includes the determinants of tropical deforestation used in OLS 2 of Table 3.6.

[c] Model 2 adds land management controls and household socio-economic characteristics as used in OLS 3 of Table 3.6.

[d] Model 3 replaces self-reported biophysical controls with the ones obtained from remote sensing imagery as done in OLS 4 of Table 3.7.

[e] Labor in 1996 is proxied by interacting number of males and females in 2005 with the dummy that indicated residency in the parcel in 1996

[f,h,i] Distance to city, hectares in high elevation and hectares with poor soil was calculated in ArcMap using the Atlas Digital de Costa Rica (2004).

[g] Parcel size is the one obtained from aerial photos and not the one self-reported during the household survey.

Table 3.14: Treatment effect estimates

Average Treatment Effect on the Treated	***PSA Outcomes*** [a,b,c,d]						
	(1)		***(2)***		***(3)***		
	Model 1	***Model 2***	***Model 1***	***Model 2***	***Model 1***	***Model 2***	***Model 3***
Nearest-neighbor propensity score	8.381	16.425	1.976	2.175	6.522	12.686	15.398
	(0.124)*	(0.122)*	(0.327)	(0.245)	(0.103)*	(0.008)***	(0.027)**
	[0.204]	[0.394]	[0.296]	[0.291]	[0.024]**	[0.002]***	[0.047]**
Radius propensity score	3.092*	4.852*	2.723*	2.483	2.859	4.647	11.177*
	(0.110)	(0.138)	(0.143)	(0.199)	(0.515)	(0.228)	(0.082)
Kernel (Gaussian) propensity score	4.472	7.554	2.093	2.166	3.693	10.170**	13.648**
	(0.202)	(0.245)	(0.244)	(0.243)	(0.475)	(0.030)	(0.046)
Observations	163	152	163	152	111	104	115
# PSA participants	44	42	44	42	44	42	46
# PSA participants off common support	2	2	2	2	2	2	0

P-values in parenthesis using bootstrapped standard errors with 999 repetitions. *P*-values in squared parenthesis using Abadie-Imbens bias corrected robust standard errors. Trimming level for common support is 5 percent. *** = 99% confidence, ** = 95%, * = 85%.

[a] (1) refers to changes in self-reported mature native forest cover 1996-2005, (2) refers to changes in self-reported total native forest cover 1996-2005 and (3) refers to changes in total native forest cover 1992-2005 from Aerial Photos.

[b] Model 1 is a parsimonious logit specification that includes the determinants of tropical deforestation used in OLS 2 of Table 3.6.

[c] Model 2 adds land management controls and household socio-economic characteristics as used in OLS 3 of Table 3.6.

[d] Model 3 replaces self-reported biophysical controls with the ones obtained from remote sensing imagery as done in OLS 4 of Table 3.7.

Table 3.15: Balance-checking criteria for propensity score matching using self-reported household data

Variables	***Model 1*** [a]			***Model 2*** [b]		
	NN	***Radius***	***Kernel***	***NN***	***Radius***	***Kernel***
Outcome: Change in Self-Reported Mature Native Forest Cover 1996-2005 [c]						
Balancing on covariates used during matching						
Distance to forestry office	0.267	0.230	0.480	0.001***	0.360	0.135
Parcel size	0.425	0.282	0.807	0.251	0.491	0.499
Percent of parcel with steep slope	0.227	0.061*	0.877	0.312	0.100*	0.437
Self-reported 1996 native forest	0.430	0.003***	0.602	0.381	0.110	0.545
Household labor force in 1996[d]	0.394	0.823	0.803	0.388	0.833	0.499
Balancing on covariates not used during matching						
Percent of parcel with poor soil	0.288	0.313	0.105	0.565	0.543	0.578
D - Experience with forest plantations before 1996	0.000***	0.262	0.043**	0.644	0.597	0.557
D - Forest management plan pre-1996	1.000	0.063*	0.198	0.308	0.305	0.689
D - Previous participation in other forest programs	0.821	0.043**	0.090*	0.170	0.268	0.252
D - Resident on parcel in 1996	0.804	0.122	0.539	0.290	0.567	0.850
Years of education of respondent	0.065*	0.836	0.730	0.443	0.757	0.937
Age	0.199	0.814	0.807	0.298	0.872	0.539
D - From Central Valley	0.045**	0.006***	0.003***	0.808	0.092*	0.496
				Balancing on covariates not used during matching		
Distance to city[e]	0.054*	0.001***	0.106	0.002***	0.010*	0.026**
Parcel size from aerial photos[f]	0.233	0.458	0.673	0.004***	0.685	0.058*
Hectares in high elevation[g]	0.309	0.190	0.221	0.218	0.182	0.224
Hectares with poor soil[h]	0.096*	0.352	0.504	0.055*	0.649	0.737

P-values from standard t-tests in parentheses. *** = 99% confidence, ** = 95%, * = 90%; NN refers to nearest neighbor propensity score matching.

[a] Model 1 is a parsimonious logit specification that includes the determinants of tropical deforestation used in OLS 2 of Table 3.6.

[b] Model 2 adds land management controls and household socio-economic characteristics as used in OLS 3 of Table 3.6.

[c] Mature native forest includes intervened and non-intervened primary (>20 years) natural forest.

[d] Labor in 1996 is proxied by interacting number of males and females in 2005 with the dummy that indicated residency in the parcel in 1996.

[e,g,h] Distance to city, hectares in high elevation and hectares with poor soil was calculated in ArcMap using the Atlas Digital de Costa Rica (2004).

[f] Parcel size is the one obtained from aerial photos and not the one self-reported during the household survey.

Table 3.16: Balance-checking criteria for propensity score matching using data from aerial photos

Variables		*Model 1*[a]			*Model 2*[b]			*Model 3*[c]	
	NN	*Radius*	*Kernel*	*NN*	*Radius*	*Kernel*	*NN*	*Radius*	*Kernel*
Outcome: Change in Total Native Forest Cover 1992-2005 from Aerial Photos[d]									
Distance to forestry office	0.962	0.386	0.534	0.020**	0.553	0.022**	0.290†	0.912†	0.155†
Parcel size	0.838	0.305	0.987	0.297	0.306	0.250	0.145†	0.237†	0.132†
% of parcel with steep slope	0.352	0.026**	0.609	0.678	0.057*	0.998	0.245†	0.038**†	0.086†
Native forest in 1992 from aerial photos	0.975	0.060*	0.802	0.008**	0.301	0.005***	0.494	0.044**	0.128
Household labor force in 1996[e]	0.285	0.679	0.649	0.665	0.983	0.257	0.024**	0.621	0.113
Balancing on covariates not used during matching									
Percent of parcel with poor soil	0.041**	0.568	0.207	0.700	0.555	0.432	0.000***†	0.523†	0.000†
D - Experience with forest plantations before 1996	1.000	0.564	0.547	0.821	0.952	0.770	0.004***	0.171	0.003***
D - Forest management plan pre-1996	0.497	0.006***	0.071*	0.250	0.179	0.502	0.022**	0.235	0.277
D - Previous participation in other forest programs	0.694	0.019**	0.197	0.631	0.185	0.952	0.030**	0.550	0.040**
D - Resident on parcel in 1996	0.600	0.092*	0.857	0.598	0.544	0.276	0.117	0.498	0.278
Years of education of respondent	0.348	0.645	0.373	0.061*	0.897	0.060*	0.003	0.753	0.043
Age	0.018**	0.934	0.312	0.158	0.627	0.172	0.159	0.296	0.260
D - From Central Valley	0.004***	0.002***	0.000***	0.013**	0.262	0.008***	0.348	0.413	0.160
				Balancing on covariates not used during matching					
Distance to city[f]	0.000***	0.000***	0.000***	0.000***	0.002***	0.000***	0.120	0.163	0.520
Parcel size from aerial photos[g]	0.175	0.509	0.243	0.000***	0.451	0.000***	0.412	0.041**	0.071*
Hectares in high elevation[h]	0.142	0.142	0.142	0.073*	0.074*	0.074*	0.042**	0.043**	0.043**
Hectares with poor soil[i]	0.846	0.265	0.299	0.004***	0.976	0.263	0.908	0.919	0.588

P-values from standard t-tests in parentheses. *** = 99% confidence, ** = 95%, * = 90%. NN refers to nearest neighbor propensity score matching.

[a] Model 1 is a parsimonious logit specification that includes the determinants of tropical deforestation used in OLS 2 of Table 3.6.

[b] Model 2 adds land management controls and household socio-economic characteristics as used in OLS 3 of Table 3.6.

[c] Model 3 replaces self-reported biophysical controls with the ones obtained from remote sensing imagery as done in OLS 4 of Table 3.7.

[d] Total native forest includes intervened and non-intervened primary (>20 years) and secondary (<20 years) natural forest.

[e] Labor in 1996 is proxied by interacting number of males and females in 2005 with the dummy that indicated residency in the parcel in 1996.

[f,h,i] Distance to city, hectares in high elevation and hectares with poor soil was calculated in ArcMap using the Atlas Digital de Costa Rica (2004).

[g] Parcel size is the one obtained from aerial photos and not the one self-reported during the household survey.

† These self-reported biophysical controls were not used during matching using logit model specification 3.

Table 3.17: Robustness checks with additional constraints on counterfactual selection and using imputation for missing data

Average Treatment Effect on the Treated	*PSA Outcomes*[a,b]			
	(1)	***(2)***	***(3)***	
	Model 2	***Model 2***	***Model 2***	***Model 3***
Propensity score matching without proxy for household labor force in 1996				
Nearest-neighbor propensity score	16.425	2.050	11.932	12.795
	(0.159)	(0.313)	(0.029)**	(0.109)*
	[0.095]*	[0.381]	[0.033]**	[0.074]*
Radius propensity score	4.682*	2.466	4.594	10.323*
	(0.139)	(0.201)	(0.235)	(0.139)
Kernel (Gaussian) propensity score	9.496	2.134	8.645*	11.071*
	(0.218)	(0.249)	(0.071)	(0.124)
Observations	152	152	104	115
# PSA participants	42	42	42	46
# PSA participants off common support	2	2	2	2
Propensity score matching using multiple imputation by chained equations				
Nearest-neighbor propensity score	7.000	7.638	16.172	7.282
	(0.251)	(0.107)*	(0.020)**	(0.115)*
	[0.048]*	[0.007]***	[0.014]**	[0.104]*
Radius propensity score	10.005*	7.388*	16.996**	8.552*
	(0.088)	(0.125)	(0.017)	(0.079)
Kernel (Gaussian) propensity score	6.195	4.769	16.107**	7.924*
	(0.225)	(0.235)	(0.020)	(0.074)
Observations	203	203	137	137
# PSA participants	50	50	50	50
# PSA participants off common support	3	3	2	2

P-values in parenthesis using bootstrapped standard errors with 999 repetitions. Trimming level for common support is 5 percent. *** = 99% confidence, ** = 95%, * = 85%.

[a] (1) refers to changes in mature native forest cover from self-reports, (2) refers to changes in native forest cover from self-reports and (3) refers to changes in native forest cover from aerial photos.

[b] Model 1 is a parsimonious logit specification that includes the determinants of tropical deforestation used in OLS 2 of Table 3.6, model 2 adds land management controls and household socio-economic characteristics as used in OLS 3 of Table 3.6, and model 3 replaces self-reported biophysical controls with the ones obtained from remote sensing imagery as done in OLS 4 of Table 3.7.

Table 3.18: Spatial spillover effect of PSA on deforestation using matching

PSA Outcome	*Change in Self-Reported Mature Native Forest Cover 1996-2005*[a]	*Change in Total Native Forest Cover 1992-2005 from Aerial Photos*[b]
Treatment group: Immediate neighbors to PSA participants Control group: Non-immediate neighbors to PSA participants		
Nearest-neighbor propensity score	5.779 (0.288) [0.048]**	4.984 (0.426) [0.473]
Radius propensity score	3.209* (0.128)	3.937 (0.549)
Kernel (Gaussian) propensity score	3.379 (0.299)	4.961 (0.472)
Treatment group: Parcels with PSA contracts Control group: Non-immediate neighbors to PSA participants		
Nearest-neighbor propensity score	16.425 (0.250) [0.371]	10.019 (0.097)* [0.499]
Radius propensity score	7.524 (0.153)	9.912* (0.055)
Kernel (Gaussian) propensity score	13.187 (0.296)	8.615* (0.061)

The ATT estimators were calculated using the Model 2 and Model 3 from Table 3.13.
P-values in parenthesis using bootstrapped standard errors with 999 repetitions. *P*-values in squared parenthesis using Abadie-Imbens bias corrected robust standard errors. Trimming level for common support is 5 percent. *** = 99% confidence, ** = 95%, * = 85%.
[a] Mature native forest includes intervened and non-intervened primary (>20 years) natural forest.
[b] Total native forest includes intervened and non-intervened primary (>20 years) and secondary (<20 years) natural forest.

Table 3.19: Spatial spillover effect of PSA on deforestation using OLS

Dependent Variable	*Change in Self-Reported Mature Native Forest Cover 1996-2005[a]*	*Change in Total Native Forest Cover 1992-2005 from Aerial Photos[b]*	*Mature Forest Cover 2005 from Self-Reports[a]*	*Total Native Forest Cover 2005 from Aerial Photos[b]*
Intercept	-19.710 (11.433)*	-85.287	-0.103 (55.768)	-290.435 (94.599)***
PSA	13.253 (4.787)***	8.945 (6.370)	-0.944 (23.351)	11.863 (19.468)
Distance to nearest PSA participant	0.441 (0.414)	2.115 (0.671)***	-2.378 (0.242)	1.934 (2.050)
Distance to forestry office	0.202 (0.120)*	na	0.468 (0.587)	na
Parcel size	-0.006 (0.009)	na	0.811 (0.042)***	na
Percent of parcel with steep slope	-0.093 (0.072)	na	0.354 (0.349)	na
Ln (Self-reported native forest in 1996)	-4.058 (1.497)***	na	11.295 (7.300)	na
Household labor force in 1996[c]	-0.511 (1.194)	-0.011 (1.251)	-23.388 (5.826)***	-2.756 (3.823)
Percent of parcel with poor soil	0.049 (0.068)	na	-0.250 (0.330)	na
D - Experience with forest plantations before 1996	5.428 (3.453)	-1.064 (4.613)	10.186 (16.843)	-7.770 (14.098)
D - Forest management plan pre-1996	4.344 (4.498)	7.292 (6.281)	14.996 (21.942)	35.915 (19.196)*
D - Previous participation in other forest programs	4.471 (4.569)	10.399 (6.551)	20.110 (22.290)	13.031 (20.019)
D - Resident on parcel in 1996	-0.390 (6.281)	2.782 (7.828)	85.762 (30.636)***	51.676 (23.922)*
Years of education of respondent	-0.495 (0.379)	-0.446 (0.511)	-4.904 (1.851)***	3.929 (1.560)**
Age	0.421 (0.155)***	0.138 (0.209)	-0.458 (0.756)	-0.173 (0.639)
D - From Central Valley	3.955 (4.036)	5.869 (5.014)	12.071 (19.688)	-13.288 (15.322)
Ln (Distance to city)[d]	na	6.241 (3.468)*	na	13.560 (10.597)
Ln (Parcel size)[e]	na	11.142 (4.103)***	na	28.838 (12.540)**
Hectares in high elevation[f]	na	0.385 (0.061)***	na	0.426 (0.187)**
Ln (Native forest in 1992 from aerial photos)	na	-12.570 (3.430)***	na	22.686 (10.483)*
Percent of parcel with poor soil[g]	na	0.235 (0.123)*	na	-0.213 (0.375)
Canton fixed effects	Yes	Yes	Yes	Yes
Observations	104	115	104	115
R-Squared	0.280	0.576	0.874	0.552
Prob > F	0.022	0.000	0.000	0.000

Standard errors in parenthesis, *** = 99% confidence, ** = 95%, * = 90%.
[a] Mature native forest includes intervened and non-intervened primary (>20 years) natural forest.
[b] Total native forest includes intervened and non-intervened primary (>20 years) and secondary (<20 years) natural forest.
[c] Labor in 1996 is proxied by interacting number of males and females in 2005 with the dummy that indicated residency in the parcel in 1996.
[d,f,g] Distance to city, hectares in high elevation and hectares with poor soil was calculated in ArcMap® using the Atlas Digital de Costa Rica (2004).
[e] Parcel size is the one obtained from aerial photos and not the one self-reported during the household survey.

Table 3.20: Unconfoundedness test I

Dependent Variable	***Total Native Forest Cover 1986 from Aerial Photos***	***Total Native Forest Cover 1992 from Aerial Photos***
Intercept	-259.678*	-266.111 (164.215)
PSA	-6.810 (13.473)	13.865 (16.338)
Ln (Distance to city)[a]	11.440 (12.605)	10.460 (13.945)
Ln (Parcel size)[b]	40.517 (10.285)***	10.523 (16.338)
Hectares in high elevation[c]	0.360 (0.171)**	-0.027 (0.360)
Ln (Native forest in 1992 from aerial photos)	18.458 (9.007)**	na
Ln (Native forest in 1986 from aerial photos)	na	39.272 (21.640)*
Household labor force in 1996[d]	-2.639 (3.644)	-2.041 (4.304)
Percent of parcel with poor soil[e]	-0.499 (0.528)	-0.224 (0.528)
D - Experience with forest plantations before 1996	-4.165 (12.502)	-8.541 (12.917)
D - Forest management plan pre-1996	39.797 (29.637)	24.066 (31.237)
D - Previous participation in other forest programs	13.378 (17.232)	-10.538 (16.964)
D - Resident on parcel in 1996	47.300 (33.536)	41.186 (34.037)
Years of education of respondent	3.218 (2.544)	4.737 (2.881)
Age	-0.317 (0.444)	0.259 (0.429)
D - From Central Valley	-17.014 (12.889)	-25.084 (13.601)*
Canton fixed effects	Yes	Yes
Observations	115	115
R-Squared	0.587	0.471
Prob > F	0.000	0.000

Standard errors in parenthesis, *** = 99% confidence, ** = 95%, * = 90%.

[a,c,e] Distance to city, hectares in high elevation and hectares with poor soil was calculated in ArcMap® using the Atlas Digital de Costa Rica (2004).

[b] Parcel size is the one obtained from aerial photos and not the one self-reported during the household survey.

[d] Labor in 1996 is proxied by interacting number of males and females in 2005 with the dummy that indicated residency in the parcel in 1996.

Table 3.21: Unconfoundedness test II

PSA Outcome	***Total Native Forest Cover 1986 from Aerial Photos***		***Total Native Forest Cover 1992 from Aerial Photos***	
	Model 2[a]	***Model 3[b]***	***Model 2[a]***	***Model 3[b]***
Nearest-neighbor propensity score	-10.193	25.184	-5.526	-14.791
	(0.760)	(0.347)	(0.810)	(0.574)
	[0.119]	[0.005]***	[0.552]	[0.402]
Radius propensity score	23.727	10.011	19.255	21.221
	(0.106)	(0.603)	(0.242)	(0.131)
Kernel (Gaussian) propensity score	-1.743	12.705	-7.426	2.083
	(0.937)	(0.618)	(0.724)	(0.920)

The ATT estimators were calculated using the Model 2 and Model 3 from Table 3.13.
P-values in parenthesis using bootstrapped standard errors with 999 repetitions. *P*-values in squared parenthesis using Abadie-Imbens bias corrected robust standard errors. Trimming level for common support is 5 percent. *** = 99% confidence, ** = 95%, * = 90%.
[a] Model 2 adds land management controls and household socio-economic characteristics as used in OLS 3 of Table 3.6 except for 1992 native forest from aerial photos.
[b] Model 3 replaces self-reported biophysical controls with the ones obtained from remote sensing imagery as done in OLS 4 of Table 3.7 except for 1992 native forest from aerial photos..

APPENDICES

Appendix 1: Correlations between differences in area of mature native forest in Sarapiquí in 2005 as reported by landowners and obtained from aerial photos, and selected variables

Variable	*Difference*[a,b,c]		
	Overall	***Non-PSA***	***PSA***
D - From Central Valley	-0.029 (132)	0.127 (82)	-0.139 (50)
D - Resident on parcel in 2005	-0.051 (128)	0.139 (78)	-0.072 (50)
D - Resident on parcel in 1996	0.035 (119)	0.033 (73)	0.023 (46)
Years of education of respondent	-0.146 (129)	-0.005 (79)	-0.213 (50)
Number of men in family	0.065 (130)	0.014 (80)	0.109 (50)
Number of women in family	0.098 (130)	0.050 (80)	0.089 (50)
Age of respondent (years)	0.028 (130)	0.038 (80)	0.027 (50)
D - Sole owner of parcel	0.023 (132)	-0.184 (82)	0.076 (50)
D - Inherited parcel	0.010 (132)	0.071 (82)	-0.008 (50)
Family members working on parcel	0.081 (125)	0.004 (77)	0.087 (48)
D - Children will manage land in future	0.007 (130)	-0.087 (80)	0.028 (50)
D - Secondary occupation	0.058 (131)	0.056 (81)	0.112 (50)
Self-reported hectares of primary forest in 1996	0.855* (132)	0.374* (82)	0.889* (50)
Self-reported of natural forest regeneration in 1996	-0.028 (132)	-0.256 (82)	-0.015 (50)
Self-reported hectares of forest plantations in 1996	-0.021 (132)	0.012 (82)	-0.035 (50)
Self-reported hectares of crops in 1996	0.003 (132)	0.151 (82)	-0.026 (50)
Self-reported hectares of pastures in 1996	0.047 (132)	-0.015 (82)	0.123 (50)
D - Forest fenced in 1996	0.009 (132)	-0.019 (82)	0.077 (50)
D - Experience with forest plantations before 1996	0.102 (130)	0.186 (80)	0.153 (50)
D - Money loans from 1996 to 2005	0.125 (130)	-0.043 (80)	0.212 (50)
D - Financial investment (e.g. savings account)	0.063 (130)	-0.006 (80)	0.105 (50)
Index of Environmentalism	0.182 (132)	-0.117 (82)	0.263 (50)
D - Forest management plan pre-1996	0.148 (132)	0.269 (82)	0.132 (50)
D - Previous participation in other forest programs	0.100 (130)	0.192 (80)	0.080 (50)
D - Forest logged in past 50 years	0.017 (130)	-0.003 (80)	0.020 (50)
Number of kilometers to nearest forestry office	0.006 (121)	0.070 (75)	-0.024 (46)
Number of kilometers to nearest agricultural office	0.006 (120)	0.068 (75)	0.009 (45)
Parcel size (hectares)	0.774* (132)	0.223 (82)	0.848* (50)
Percent of parcel with poor soil	-0.013 (125)	0.073 (77)	-0.062 (48)
Percent of parcel with steep slope	0.016 (128)	0.272 (78)	-0.054 (50)

[a] Difference refers to area of native forest in 2005 from self-reports minus the one obtained from aerial photos
[b] Asterisk indicates correlation coefficient significant at the 99% confidence level
[c] Number of observations in parenthesis

Appendix 2: Correlations between self-reported biophysical controls and the ones obtained from remote sensing imagery

	Distance to forestry office	Parcel size	% of parcel with steep slope	% of parcel with poor soil	Distance to city	Parcel size from aerial Photos	Hectares in high elevation	Hectares with poor soil
Distance to forestry office	1.000							
Parcel size	0.025	1.000						
% of parcel with steep slope	0.141	0.0269	1.000					
% of parcel with poor soil	0.006	-0.027	0.053	1.000				
Distance to city	0.396*	0.115	0.082	0.026	1.000			
Parcel size from aerial Photos	0.022	0.379*	0.107	-0.165	0.173	1.000		
Hectares in high elevation	0.142	0.092	0.236*	0.068	0.123	0.235*	1.000	
Hectares with poor soil	0.300*	-0.010	-0.036	-0.144	0.470*	0.053	-0.057	1.000

Chapter 4

MATCHING ANALYSIS USING
BINARY AND CONTINUOUS TREATMENT:
PAYMENTS FOR ENVIRONMENTAL SERVICES AND THEIR IMPACT ON FOREST TRANSITION IN COSTA RICA USING VARIUOS DEFINITIONS OF PROGRAM OUTCOME

4.1 INTRODUCTION

Tropical deforestation is one of the most serious environmental problems in recent times. It has become an issue of global concern because of the relevance of tropical forests in biodiversity conservation and in limiting the greenhouse effect. At the local level, deforestation can negatively impact economic activity by reducing the supply of forest products and increasing siltation, flooding and soil degradation (Culas, 2007). In many regions, it threatens the livelihood and cultural integrity of forest-dependent people.

Economists started contributing to the literature on the causes and potential consequences of tropical forest destruction in the mid 1980s, and since then, there has been steady progress in the economic analysis of tropical forest loss. The 'first wave' of studies focused on the economic causes of tropical deforestation, and tended to be dominated by statistical analyses across tropical countries, or for selective countries and regions. More recently, a ‘second wave’ of studies has focused on modeling and analyzing the economic behavior of agricultural households, timber concessionaries and other agents within tropical countries who affect deforestation through their land use decisions (Barbier and Burgess 2001).

Many studies of tropical deforestation have relied on secondary data. One branch of the literature employs aggregate cross country and/or time-series data to analyze the effect of income, policies, and other country characteristics. These studies typically estimate a reduced-form specification for a deforestation equation without trying to disentangle the various channels through which income and other factors can affect deforestation at a more disaggregated level (Deacon 1999; Koop and Tole 1999; Barbier and Burgess 2001). Another branch of the literature uses national census data, often in combination with remote sensing, to model deforestation at the meso-scale (Pfaff 1999; Chomitz and Thomas 2003). These studies are often focused exclusively on biophysical and locational factors that are the most direct or immediate causes of deforestation (e.g. the effect of more roads into a given area on forest cover). Socio-economic factors are known to be important at the household level but are not always available at more aggregate levels of analysis (Geoghegan *et al.* 2001). Certainly, one must look beyond the micro studies if one is to understand how economy-wide factors affect the immediate causes of deforestation and establish a bridge between micro-studies of deforestation and cross-country analyses (López and Galinato 2005).

While tropical deforestation continues to receive immense attention as a case where the dictates of economic development and ecosystem conservation regularly clash, some researchers have noted a new dynamic in some tropical forest regions. Alexander Mather coined the term ‘forest transition’ to describe one of the first empirical generalizations to emerge from research seeking global empirical regularities relevant to the transition to a sustainable society (Kates *et al.* 2002). Derived from historical studies of forests, the idea is that forest cover changes in predictable ways as societies undergo economic development, industrialization and urbanization (Mather 1990; Walker 1993; Mather and Needle 1998).

Specifically, a large decline in forest cover occurs; then the trend turns around, and a slow increase in forest cover takes place (Rudel 1998).

According to Rudel *et al.* (2005), a 'forest transition' occurs when decline in forest cover ceases and recoveries in forest cover begin. These authors say that forest transitions have occurred in two, sometimes overlapping, circumstances. In some places economic development has created enough non-farm jobs to pull farmers off of the land. In other places a scarcity of forest products has prompted governments and landowners to reforest. Chazdon (2008) points out that despite continued forest conversion and degradation, forest cover is increasing in countries across the globe; new forests are regenerating on former agricultural land; and forest plantations are being established for commercial and restoration purposes. Baptista and Rudel (2006) study the history of forest cover in southern Brazil, concluding that forestation replaced deforestation between 1997 and 1980. They find that an increase in the extent of planted forest close to urban areas explains much of the turnaround in forest cover trends. They caution that the new forest is substantially different from the original forest and provides some (e.g., carbon sequestration) but not all (e.g., biodiversity) ecosystem services.

In Costa Rica, a key study by Sader and Joyce (1988) estimated that between 1940 and 1984, the country lost about 50% of its original forest cover. The study reported that by 1984, only 17% of the country's primary forest cover remained. Recent studies document a slowing of deforestation during the last two decades (Helmer 2000; Sánchez-Azofeifa *et al.* 2001; Kerr *et al.* 2002; Kleinn 2002; Joyce 2006).

Given the potential of forest transitions for slowing soil erosion, improving soil quality, and slowing climate change through carbon sequestration, can governments speed the transitions up, or, once they have begun, ensure that the transitions continue? Payments for ecosystem services (PES) represent a new, more direct way to promote conservation that can impact both existing and new forest. Theoretical assessments praise the advantages of

PES over indirect approaches, but in the tropics PES has remained incipient (Wunder 2007). In the tropics, the most prominent PES system has been developed over a decade in Costa Rica (Robertson and Wunder 2005). In the Costa Rican system of PES, landowners enrolled in the scheme agree to conserve their forests, or establish reforestation, afforestation, or agroforestry areas. In return, they receive a per-hectare annual payment from a state-run national forest fund.

Parallel to the literature on tropical deforestation, previous attempts to estimate the causal impact of the Costa Rican system of PES (Sánchez-Azofeifa *et al.* 2007; Pfaff *et al.* 2008) have been based on the combination of remote sensing data with secondary data primarily on bio-physical characteristics such as road density and soil quality. Previous literature has also focused on the role of PES in reducing deforestation, or loss of existing forest cover. However, it is clearly also relevant to ask what impact PES has on the forest transition in Costa Rica, and given that this dynamic has been closely tied with socio-economic development, it is critical to incorporate socio-economic characteristics into the analysis.

This paper contributes to understanding of the causal impact of PES by analyzing the effect of the Costa Rican system of PES on several dimensions of forest cover (forest gain, forest loss and net deforestation), using census data at the tract level combined with remote sensing data on land use and biophysical land characteristics for the entire country. To isolate the causal impact of PES, matching estimators are applied to identify appropriate controls for census tracts that had land placed under PES contracts during the first eight years of the program. Tracts in the program are defined by both a binary measure of whether any PES contracts were located in a given tract and a continuous measure of the hectares under PES contract in a given tract. The control tracts selected through various matching procedures are used to estimate the counterfactual (e.g. forest gain would have occurred had no land in the census tract been enrolled in the program). I find that the program has no statistically significant effect on existing forest (i.e. no effect on forest loss), but it does have a statistically significant and positive effect on the establishment of new forest (i.e. positive effect on forest gain and net deforestation). This suggests that in Costa Rica, PES is making a significant contribution to the forest transition.

4.2 COSTA RICAN SETTING AND CONSERVATION POLICIES

4.2.1 Historical background of Costa Rican deforestation

The Costa Rican government has never implemented a forest inventory system to take place at regular intervals through a standardized methodology. Sader and Joyce (1988) represents the first comprehensive study of deforestation in Costa Rica. According with these authors, the period from 1940 to 1984 showed that the relatively undisturbed forest area remaining in 1940, 1950, 1961, 1977, and 1983 occurred on 67%, 56%, 45%, 32% and 17% of the country's area, respectively. This analysis indicated a strong relationship between the transportation network and forest alteration. The surge in forest alteration rates between 1977 and 1983 was related to major forest alteration in the northeastern portion of the country after the highway through the *Zurquí* tunnel from *San José* to *Limón* was completed in 1978.

Sader and Joyce (1988) also found a strong relationship between forest alteration and life zones for the period between 1940 and 1984. Between 1940 and 1977, the largest amount of forest was cleared in the tropical moist life zone, followed by the premontane wet zone. However, forest alteration rates in all life zones were much higher in the 1977 to 1983 period than all earlier periods.

Sader and Joyce (1988) explain the forest clearing patterns associated with slope gradient. Between 1940 and 1950, the 31-45% percent class had the largest amount of forest area cleared and the 0-5% slopes had the least amount of forest cleared. According with these authors, this early trend (with steeper slopes cleared at higher rates than 0-5% slopes) reflects the availability (both in extent and accessibility) of forested land. Forest clearing on shallow slopes before 1950 was probably low because the 0-5% slopes of the Atlantic lowland were inaccessible. The historical location of settlement areas, the high proportion of land in intermediate slopes, and low proportion of land area in shallow explain the early clearing patterns. However, there were deviations from this general rule during 1950 to 1961 and during the 1970s when clearing for cattle grazing was at its peak, especially in the northwest Pacific region where most of the land in the 0-5% slope category had already been cleared of forest vegetation. Between 1961 and 1977, the forest clearing rate dropped considerably on steeper slopes and increased substantially on shallow slopes. By 1983 and inverse linear relationship existed between primary forest reduction and slope gradient, but even the slopes > 60% supported less than one-third of the total area in original forest.

Costa Rica's deforestation rate between 1976 and 1980 had been estimated at 3.19% per year (FAO 1999). This high deforestation rate ranked the country as fifth in the world (in terms of percentage). A study by Sánchez-Azofeifa (2001) based on the analysis of Landsat satellite TM sensor data acquired in 1986 and 1991 (which covered about 50% of the country) showed alteration of undisturbed forest to be 225,000 ha or about 45,000 ha per year, and reported that 29% of Costa Rica's total area was covered with closed forest in 1991 with a deforestation rate of 4.2% per year for this period. The analysis of forest loss between 1986 and 1991 indicated that deforestation has almost eliminated forest cover in the tropical (only 5% remaining) and premontane (only 2% remaining) moist forest zones. The only life zones with closed forest cover greater than 80% forest were the lower-montane and montane areas with the highest precipitation and most inaccessible topography (Sánchez-Azofeifa 2001).

A study (CCT/CIEDES, 1998) using Landsat satellite data acquired during 1986/87 and 1996/97 for most of the country showed the average annual loss of existing forest to be 16,400 ha per year. However, the same study showed an increase of 126,772 ha due to the establishment of secondary forest and regeneration. Consequently, the net loss of forest was estimated to be about 3,800 ha per year during this 10-year period. According with FAO

(2006) Costa Rica had 2,391,000 hectares of forest in 2005 which represents 46.8% of the total land area of the country.

According with Sánchez-Azofeifa (1996), dynamics of deforestation in Costa Rica has been decreasing its pace significantly, as a result of several elements which combine themselves as the resource is waning. Some of these are: (1) an increase in the cost of wood, this provokes a trend to reduce per capita demand, and the search for technological solutions by means of substitute products; (2) the increase in forest efficiency and exploitation in situ, thorough a reduction of wood volumes that are burned or wasted in situ, an increase is also observed in the number of exploitable species; (3) increased efficiency at the industrial level including improvements in the exploitable yields at the saw mill, (4) a greater desire to protect forest by the organized rural population which now defend and protect certain areas, (5) the increase of private reserve areas, (6) the development of financial incentives by the central government for the preservation of forest, and (7) the presence of several joint implementation initiatives. Pfaff *et al.* (2004) say that relative returns have also changed because of increased returns form forested land. One important change is the rise in ecotourism since the early 1990s. Government is the dominant provider of forest 'eco-services', and also has developed a program of payments for multiple environmental services which supports forested land uses. Forest returns also exist in 'sustainable forestry' and 'shade coffee', in part due to timber and coffee labeling programs.

4.2.2 Causes and underlying driving forces of deforestation in Costa Rica

A statistical analysis of 53 tropical countries has attempted to explain the aggregate economic determinants of tropical deforestation (Barbier and Burgess 1997). The results indicate that increased population density increases forest clearance, whereas rising income per capita and agricultural yields reduce the demand for forest clearence. Several surveys have illustrated and synthesized the important findings of the growing literature on tropical deforestation (Brown and Pearce 1994; Barbier 1997; Kaimowitz and Angelsen 1998; Angelsen and Kaimowitz 1999; van Kooten, Sedjo and Bulte 1999; Geist and Lambin 2002;

Barbier 2004). These surveys suggest the following key factors have an important influence on tropical deforestation both within and across countries:

- Income
- Population growth/density
- Agricultural prices/returns
- Agricultural yields
- Agricultural exports/export share
- Logging prices/returns/production
- Roads and road building
- Scale factors (size of forest stock, land area, etc.)
- Institutional factors (political stability, property rights, rule of law, etc.)

Few studies have focused on the agents of forest land clearing and how the agents' decision to maintain or convert forest land is influenced by the agent's socio-economic characteristics, such as income level, size of household, and land holdings (Parks *et al.* 1998). These studies indicate that increasing agricultural output prices, tenure insecurity and accessibility to markets through road building may be correlated with increasing deforestation, whereas increasing off-farm wages and employment are correlated with reduce deforestation (Barbier and Burgess 2001).

Spatially explicit models of land use (e.g. Chomitz and Gray 1996) make the assumption that several variables can serve as proxies for several unobserved processes that impact land-use/land-cover change (LULC). For a given point in the landscape, these processes have resulted in a particular LULC, and they probably include human decisions aimed at maximizing land rent such that location and land quality determine land use, typical of a Von Thünen model.

The dynamics of LULC in Costa Rica during the last 30 years have generally been driven by the expansion of the agricultural and cattle frontier (CCT 1982, Harrison 1991, Quesada-Mateo 1990, Ramirez and Maldonado 1988 cited by Sánchez-Azofeifa 1996). It has been shown that the price and demand for meat and available low interest loans and credit, led to the dramatic increase in cattle grazing and subsequent forest clearing during the 1950 to 1973 period. Subsequent to 1973, with falling meat price together with an economic crisis and the end of easy credit, the cattle industry went into a decline and mush pasture was abandoned (Sader and Joyce 1988).

In the mid-1980s, the country was still recovering from the economic recession and the forest industry was operating at reduced levels until 1987 when there was a sharp increase in forest industry production after passing the 1986 forestry law. In 1988, the Forest General Direction (*Dirección General Forestal*, DGF) had issued permits that allowed logging on 10,000 ha, about half of which involved existing forest for which management plans were required and the remainder were for removing trees from existing pasture or converting forest to cultivated land. According with Pfaff and Sánchez-Azofeifa (2004), the last two decades have brought a slowing of deforestation in Costa Rica due in part to falling output prices inducing, for instance, significant abandonment of cattle across the Guanacaste Peninsula. Relative returns have also changed because of increased returns from forested land and the rise in ecotourism since the early 1990s.

Veldkamp *et al.* (1992) links a quantitative inventory of deforestation in the Atlantic zone of Costa Rica to possible driving factors, like accessibility and soil quality. They tested the hypothesis that deforestation preferentially takes place along major rivers, along roads, and on fertile soils. The main conclusion was that deforestation took place preferentially along the main rivers, especially before 1960 when the forest was only accessible by boat. Later, when roads became available, the importance of rivers decreased sharply. The search for agricultural land was one of the reasons for forest clearance, as is shown by preferential deforestation on fertile soils.

A study by Helmer (2000) of the landscape ecology of tropical secondary forest in Montane Costa Rica tests the hypothesis that the variables road distance, elevation, human population density, soil type, slope, and protection status are related to potential returns from land or feasibility of access and thereby influence LULC. He concluded that the odds of finding secondary forest or old growth, relative to agriculture, significantly decreased with increasing population density or surrounding agriculture, on unprotected lands, in highly populated areas (greater than 50 persons km^2), in the lower montane moist forest zone and for the less steep slope class of 30-60% slopes.

According with Kerr *et al.* (2002), deforestation in Costa Rica arises primarily through transformation of forests into agricultural land rather than through logging pressure. In their study of the dynamics of deforestation in Costa Rica, they reported that transport costs and access to markets appear to play an important role in deforestation where further the land is from a market center the less likely is to be cleared. They did not find significant impacts of local population density saying that possibly cities are protecting their few remaining forests, or densely populated areas have exhausted the available productive land. Their indirect measures of productivity (i.e. characteristics of the land that could affect the returns in different land uses) were stronger explanatory factors that direct measures of productivity and returns. Good life zones are significantly more likely to be cleared than medium life zones. Areas with bad soil and poor life zones are significantly less likely to be cleared. In their use of proxies for unobserved dynamics, they found that proportion of forest cleared may induce or simply predict more clearing, but when very little is left clearing may slow, as remaining land is of low value. Regarding previous clearings, they found that a higher level of recent clearing significantly increases the probability of future clearing.

Observed changes in deforestation over time could be explained by the fact that observed factors in returns to cleared land uses change over time, and that land users are working their way through a distribution of unobservable elements of returns. As the forest is cleared and economic activity increases, it stimulates further investment in infrastructure.

These changes would raise returns in ways we cannot observe. Thus as more land in an area is cleared, the hazard rate may rise. This suggests one measurable proxy for endogenous local development, past clearing in the area (Kerr *et al.* 2002).

According with Pfaff and Sánchez-Azofeifa (2004), in Costa Rica the forest clearing occurred depending upon biophysical features such as where coffee can and cannot grow, due to variations in soil quality and precipitation, or the natural location for a port. In fact, expansion given strong prices occurred for cattle in the north, coffee in the center and, as multinational expanded, also banana plantation in the Atlantic region. Such production and its effect on forests varied over space within Costa Rica in part because of ecological constraints such as variations in precipitation and temperature.

4.2.3 Payments for ecosystem services

Although global forest loss has occurred for centuries, rapid rates of tropical deforestation have only become an international concern in the last twenty-five years or so. Economists began studying such problems in the mid 1980s, and since then, there has been steady progress in the economic analysis of tropical forest loss (Barbier 2001).

Costa Rica is often hailed as a model for how developing nations can balance the conservation of nature and economic development (Sánchez-Azofeifa *et al.* 2001). This country has been one of the first ones around the tropics in responding to the new paradigm that is emerging in the world of environmental conservation where conservation tries to capture the interest of those who influence the activities that degrade the building blocks of nature−genes, species, and ecosystems, along with the air, water, and land with which these interact (Mainka *et al*. 2008). The Costa Rican government has set aside almost one-fourth of the nation’s land for conservation and has been active in discussions on the uses of protected areas for biodiversity inventory, ecotourism, carbon sequestration, and bio-prospecting for medicines (Quesada-Mateo 1990 cited by Sánchez-Azofeifa *et al.* 2001).

Costa Rica's Strategy for Sustainable Development (ECODES) report warned that deforestation impacts would result in habitat loss and general environmental deterioration of drainage basins. In response to this concern and aligned with the new paradigm in conservation, Costa Rica established in 1997 the first long-term, large-scale payment for ecosystem services initiative for tropical forests, Costa Rican Program of Payments for Environmental Services (*Programa de Pago por Servicios Ambientales*, PSA).

According to the Costa Rican government, PSA constitutes a financial recognition by the State granted to forest and plantation owners for the environmental services rendered by them, which directly affect the protection and improvement of the environment. The basic principle of PSA is that forestry is no longer valued by the public sector as such, but rather it is the services forestry provides that are rewarded by the State (Miranda *et al*. 2006).

PSA was not developed from scratch but is the result of a steady history of reforestation and forest protection efforts, dating from at least 1969 when timber plantation expenditures were considered deductible from the income tax according with the forestry law of 1969 (Ortiz 2002). Since that year and after the establishment of this first forestry law and the launching of the General Forest Direction (*Dirección General Forestal*, DGF), Costa Rica has been channeling a process of protection and management of forest, recovery of forest cover, control of illegal logging, and institutional development to support the forest sector (Rodríguez 2002). In 1984, the Ministry of Agriculture released a study (Junkov 1984) that found only 26.1% of the national territory was covered by forest in comparison to estimated original forest cover of 67% during the 1940s (Sader and Joyce 1988). The government reacted by creating a program of low interest loans for reforestation and soil conservation called Conservation of Natural Resources (*Conservación de Recursos Naturales*, CORENA) using funds from the United States Agency of International Development (USAID). The system of credits was progressively modified by the second and third forestry laws of 1986 and 1990 respectively (No. 7032 and No. 7174). Both pieces of legislation changed radically the rules in the forestry sector, reflecting the greater participation of small producers in the policy-making decision process. This new generation of incentives included *Certificado de Abono Forestal* (CAF) created in 1986, the *Certificado de Abono Forestal por Adelantado para Pequeños Reforestadores* (CAFA) created in 1988, the *Certificado de Abono Forestal para el Manejo del Bosque* (CAFMA) created in 1992, and the *Certificado para la Protección del Bosque* (CPB) created in 1995. The creation of the CPB program was a success from its beginning among the rest of the incentives of this kind in Costa Rica. During the first year of its application, 22,000 hectares were enrolled (the average annual enrollment of CAF and CAFA was 3,000 hectares per year, and 6,000 hectares per year for the case of CAFMA). According with an official report (FONAFIFO 2005), CPB owns its success due to the fact that landowners started to receive payments only because they were protecting the forest without the need of doing anything else. The CPB program paved the way for the implementation of PSA in 1997. Appendix 1 shows the number of hectares enrolled in previous forestry programs before PSA.

The Forestry Law 7575 from 1996 prepared the ground for the implementation of PSA, subsequently; the first payments for environmental services were made in 1997. It explicitly recognizes four environmental services provided by forest ecosystems: (i) mitigation of greenhouse gas emissions; (ii) water protection for urban, rural or hydroelectric uses; (iii) protection of biodiversity for its conservation, sustainable, scientific and pharmaceutical uses; research and genetic improvement; protection of ecosystems and life forms; and (iv) provision of natural scenic beauty for tourism and scientific purposes. The law provides the regulatory basis to contract landowners for the services provided by their forests, and established the National Fund for Forest Financing (*Fondo Nacional de Financiamiento Forestal*, FONAFIFO) which is the governmental agency in charge of administering the program (Pagiola 2006). However, during the period from 1997 to 2000, there was no attempt to measure all four environmental services (i.e. mitigation of greenhouse gas emissions, watershed protection, biodiversity conservation and landscape beauty) on a given parcel at once; rather the assumption was that an identically valued bundle of these services was provided by each hectare of enrolled parcel (Sánchez-Azofeifa *et al*. 2007).[1]

In order to participate in the program, applications should include: a proof of identity or statutes of an organization, a legal authentication of representatives, proof of an official legal title on the land[2], of payment of local taxes, and of no-indebtedness to the National Health System (CCSS), an official cadastral map, and a copy of a cartographic map to indicate the location of the parcel. Moreover, a professional topographer should determine the size of the land and a forest engineer had to prepare a professional Forest Management Plan to be approved by the National System of Conservation Areas (*Sistema Nacional de Areas de Conservación*, SINAC). If applications are accepted, after the initial screening process described above, contracts are established for the forest area under consideration and government makes annual payments on a per hectare basi**s**. Landowners are required both to maintain the land under contract in forest and to protect that forest, e.g., by establishing fire breaks where relevant, excluding livestock, and refusing access to hunters. The relevant government agencies and intermediary organizations may visit the property with the contract to ensure compliance with the agreement. In addition to the direct payments, participation in the PSA Program may give landowners access to education and technical assistance provided by intermediary organizations, and it may provide greater tenure security to the landowners against potential squatters (Miranda *et al*. 2003, Porras and Hope 2005, Arriagada forthcoming). Table 4.1 describes the different types of PSA contracts issued and payments established for PSA.

[1] According with the Forestry Law, land owners neither cannot change the land use on areas covered by forest nor establish forest plantations in these areas. Exceptions include: (a) construction of houses, offices, stables, corrals, nurseries, roads, bridges or any facility created for recreation or ecotourism; (b) Infrastructure project, public or private, of national importance; (c) trees removal due to human security concerns; (d) trees removal to prevent forest fires and natural disasters.

[2] For the period between 1997 and 1998, applicants without legal titles could show proof of possession of the land at least throughout a sworn statement signed by two witnesses. Between 1999 and 2002, possession of land should be demonstrated with at least a judicial certification proving the existence of a sentence ruling the land ownership. From 2003 and so on, landowners without a legal title that meet the requisites, in terms of being forests located in priority areas, established in the Decree No 30761-MINAE will be considered for participation in the program.

Since its inception, PSA has passed throughout different administration phases. Between 1997 and 2002, the program was administered by the Ministry of The Environment (*Ministerio del Ambiente y Energía*, MINAE) through its SINAC sub-regional offices, and from 2003, the administration of PSA was completely transferred to FONAFIFO. In terms of its functioning, PSA has also evolved considerably. Initially, the program recognized three forest activities: protection of natural forest, sustainable management of natural forest and reforestation (establishment of forest plantations). Also different types of landowners have been accepted in PSA as explained in the footnote No 2. Currently (2008), the program recognizes four activities: reforestation, natural forest regeneration, protection of natural forest, and agroforestry systems. Between 1997 and 2003, payments were also made for sustainable timber management of natural forests, although this option was always controversial and was eliminated in the re-organization of the program in 2003. Agroforestry systems were included into the program in 2003 and natural forest regeneration in 2006. In 2005, the program also experienced a substantial increase of payments levels. They were raised by approximately 50% and were established in dollars with the expectation that this would reduce the rate of devaluation of the fixed payments that had previously been denominated in *Colones* (i.e. Costa Rica local currency).

In terms of priority areas to be enrolled in the program, during the initial years (1997-1998), PSA established that the whole national territory would be considered priority, but the different conservation areas administered by SINAC could evaluate and define areas that could have special priority. Specifically, in order to prioritize specific areas to be included in forest protection, SINAC could consider the following criteria: (i) protection of hydrological resources, (ii) protection of areas with endangered plant and animal species, (iii) areas close to Protected Areas, (iv) private land located inside Protected Areas, (v) areas to be part of the Mesoamerican Biological Corridor efforts (known as GRUAS), (vi) areas voluntarily enrolled in the Forest Regime with protection purposes, (vii) privates and public refuges of natural life, (viii) areas with forest land use capacity, (ix) fallow pastures, (x) areas being recognized as carbon storages, (xi) areas with forest land use capacity and high fire risk, (xii) indigenous reserves and archaeological sites, (xiii) areas where conservation of other natural resources beside forest was being promoted, (xiv) areas potentially important to produce raw materials, and (xv) other areas considered important by SINAC (MINAE 1998).

As to one of the other crucial functions − technical assistance and compliance control −FONAFIFO and SINAC are officially responsible for the monitoring of the accomplishment of the contracted goals. Specifically, and according with the Decree No 30761-MINAE, contract compliance is done by SINAC and application and payments are responsibility of FONAFIFO. Technical assistance is normally done by some non-governmental organizations (NGOs).

4.2.4 Inputs, outputs and outcomes of PSA

In general, PES represents a new, more direct way to promote conservation (Wunder 2006). Direct payments to conservation are based on a willing buyer-willing seller model where sellers deliver conservation outcomes in exchange for a negotiated payment in cash or in kind and payments are conditional on conservation outcomes (Ferraro and Kiss 2002). This mechanism is flexible and can be adapted to different conditions (FAO 2004). PES schemes in watersheds compensate upstream land holders in order to maintain or modify a particular soil use which affects the availability and/or quality of the water resource downstream. PES schemes that aim to secure biodiversity conservation direct attention to conservation of mature natural forest. PES schemes that look for carbon sequestration promote increase in net forest cover. For the Costa Rican case, PSA seeks to encourage forest protection and management by paying forest owners for the services their trees provide (Landell-Mills and Porras 2002). In particular, PSA promotes land uses that enhance carbon sequestration, biodiversity conservation, watershed protection and landscape beauty. Within the context of this program, it can be defined *inputs* (e.g. number of hectares enrolled in PSA forest conservation), *outputs* (e.g. number of hectares conserved after participation in PSA) and *outcomes* (ecosystem services).

The implementation of PSA is driven by the assumption that direct conservation payments will generate a net increase in protected ecosystems (i.e. an increase in the provision of the PSA outcome, ecosystem services). However, for the purpose of this paper, I will stick with FONAFIFO's definition of area of forest as relevant outcome to evaluate, even though I recognize that this is really just an output that generates the desired final outcome of ecosystem services. Thus, the hypothesis of my research is that "*PSA forest conservation payments generate a net increase in the area of forest*".

In studying the empirical question about the PSA causal impact on forest cover changes, it is important to consider that outputs from PSA are not necessarily a direct cause of the program given that certain areas under contract may not have been converted (deforested) because:

- Expected low returns from alternatives (low opportunity costs)
- Expected high cost of conversion (legal restrictions)
- High benefits from forest (environmental attitudes)

Studying the impacts of PSA at the census tract level is also theoretically ambiguous considering leakage and spillover issues. Wu (2000) in his study of slippage effects of the US Conservation Reserve Program (CRP) says that one unintended impact of the CRP is that it may cause non-cropland to be converted into crop production.[3] Kluender (1999) in his study about the use of forestry incentives by nonindustrial forest landowner groups says that incentive programs have been initiated with the tacit assumption that planted trees and improved forests will eventually lead to increased timber harvest from subsidized lands. However, he concludes that timber managers in some cases will engage in forestry practices regardless of assistance payments. In the context of PSA, its net impacts depend on

[3] According with Wu (2000), in the context of CRP slippage effects may exist for at least two reasons. First, some non-cropland may be brought into production as a result of increased outputs prices associated with reduced production on CRP land. Another possible reason for slippage is substitution effects when some cropland is taken out of production, farmers may substitute other land for crop production because of scale economies and fixed input effects.

behavioral adjustments promoted by the program that can also affect land not protected by PSA. For the purposes of this study, three outcome variables will be analyzed:

1) *Forest gain*: sum of hectares that were not forest but regenerated later into natural forest
2) *Forest loss*: sum of all area transitions from natural forest classes (continuous and fragmented) to all other land use classes
3) *Net deforestation*: forest gain minus forest loss

Given the stated hypothesis of this study, it is expected that PSA has a positive impact on forest gain and net deforestation, and a negative impact on forest loss. Outcome data were obtained from Landsat satellite images originally classified by a team of researchers from the Earth Observation Systems Lab at University of Alberta, *Centro Científico Tropical* and Fonafifo (EOSL-CCT-FONAFIFO 2003). For the purposes of this study, Cordero (2008) created a LULC dataset during two time periods (1992-1997 and 1997-2005) to determine program outcomes and develop transition land use matrices for the periods under study.

After the initial years of PSA implementation (1997-1998), the PSA has been moving towards a greater degree of targeting. In fact, since 2002 MINAE publishes an annual Executive Decree that defines every year the PSA prioritization criteria per conservation area which is applied for the selection of applicants. For example, the 2003 PSA decree established that the areas included in the Ecomarkets project will receive higher priority including the areas located inside the Mesoamerican Biological Corridor. [4,5] The 2008 PSA decree gives priority to all biological corridors included in GRUAS II.[6] Different agreements

[4] The World Bank-funded Ecomarkets Project for Costa Rica aims to increase forest conservation by supporting the development of markets and private sector providers for environmental services supplied by privately owned forests including protection of biological diversity, greenhouse gas mitigation, and provision of hydrological services (source: www.worldbank.org). The first Ecomarkets payments started in 2001.

[5] The Mesoamerican Biological Corridor is a large habitat corridor in Mesoamerica, stretching from Mexico southeastward through most of Central America, connecting several national parks. It was started in 1998 to keep 106 critically endangered species from going extinct.

[6] GRUAS is an ecosystem mapping participative process directed by MINAE and carried out between 1995 and 1997 (Wo Ching 2006). The proposed GRUAS biodiversity corridors resulted from government efforts to

with private and public companies also have influenced areas to be targeted by the program. Hydroelectric Platanar (1999 and following), and Florida Ice and Farm (2001-2009) represent two cases where private funding has been directed to PSA in order to protect specific areas of Costa Rica. In 2006 and according with the Law No 8355, the governments of Costa Rica and Germany (KFW) signed a cooperation agreement to support PSA in *Huetar Norte*. In sum, the move towards a more targeted program responds also to a move towards a more market-based payment system, since donors are directing payments towards areas of higher environmental value according with their own conservation interests.[7] In order to isolate the causal effect of PSA is important to incorporate these variations in the implementation of PSA throughout the years that can capture differences in program implementation and impact around the country.

In relation to the program outcomes to be analyzed in this paper, forest gain and net deforestation for example relate to policy goals of stakeholders interested in promoting land uses related with carbon sequestration. Impact on forest loss is relevant for stakeholders more interested in protecting mature forest to secure water provision from nearby watersheds.

In order to capture regional variation in the implementation of PSA, I will group conservation areas where it is believed PSA could have a similar impact.[8] This stratification will allow later to estimate not only national estimates of program impact but also identify regional impacts on program outcome. Table 4.2 shows how PSA is distributed among the conservation areas of Costa Rica. According with Table 4.2, *Tempisque*, *Arenal-Huetar Norte* and *Cordillera Volcánica Central* are the three conservation areas with the highest

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identify national priorities for sites on which the state could invest in biodiversity protection, including as part of the Mesoamerican Biological Corridor (Powell *et al.* 2000). In 2007, GRUAS II was launched presenting some updates with the main purpose of filling the existing gaps in the current Costa Rican conservation system (SINAC-MINAE 2007).

[7] This statement not only apply for the case of international donors like KFW, but also to private donors including for example hydroelectric companies interested in protect watershed areas.

[8] Costa Rica is under the jurisdiction of eleven large Conservation Areas which were created in 1998, overseen by divisions of SINAC. Over 25% of the national territory i.e. 3,221,636 acres (13,037 km²) is included in the national parks, refuges and protected zones within these eleven Conservation Areas (source: www.sinaccr.net). For the purposes of this study, *Isla del Coco* won’t be included.

number of PSA tracts (i.e. rural census tracts that contain at least one PSA protection contract signed between 1998 and 2004) and with the largest area protected by PSA. Table 4.2 also shows that *Tortuguero* and *Osa* are the conservation areas with the lowest number of PSA tracts and area protected by the program. Table 4.2 also shows *Arenal Tilarán* as one the areas with the smallest area protected by PSA.

There is 10 conservation areas in Costa Rica presented in Table 4.2. In order to group areas that have a similar behavior in terms of PSA participation and impact, I used four criteria as follows:[9]

1. Land use capacity: conservation areas were grouped in a way that land use capacity is similar across the land within each group
2. Conservation area organization: this criterion measures the administrative organization of each conservation area (e.g. managerial capacity and director leadership), and the existence of NGOs that facilitate the process of PSA participation
3. Land tenure: this criteria grouped areas where land titling is similar
4. Future expectative: this criterion aims to capture other factors that can affect the value of the land. For example in *Tempisque*, the high interest of foreign tourists to buy land has increased enormously the price of the hectare, especially in areas close to the Pacific Ocean

Following the criteria defined above, conservation areas were grouped as follows:

- Group 1: *Arenal-Huetar Norte* (ACHN)
- Group 2: *Tempisque* (ACT) - *Arenal Tilarán* (ACAT) - *Guanacaste* (ACG)
- Group 3: *Cordillera Volcánica Central* (ACCVC)
- Group 4: *La Amistad Caribe* (ACLAC) - *Tortuguero* (ACTO)

[9] I thank Dr. Edgar Ortiz, professor at Instituto Tecnológico de Costa Rica, Carlos Rodríguez, Vice President and CBC Director Mexico and Central America Field Division of Conservation International, Emel Rodríguez, Director of *Tempisque* conservation area, Edilma Morales, Director of *Osa* conservation area, and personnel of MINAE, SINAC and FONAFIFO for assistance in grouping conservation areas with similar behavior in terms of PSA participation and impact.

- Group 5: *Pacífico Central* (ACOPAC) - *La Amistad Pacífico* (ACLAP)
- Group 6: *Osa* (ACOSA)

Table 4.3 shows the five groups and the criteria used to group conservation areas. Figure 4.1 shows the segmentation done by INEC in order to implement the 2000 census, considering only the rural census tracts that will be included in this study. Table 4.4 shows the number of PSA protection contracts signed between 1998 and 2004 by PSA implementation period and by conservation area group.

4.3 RESEARCH METHODOLOGY

4.3.1 Roy-Rubin model of causal effect

In the context of a conservation initiative that pays landowners to conserve their forest resources (e.g. PSA), we can observe how the conservation outcome (e.g. forest cover) varies between regions with landowners who are receiving payments as compared to regions where no landowners are enrolled in the program.[10] In the prototypical model of the evaluation literature, we can say that either the region is treated or not. There is a hypothetical (potential) forest cover outcome for both states of the world (i.e. treated vs. non-treated). The "causal effect" is defined then as the difference between these two *potential outcomes*. This approach to evaluation was developed by Rubin (1974, 1977, and 1978) and now is known as the Roy (1951) and Rubin (1974) model (RRM). In this literature, the term *treatment* is used interchangeably with *cause*. It refers to any variable whose impact on some outcome is the object of the study. In the environmental economics field, examples of treatment-outcome pairs include protected areas and species conservation (e.g. Greenstone and Gayer 2007, Ferraro *et al*. 2007), forest reserves and income of local people (e.g. Blessings *et al.* 2006), and pollution regulation (Greenstone 2004).

[10] Throughout this paper, "regions" will refer to potential units of analysis beside households (e.g. grid cells, census tracts or districts). PSA regions will refer to regions with landowners that are receiving PSA payments.

To truly know the effect of PSA, we should compare the forest cover of PSA regions with the forest cover that would have resulted had that region not participated in the program. The impossibility of observing this so-called *counterfactual outcome* creates the evaluation problem. Within the framework of a *potential outcome model* (POM), which assumes that every element of the target population is potentially exposed to the treatment, the triple (Y_{1i}, Y_{0i}, D_i, i=1,..,N), forms the basis of treatment evaluation. In the context of PSA, the categorical variable D takes the values 1 when region contain landowners that receive PSA payments and 0 otherwise; Y_{1i} measures the forest cover for region i in the program and Y_{0i} measures forest cover when not in the program. In addition, each region has a vector of characteristics, referred to as covariates, pretreatment variables or exogenous variables, and denoted by X_i. Given that each region is either a participant in PSA or a non-participant, we observe for each region the triple (Y_i, X_i, D_i), where Y_i is the *realized outcome*:

$$Y_i \equiv Y_i(D_i) = \begin{cases} Y_i(0) \; if \; D_i = 0, \\ Y_i(1) \; if \; D_i = 1. \end{cases} \tag{4.1}$$

In the context of PSA, after landowners in a region has decided to enroll in the program and some time enough to see some effects on forest cover has passed, we can calculate the individual gain from PSA which is measured by $\tau_i = (Y_{1i} - Y_{0i})$. In this *ex-post* evaluation of program impact scenario, the fundamental evaluation problem arises because only one of the potential outcomes is observed for each region i (i.e. either forest cover after PSA participation or forest cover after non-participation).

Certainly, due to the inherent problems of observability mentioned above, there will be never be an opportunity to estimate program impacts upon forest cover on particular regions with confidence. Yet, one might still hope to be able to assess the population average of gains from PSA, since we know that the population averages E[·] of the frequency distributions of Y_{1i} and Y_{0i} can be estimated for participant and non-participant regions, respectively (Frondel and Schmidt 2005). The average causal effect of D_i = 1, relative to D_i = 0, is measured by the population average treatment effect (ATE):

$$\tau_{ATE} = \mathrm{E}[Y_i(1) - Y_i(0)], \qquad (4.2)$$

where the short hand notation E[·|D=1] denotes the mean in the population of all regions that participate in PSA (D=1) and these expectations are with respect to the probability distribution over this population of PSA regions.[11] The average treatment effect on the treated (ATT) is defined as follows:

$$\tau_{ATT} = \mathrm{E}[Y_i(1) - Y_i(0) \mid D = 1]. \qquad (4.3)$$

The most commonly-used evaluation parameters are means like the ones defined in (4.2) and (4.3) (see Heckman *et al.* 1997; Heckman *et al.* 1998a; Heckman *et al.* 1998b; Frondel and Schmidt 2005; Ravallion 2008). Heckman and Robb (1984) and Heckman, Ichimura, and Todd (1997) argue that the subpopulation of treated units is often of more interest than the overall population in the context of narrowly targeted programs. ATT will be the focus of this paper (i.e. the average effect of PSA on participant regions).

In the use of observational data generated under nonrandom treatment assignment, the consistent estimation of ATT will be threatened by several complications that include, for example, possible correlation between the outcomes and treatment, omitted variables, and endogeneity of the treatment variable (Cameron and Trivedi 2005). In particular, the counterfactual mean for those PSA regions − $\mathrm{E}[Y(0)|D=1]$ − is not observed, then one has to choose a proper substitute for it in order to estimate ATT. In an *ex-post* evaluation of PSA, we can use the mean forest cover of non-participant regions $\mathrm{E}[Y(0)|D=0]$, however in non-experimental studies this is usually not a good idea, because it is most likely that components which determine PSA participation also determine forest cover. Moreover, in a voluntary initiative like PSA, we might anticipate that those who volunteer differ from the wider eligible population of landowners in terms of their expected gains from the program (endogenous selection). Landowners in some regions may perceive greater benefits from participation in the program and for that reason they decide to participate. Thus, the forest cover of properties from PSA and non-PSA groups will differ even in the absence of PSA

[11] Distributions of (D_i, Y_i, X_i) refer to the distribution induced by the random sampling from the population.

leading to a *self-selection bias*. This bias is not likely to be zero for most environmental applications (Bennear 2006).

In observational studies where assignment to treatment is not random one has to invoke a set of *identifying assumptions* (i.e. assumptions that allow you to identify the true causal effect). In fact RRM clarifies that the average causal treatment effect is generally not identified. Identification is obtained by untestable assumptions, and their plausibility depends on the substance of the economic problem analyzed and the data available (Lechner 2002).

Assumption 1 (*Unconfoundedness or Conditional Independence Assumption*)

Under this assumption, we can say that given the set of observable covariates X which are not affected by treatment, potential outcomes are independent of treatment assignment:

$$(Y_i(0),\, Y_i(1)) \perp D_i |\, X_i. \tag{4.4}$$

This implies that selection is solely based on observable characteristics and that all variables that influence treatment assignment and potential outcomes simultaneously are observed by the researcher (Caliendo and Kopeinig 2005). Under this assumption, we say that there is *selection on observables*.

Assumption 2 (*Overlap or Common Support*)

This assumption rules out the phenomenon of perfect predictability of D given X:

$$0 < P(D=1|X) < 1 \tag{4.5}$$

It ensures that regions with the same X values have a positive probability of being both participants and non-participants (Heckman, LaLonde and Smith 1999). We shall say that treatment assignment is strongly ignorable given a vector of covariates by combining both the unconfoundedness and overlap assumptions (Rosenbaum and Rubin 1983). Heckman *et al*. (1998b) discovery of the empirical importance of imposing a common support condition in reducing bias as conventionally measured demonstrates the benefit of a nonparametric approach to econometrics. Rigorous application of nonparametric methods entails careful specification of the domain over which estimators can be identified.

There has been some controversy about the plausibility of assumptions 1 and 2 in economic settings. Imbens (2007) offer three arguments for considering these assumptions. First, a natural starting point in the evaluation of any program is a comparison of average outcomes for treated and control units, and then an adjustment of any difference in average outcomes for differences in exogenous background characteristics. Second, almost any evaluation of a treatment involves comparisons of units who received the treatment with units who did not, and where the key is to identify which units best represent the treated units had they not been treated. Third, even when agents optimally choose their treatment, two agents with the same values for observed characteristics may differ in their treatment choices without invalidating the unconfoundedness assumption if the difference in their choices is driven by differences in unobserved characteristics that are themselves unrelated to the outcome of interest.

Given strongly ignorable treatment assignment one can identify the population average treatment effect τ by first estimating the average treatment effect for a subpopulation with covariates $X = x$, and then we can show:

$$\begin{aligned} \tau(x) &\equiv E\,[Y_i(1) - Y_i(0)|X_i = x\,] = \,[E\,[Y_i(1)|X_i = x] - E\,[Y_i(0)|X_i = x] \\ &= E\,[Y_i(1)|X_i = x\,, D_i = 1] \,-\, [E\,[Y_i(0)|X_i = x, D_i = 0] \\ &= \,E\,[Y_i|X_i = x, D_i = 1] - E\,[Y_i|X_i = x, D_i = 0] \end{aligned} \tag{4.6}$$

The second line in equation (4.6) holds because of the ignorability of treatment conditional on X. Now, to make the last line feasible, one needs to be able to estimate the expectations $E\,[Y_i|X_i = x, D_i = d]$ for all values of d and x in the support of these variables. This is where the overlap assumption enters. If this assumption is violated at $X = x$, it would be infeasible to estimate both $E\,[Y_i|X_i = x, D_i = 1]$ and $E\,[Y_i|X_i = x, D_i = 0]$ because at those values of x there would be either only treated or only control units.

One can weaken the unconfoundedness in a different direction if one is only interested in the average effect for the treated (see, for example, Heckman, Ichimura and Todd 1997; Imbens 2004; Abadie and Imbens 2006a). In the case one need only assume:[12]

Assumption 3 (*Unconfoundedness for Controls*)

$$Y_i(0) \perp D_i | X_i. \tag{4.7}$$

and the weaker overlap assumption

Assumption 4 (*Weak Overlap*)

$$P(D=1|X) < 1 \tag{4.8}$$

Finally, to make the model's representation of outcomes adequate for causal analysis, the *stable-unit-treatment-value assumption* (SUTVA) has to be satisfied for all members of the population (Rubin 1986). In economics, this is sometime referred to as no-macro-effect or partial equilibrium assumption. SUTVA, as implied by its name, is a basic assumption of causal effect stability that requires that the potential outcomes of individuals be unaffected by potential changes in the treatment exposures of other individuals (Morgan and Winship 2007). In the words of Rubin (1986:961), who developed the term,

> SUTVA is simply the a priory assumption that the value of *Y* for unit *u* when exposed to treatment *t* will be the same no matter what mechanism is used to assign treatment *t* to unit *u* and no matter what treatments the other units receive.

Rather than consider SUTVA as overly restrictive, researchers should always reflect on the plausibility of SUTVA in each application and use such reflection to motivate a clear discussion of the meaning and scope of a causal effect estimate (Morgan and Winship 2007).

4.3.2 Propensity score methods

Program evaluation offers different approaches that take account of the selection issue inherent to non-experimental programs in order to approximate the counterfactual

[12] Assumption 3 and 4 are sufficient for identification of ATT because the moments of the distribution of $Y_i(1)$ for the treated are directly estimable (Imbens 2004).

outcome. Specifically, matching methods allow explaining selection into the program based in terms of observable characteristics that affect program participation and outcome. By definition, matching is a method of sampling from a large reservoir of potential controls to produce a control group of modest size in which the distribution of covariates is similar to the distribution in the treated group (Rosenbaum and Rubin 1983). This method assumes that selection can be explained purely in terms of observable characteristics which rule the choice of the match. A practical concern exists in that, as the number of characteristics used in the match increases, the chances of finding a match are reduced. Rosenbaum and Rubin (1983) showed that matching on a single index reflecting the probability of participation could achieve consistent estimates of the treatment effect. This index is the *propensity score.*

Use of propensity score has become a common tool for reducing bias in observational studies. Since the work by Rosenbaum and Rubin (1983) there has been considerable interest in methods that avoid adjusting directly all covariates, and instead focus on adjusting for differences in the propensity score, the conditional probability of receiving the treatment. According with the unconfoundedness, conditioning on all relevant covariates is very limiting in case of a high dimensional vector X. For instance, if X contains s covariates which are all dichotomous, the number of possible matches will be 2^s. To deal with this dimensionality problem, Rosenbaum and Rubin (1983) suggest using the so-called *balancing score, b(X).* They show that if potential outcomes are independent of treatment conditional on covariates X, they are also independent of treatment conditional on a balancing score. The propensity score $Pr(D = 1|X) = e(X)$, i.e. the probability for an individual to participate in a treatment given his observed covariates X, is one possible balancing score.[13]

One of the principle advantages of this method is that adjusting for the propensity score amounts to matching or subclassifying on a scalar, which is significantly easier than matching or subclassifying on many covariates (Imai and Dyk 2004).

[13] Rosenbaum and Rubin (1983) show that the propensity score, $e(X)$, is a balancing score and that any score that is 'finer' than the propensity score is a balancing score; moreover, X is the finest balancing score and the propensity score is the coarsest.

Propensity score methods can be implemented in a number of different ways. One can divide the sample into subsamples with approximately the same value of the propensity score, a technique known as blocking. Alternatively, one can directly match on the propensity score. According with Imbens (2007) the relative merits of these estimators will depend on whether the propensity score is more or less smooth than the regression functions, or whether additional information is available about either the propensity score or the regression functions.

4.3.2.1 Matching on the propensity score

Given that unconfoundedness assumption holds and assuming that there is overlap between both groups (i.e. we have strong ignorability), the propensity score matching estimator for ATT can be written in general as:

$$\tau_{PSM}^{ATT} = E_{P(X)|D=1}\{E[Y(1)|D = 1, e(X)] - E[Y(0)|D = 0, e(X)]\}. \qquad (4.9)$$

To put it in words, the propensity score matching estimator is simply the mean difference in outcomes over the common support, appropriately weighted by the propensity score distribution of participant regions.

The most straightforward propensity score matching estimator is nearest neighbor matching (NN) where the region from the control group is chosen as a matching partner for a treated region that is closest in terms of propensity score. Several variants of NN matching are proposed, e.g. NN matching 'with replacement' and 'without replacement'. In the former case, an untreated individual can be used more than once as a match, whereas in the latter case it is considered only once.

NN matching faces the risk of bad matches, if the closest neighbor is far away. This can be avoided by imposing a tolerance level on the maximum propensity score distance (caliper). Imposing a caliper works in the same direction as allowing for replacement. Bad matches are avoided and hence the matching quality rises (Caliendo and Kopeinig 2005).

Dehejia and Wahba (2002) suggest a variant of caliper matching which is called radius matching (RM). The basic idea of this variant is to use not only the nearest neighbor within each caliper but all of the comparison members within the caliper.

NN uses only the nearest neighbor of the treated observation and RM uses a few observations from the comparison group that are within the defined radius. Kernel matching (KM) is a non-parametric matching estimator that uses a different definition of neighborhood by using all individuals in the control group to construct the counterfactual outcome. Thus, one major advantage of this approach is the lower variance which is achieved because more information is used. A drawback of this method is that possibly observations are used that are bad matches. Hence, the proper imposition of the common support condition is of major importance for KM.

In the context of matching on the propensity score, matching with replacement involves a trade-off between bias and variance. If we allow replacement, the average quality of matching will increase and the bias will decrease (Caliendo and Kopeinig 2005). This is of particular interest in cases where we don't have a significant overlap in the propensity scores between treatment and control groups. This can be overcome by allowing replacement, which in turn reduces the number of distinct non-participants used to construct the counterfactual outcome and thereby increases the variance of the estimator (Smith and Todd 2005).

4.3.2.2 Blocking on the propensity score

Rosenbaum and Rubin (1983) suggest that with strongly ignorable treatment assignment, subclassification on a balancing score can also produce unbiased estimates of treatment effects. Direct adjustment with subclass total weights (e.g. subclasses weighted by the number of observations in each subclass) can be applied to the subclass differences in program outcome to estimate the average treatment effect without engaging in functional form assumptions that relate program and outcome. Imbens (2004) describes the method that Rosenbaum and Rubin (1983) propose as "blocking propensity score estimator" as follows:

using the estimated propensity score, divide the sample into M blocks of units approximately equal probability of treatment, letting J_{im} be an indicator for unit i being in block m. One way of implementing this is by dividing the unit interval into M blocks with boundary values equal to m/M for $m = 1,\ldots,M - 1$, so that $J_{im} = 1\{(m-1)/M < e(X_i) \leq m/M\}$, for $m = 1,\ldots,M$. Within each block there are N_{dm} observations with treatment equal to d, $N_{dm} = \sum_i 1\{D_i = d, J_{im} = 1\}$. Given these subgroups, estimate within each block the average treatment effect as if random assignment holds,

$$\hat{\tau}_m = \frac{1}{N_{1m}} \sum_{i=1}^{N} J_{im} D_i Y_i - \frac{1}{N_{0m}} \sum_{i=1}^{N} J_{im} (1 - D_i) Y_i. \tag{4.10}$$

Then estimate the overall average treatment effect on the treated as:

$$\hat{\tau}_{block}^{ATT} = \sum_{m=1}^{M} \hat{\tau}_m \frac{N_{1m}}{N} \tag{4.11}$$

Cochran (1968) analyzing a case with a single covariate shows that using five blocks remove at least 95% of the bias associated with that covariate. Since all bias, under unconfoundedness, is associated with the propensity score, this suggests that under normality five blocks removes most of the biases associated with all the covariates.

4.3.3 Mixed methods

A number of approaches have been proposed that combine regression with different matching algorithms. According with Imbens (2004), these methods appear to be the most attractive in practice and the motivation for these combinations is that incorporating regression may eliminate remaining bias and improve precision. This is also useful because neither matching nor the propensity score methods directly address the correlation between the covariates and the outcome. Similarly, because matching is consistent with few assumptions beyond strong ignorability, thus methods that combine matching and regressions are robust against misspecification of the regression function (Imbens 2004). According with Rosenbaum and Rubin (1985), matching methods that treat the $e(X)$ (i.e. the propensity score) as just one of many matching covariates may fail to eliminate bias in some covariates because close mean matching may not be attained on $e(X)$. The benefit associated with combining methods is made explicit in the notion developed by Robins and Ritov (1997) of *double robustness*. They propose a combination of weighting and regression where, as long as the parametric model for either the propensity score or the regression functions is specified correctly, the resulting estimator for the average treatment effect is consistent (Imbens 2004).

4.3.3.1 Weighting and regression

Another set of propensity-score estimators use the propensity scores as weights to create a balance sample of treated and control observations. Following Imbens (2004) recommendation, one can estimate the following regression function by weighted least squares:

$$Y_i = \alpha + \tau\, D_i + \varepsilon_i \tag{4.12}$$

with weights equal to:

$$\lambda_i = \sqrt{\frac{D_i}{e(X_i)} + \frac{1 - D_i}{1 - e(X_i)}}. \tag{4.13}$$

Without the weights the least squares estimator would not be consistent for the average treatment effect; the weights ensure that the covariates are uncorrelated with the treatment indicator and hence the weighted estimator is consistent (Imbens 2004).[14]

4.3.3.2 Matching and Regression

Simulations and analytic work in Rubin (1973) indicate that linear regression using matched samples is the most robust method to estimate treatment effects. Later work by a

[14] The weights use the propensity score to create a balanced sample of treated and control observations (i.e. potential outcomes are independent of treatment conditional on the propensity score). Rosenbaum and Rubin (1983) show that the propensity score is a balancing score and show that if potential outcomes are independent of treatment conditional on covariates X, they are also independent of treatment conditional on a balancing score like the propensity score. Then weights can undo the unbalance on the covariates in a similar way propensity score does.

number of authors Rubin (1978), Heckman *et al.* (1998b), Rubin and Thomas (2000) found similar results.

Let $\hat{Y}_i(0)$ and $\hat{Y}_i(1)$ be the observed or imputed potential outcomes for unit *i*. These estimated potential outcomes equal observed outcomes for some unit *i* and its match $\ell(i)$. The bias in their comparison, $\mathrm{E}\left[\hat{Y}_i(1)-\hat{Y}_i(0)\right]-\left(Y_i(1)-Y_i(0)\right)$ arises from the fact that covariates for units *i* and $\ell(i)$, X_i and $X_{\ell(i)}$ are not equal, although because of the matching, they will be close. Following Imbens (2004) to further explore this, define for each unit (focusing on the single match case):

$$\hat{X}_i(0)=\begin{cases}X_i & if\ D_i=0,\\ X_{\ell(i)} & if\ D_i=1,\end{cases}$$

and

$$\hat{X}_i(1)=\begin{cases}X_{\ell(i)} & if\ D_i=0,\\ X_i & if\ D_i=1\end{cases}$$

If the matching is exact, $\hat{X}_i(0)=\hat{X}_i(1)$ for each unit. If, however, the matching is not exact there will be some discrepancies that lead to potential bias. The difference $\hat{X}_i(0)-\hat{X}_i(1)$ will therefore be used to reduce the bias of the simple matching estimator.

Suppose unit *i* is a treated unit with D_i = 1. In that case $\hat{Y}_i(1)=Y_i(1)$ (i.e. the imputed outcome corresponds to the observed outcome because *i* is in treatment group) and $\hat{Y}_i(0)$ is imputed value for $Y_i(0)$ for this unit which is obtained using its match. This imputed value is unbiased for $\mu_0(X_{\ell(i)})$ (since $\hat{Y}_i(0)$ = $Y_{\ell(i)}$), but not necessarily for $\mu_0(X_i)$. One therefore may wish to adjust $\hat{Y}_i(0)$ by an estimate of $\mu_0(X_i)-\mu_0(X_{\ell_1(i)})$. Typically these corrections are taken to be linear in the difference in the covariates for unit Two *i* and its match, that is, of the form $\beta_0'\left[\hat{X}_i(1)-\hat{X}_i(0)\right]=\beta_0'[X_i-X_{\ell_1(i)}]$. Rubin (1973) proposed three corrections, which differ in how β_0 is estimated.[15]

[15] For the purposes of this paper, I will use the second correction proposed by Rubin (1973). The first correction imputes the potential outcome using the single matched control observation which heavily restricts the use of the rich dataset on controls available for this study. The third correction estimates the same regression function

To introduce Rubin's first correction, note that one can write the matching estimators as the least squares estimator for the regression function

$$\hat{Y}_i(1) - \hat{Y}_i(0) = \tau + \varepsilon_i. \tag{4.14}$$

Remember that $\hat{Y}_i(1)$ and $\hat{Y}_i(0)$ can correspond either to the observed outcome or the imputed one depending if i is in the treatment or the control group. The representation in (4.14) suggests modifying the regression function to

$$\hat{Y}_i(1) - \hat{Y}_i(0) = \tau + \left[\hat{X}_i(1) - \hat{X}_i(0)\right]'\beta + \varepsilon_{i,} \tag{4.15}$$

and again estimating τ by least squares.

The second correction is to estimate $\mu_0(x)$ directly by taking all control units, and estimate a linear regression of the form

$$Y_i = \alpha_0 + \beta_0' X_i + \varepsilon_i, \tag{4.16}$$

by least squares. If unit i is a control unit, the correction will be done using an estimator for the regression function $\mu_0(x)$ based on a linear specification $Y_i = \alpha_1 + \beta_1' X_i + \varepsilon_i$ estimated on the treated units. Abadie and Imbens (2006a) show that if this last correction is done nonparametrically, then the resulting matching estimator is consistent and asymptotically normal, with its bias dominated by the variance.[16]

The third method is to estimate the same regression function using only the controls that are used as matches, with weights corresponding to the number of times a control observation is used as a match. Compared with the previous method this approach is potentially less efficient as it discards some control observations and weights some more than

for the controls, but using only those that are used as matches for the treated units. According with Abadie and Imbens (2006a) and Imbens (2004), this third approach may be less efficient as it can potentially discards many control observations (as it is the case for this study which will be showed in the results section).

[16] Predictive values of potential outcomes (i.e. $\hat{Y}_i$) obtained from the regression are used to impute the counterfactual potential outcome. This counterfactual from regression will be $\hat{Y}_i(0)$ in case i is in the treatment group (using specification shown in (4.16)) otherwise the counterfactual from regression will be $\hat{Y}_i(1)$ in case i is in the control group (using the linear specification $Y_i = \alpha_1 + \beta_1' X_i + \varepsilon_i$).

others. It has the advantage of only using the most relevant controls. This is also one of the matching estimators considered by Abadie and Imbens (2006a).

4.3.4 Estimates of PSA causal effect with a continuous treatment

The original propensity score was developed to estimate the causal effects of a binary treatment (e.g. PSA vs. non-PSA); however, in many observational studies, the treatment may not be binary or even categorical. Recently, methods that extend this framework to multi-valued and continuous treatments have been introduced. Lechner (2002) extends the conventional two-states framework to allow for mutually exclusive treatments. Imbens (2000) extends Rosenbaum and Rubin's (1983) conditions for the validity of the propensity score to multi-valued treatments, while Hirano and Imbens (2004) extend the results to continuous treatments. Both of these papers employ the concept of a *generalized propensity score* (GPS). Imai and van Dyk (2004) establish a method to estimate causal effects in observational studies that can be adapted to different treatment regimes including the case when we have a continuous treatment. Behrman, Cheng and Todd (2004) also has extended propensity score methods to the case of a continuous treatment.

4.3.4.1 The generalized propensity score and the dose-response function

Hirano and Imbens (2004) develop the GPS methodology in the context of the potential outcomes model for the estimation of causal effect of treatments. In what follows I closely follow their presentation.

Suppose we have a random sample of units, indexed by $i=1,\ldots,N$. For each unit i there exists a set of potential outcomes $Y_i(t)$ for $t \in \Im$, referred to as the unit level dose-response function. In the continuous case, $\Im$ is an interval $[t_0,t_1]$, whereas in the binary case it would be $\Im=\{0,1\}$. The objective is to estimate the *average dose-response function* (DRF) $\mu(t)= E[Y(t)]$. For each unit i, we observe a vector of covariates Xi, the level T_i of the treatment that unit i actually receives, with $T_i \in [t_0,t_1]$, and the potential outcome corresponding to the level of treatment received, $Y_i = Y_i(T_i)$. In the remainder of this section the subscript i will be omitted to simplify notation.

Similar to the case of estimation of binary treatment effects (Rosenbaum and Rubin 1983), an unconfoundedness assumption is needed. A key insight from Imbens (2000), and Hirando and Imbens (2004) is a weak version of unconfoundedness:[17]

$$Y_i(t) \perp T_i |\, X_i \; for \; all \; t \in \mathfrak{I} \tag{4.17}$$

Under the weak unconfoundedness assumption, the average DRF could be derived by estimating average outcomes in subpopulations defined by pre-treatment covariates and different levels of the treatment. However, as the number of pre-treatment covariates increases, it becomes difficult to simultaneously adjust for all covariates in X (Flores-Lagunes *et al.* 2007). In analogy to the binary treatment case in Rosenbaum and Rubin (1983), this dimensionality problem is solved by employing the GPS.

The GPS can be defined as follows. Let the conditional (on pre-treatment covariates) density of the treatment be given by:

$$r(t, x) = f_{T|X}(t|X = x) \tag{4.18}$$

Then, the GPS is the conditional density of receiving a particular level of the treatment, t=T:

$$R = r(T, X) \tag{4.19}$$

The function $r(\cdot,\cdot)$ defines both the GPS (which is a single random variable at level T of the treatment and X, $r(T,X)$) and a family of random variables indexed by t, $r(t,X)$.

The GPS has a balancing property similar to the balancing property of the propensity score for binary treatments (Kluve *et al*. 2007). Within strata with the same value of $r(T,X)$

[17] It is referred to as weak unconfoundedness since it does not require joint independence of all potential outcomes, but instead requires conditional independence to hold for each value of the treatment.

the probability that T=t does not depend on the value of X, i.e. the GPS has the property that $X \perp \mathbf{1}\{T = t\} | r(t,X)$. Hirano and Imbens (2004) emphasize that this is a mechanical implication of the definition of the GPS and does not require unconfoundedness. In combination with unconfoundedness, however, it implies that assignment to treatment is uncounfounded given the GPS. That is, Hirano and Imbens (2004) prove that, if assignment to treatment is weakly uncounfounded given covariates X, then it is also weakly uncounfounded given the GPS.

Given this result, it is possible to use the GPS to remove bias associated with differences in covariates. Bias-removal under the weak unconfoundedness assumption is achieved in two steps (Imbens 2000; Hirano and Imbens 2004). The first step is to estimate the conditional expectation of the outcome as a function of the observed treatment level (T_i) and the GPS (R_i):

$$\beta(t,r) \equiv E[Y(t)|r(t,X) = r] = E[Y|t = T, r(T,X) = r]. \qquad (4.20)$$

$\beta(t,r)$ is the conditional mean of the outcome Y given the *observed* value of the treatment and the probability of receiving that value (Flores-Lagunes *et al.* 2007).

The second step is to estimate the DRF at each particular level of the treatment. This is implemented by averaging the conditional expectation function (i.e. $\beta(t,r)$) over the values of GPS (R_i) at that particular level of the treatment:

$$\mu(t) = E[Y(t)] = E\big[\beta\big(t, r(t,X)\big)\big]. \qquad (4.21)$$

Imbens (2000) and Hirando and Imbens (2004) demonstrate that under the weak unconfoundedness assumption, estimating values of the DRF adjusting for the GPS in this way removes all selection bias.

The procedure does not average over the GPS R=$r(T,X)$, but instead it averages over the score evaluated at the treatment level of interest $r(t,X)$. Hirano and Imbens (2004) also emphasize that the regression function $\beta(t, r)$ does not have a causal interpretation, but that

$\mu(t)$ corresponds to the value of the DRF for treatment value t, which compared to another treatment level t' does have a causal interpretation (Kluve *et al.* 2007).

Previous applications of continuous treatment (see Bia and Mattei 2007; Flores-Lagunes *et al.* 2007; Fryges and Wagner 2007; Kluve *et al.* 2007) have only considered positive doses of treatment with the purpose of focusing on the average responses of those individuals. For the purpose of this paper, I will also focus the analysis on census tracts that contain at least one PSA forest conservation contract signed between 1998 and 2004 (i.e. focus on positive treatments).

4.4 DATA

4.4.1 Unit of observation

Previous studies of PSA impact and participation (e.g. Zbinden and Lee 2005; Sierra and Russman 2006; Arriagada *et al.* forthcoming; Sills *et al.* forthcoming) recognized that landowners make decisions about program participation and program outcome (i.e. forest cover), and thus they are the ideal unit of analysis to analyze its causal impact. From these studies results, obtained using household surveys, in-depth case studies, interviews with government officials and forest professionals, and review of previous literature, it can be said that the factors that drive land use include a range of socioeconomic and biophysical characteristics that can only be obtained through combination of household surveys and either field data on land use or secondary spatial data.

In order to apply any of the evaluation methods proposed in this paper, it is critical to gather information on both program participants and a large pool of landowners who were eligible to participate but did not sign up for the program. Availability of national census data combined with biophysical data organized at the census tract-level makes logical the selection of census tract as the unit of observation, especially when one is interested in estimating the causal impacts of PSA at the country level. Another important advantage of using census tracts for the analysis of PSA stems from an important characteristic that program evaluation techniques share: they ignore the impact a program may have on outcomes and behavior of non-participants. These effects, known as general equilibrium effects, may arise where participants benefit also affect non-participants (Bryson *et al*. 2002). The use of a higher scale of analysis would allow embedding these effects. [18]

The availability of enough number of control units to be used during the matching process also limits the policy relevance when analyzing the PSA program at the household level. That is because the policy analyst wishes to know the effect of the program on those who participate, not just a sample from where you have available data on outcome and confounders. A region-level analysis may allow better inferences based on a more extended sample of census tracts (in fact, this study includes all the rural census tracts of Costa Rica).

During the year 2000, the National Institute of Statistics and Census (*Instituto Nacional de Estadística y Censos*, INEC) implemented the IX National Population Census and V National Housing Census. According to these censuses, Costa Rica is divided into 17,269 census tracts located in urban and rural areas.[19] In this study, I only include census tracts located in rural areas (i.e. concentrated and disperse). I did not include census tracts located in urban areas because the probability of finding PSA protection contracts is very low. In fact, only eight forest protection contracts signed between 1998 and 2004 were found within urban areas which represent only 0.24% of the total number of PSA protection contracts signed between those years.

According to the census, I found there are 8,214 rural census tracts with a mean size of 616 ha and standard deviation of 1,809 ha (coefficient of variation equals to 294%). The smallest rural tract is 0.45 ha and the biggest is 73,612 ha. From the 8,214 census tracts, only 11 (0.13%) are bigger than 17,000 ha, and then represent outliers that will be dropped from

[18] Sánchez-Azofeifa *et al.* (2007) used 5x5 km grid cells in their evaluation of PSA, Pfaff *et al.* (2008) used pixel-level units randomly selected throughout Costa Rica, and Sills *et al*. (forthcoming) used district-level data.
[19] For organization purposes, INEC divides Costa Rica in four different areas: urban, periphery urban, concentrated rural, and disperse rural following a method developed by the Ministry of Planning.

the analysis. 7 out of these 11 tracts contain a total of 96 PSA protection contracts signed between 1998 and 2004 which will also be dropped from the analysis (these 96 PSA protection contracts represent only 3% of the total number of PSA protection contracts signed between 1998 and 2004).[20] Figure 4.1 shows the 8,214 rural segments classified according to their size. The eleven biggest tracts are highlighted in red and blue. Table 4.5 shows descriptive statistics for the remaining 8,203 segments.

4.4.2 Treatment

This study will analyze the causal impact of PSA forest conservation contracts signed between 1998 and 2004 on deforestation at the level of rural census tracts. The three concepts associated with forest cover changes (forest gain, forest loss and net deforestation) defined in section 4.2.4 will be used as part of this study.

From Cordero (2008) a LULC dataset was obtained for Costa Rica during two time periods: 1992-1997 and 1997-2005. This dataset employed six different geographical datasets described in Appendix 2. The complete methodology to estimate LULC for this study is described in Cordero (2008).

Given that this paper is using census tracts as the unit of observation and a binary and continuous definition of treatment, it is necessary to define the variable that will allow to construct treatment (i.e. PSA census tracts) and control groups (i.e. non-PSA census tracts). There are 4,574 PSA contracts signed between 1998 and 2004. 72% (3,304 contracts) corresponds to forest protection. Figure 4.2 shows how the PSA protection contracts are distributed among the rural census tracts. There are 1,065 census tracts that contain at least one PSA forest conservation contract signed between 1998 and 2004. The average number of ha under PSA protection per census tract is 292.6 (standard deviation equals to 550.9 ha).

[20] In terms of observational dissimilarities of the biggest tracts with respect to the rest of the country, there are no statistically significant differences in terms of the covariates to be used later in the analysis. These outliers were dropped also because the larger the tract the less well average socio-economic characteristics from census or biophysical layers represent all hectares in that tract. These census tracts for being outliers in terms of segment size can also potentially bias the parametric estimation of propensity scores.

Figure 4.3 shows how the area under PSA protection is distributed among the census tracts included in the study.[21]

Based on census tract size and number of hectares protected by the program per tract, I estimated what is the percent of the total segment area that is protected by PSA. In this case the % will be estimated as follows:

$$\%\, tract\ area\ under\ PSA = \frac{\text{Per tract hectares protected by PSA conservation}}{\text{Tract area (ha)}} \qquad (4.22)$$

In terms of percent of segment area under PSA protection, the average percent is 15.3% with a standard deviation of 15.4% ha (coefficient of variation equals to 101%).[22] Figure 4.4 shows the histogram for the distribution of % of tract area under PSA and Figure 4.5 the kernel density estimates of the percent of rural census tract area protected by PSA forest conservation contracts signed between 1998 and 2004. According with Figures 4.4 and 4.5, only 264 rural census tracts have more than 22% of their area protected by the program, and 529 have less than 10% of their total area on PSA protection. In this study, I will use the percent of tract area under PSA as the variable that will define PSA and non-PSA census tracts. Then, PSA tracts (i.e. treatment group) will contain all tracts with more than 0% of tract area under PSA protection (i.e. it will contain census tracts with at least one PSA forest conservation contract signed between 1998 and 2004). Accordingly, non-PSA tracts (i.e. control group) will contain tracts with 0% of tract area under PSA protection. Figure 4.6 shows the areas that contain census tracts with at least one PSA forest conservation contract signed between 1998 and 2004 (green areas), and the areas that contain census tracts with no PSA forest conservation contracts signed between 1998 and 2004 (red areas).

[21] The allocation of PSA forest conservation contracts signed between 1998 and 2004 to rural census tracts follows the following rule: if the centroid of the contract polygon (shown in Figure 4.2) falls inside the census tract, then that PSA contract is assigned to that particular tract.

[22] From the 1,065 census tracts that contain at least one PSA forest protection contract, there are 8 segments where more than 100% of the tract area is protected by PSA. This result is explained because some PSA areas are located across more than one tract, then when the % of segment area under PSA is calculated I obtained % bigger than 100% just because the PSA areas in these cases are bigger than the segment size. These tracts will be dropped from the analysis. Figure 4.3 show the distribution of protected area considering only the remaining 1,057 tracts.

4.4.3 Confounders

A key problem that often plagues observational studies is the lack of randomization in assigning individuals (in this case census tracts) to either treatment or control groups. Because of this, the estimation of the effects of treatment may be biased by the existence of confounding factors (Baser 2006). Then, selection of covariates is an important step before matching. In the context of PSA, it is important to control for observable covariates that affect program participation, but can also affect program outcome (e.g. deforestation).

For the purpose of controlling confounders that can be related with PSA outcome, I base on the existing literature on tropical deforestation and previous studies of deforestation in Costa Rica presented in section 4.2.2. These previous studies present immediate and underlying causes of deforestation that systematically have been included in the literature on tropical deforestation. The variables affecting deforestation included in previous studies and to be included in this study are as follows:

Immediate causes of deforestation

- Land use capacity: I use Costa Rica's land use capacity classes, which are determined by slope, soil characteristics, life zones, risk of flooding, dry period, fog, and wind influences (see Decree 23214 from the Ministry of Agriculture and MINAE). These data will be obtained from the Costa Rica Digital Atlas 2004 (*Atlas Digital de Costa Rica 2004*, ACR).
- Off-farm employment: I proxy for off-farm employment using the Costa Rica Census 2000 that recorded number of salaried people and employment status when the census was carried on (i.e. people were asked about employment status one week before the actual census in 2000).
- Distance to roads: I measure the number of roads per census tract (ACR contains 8 types of roads which separate primary and secondary urban and rural roads). I also used density of roads to proxy for access to markets.
- Distance to markets: I proxy for access with the minimum linear distance from the center of the census tract to the nearest major city (i.e. *poblado* in ACR), to *San José*

(i.e. the country's capital) and to *Puntarenas* and *Limón* (i.e. the two main ports in Costa Rica).

- Scale factor: I use the size of each tract and forest stock in each census tract.

For the purpose of controlling confounders that can affect decisions to enroll in PSA, Pattanayak *et al.* (2003) construct a meta-analysis of the adoption of agroforestry and related conservation technologies. This comprehensive review of the literature identified five broad categories of adoption determinants: preferences, resource endowments, market incentives, bio-physical factors, and risk and uncertainty. The first two categories are most often included in studies, perhaps because proxies for preferences (e.g. age and education) and resources (e.g. land area) are relatively easy to measure. However, risk and bio-physical factors are also critically important. In particular, soil quality, plot size, extension and training are consistently significant in these models. Zbinden and Lee (2005) found that farm size, percentage of income from off-farm sources, and interaction with extension and participation in workshops are positively correlated with participation, while labor availability is negatively correlated.

According to Pattanayak *et al.* (2003), market access can also be another important factor. In the case of PSA, access to government agencies and forestry professionals are likely to influence the direct cost of participation, while access to markets and bio-physical factors that affect the profitability of other land uses (e.g. cattle ranching) are likely to be key components of the opportunity cost. Sills *et al.* (forthcoming) suggest that PSA parcels have significantly more forest cover than non-PSA parcels, both prior to and after participation in the PSA Program. Arriagada *et al.* (forthcoming) report factors that affect PSA participation decisions. While these factors are not mutually exclusive, the lack of an alternative use for the contracted land appeared to have the greatest influence on the decision to participate in PSA. Zindben and Lee (2005) report that education, access to extension, and participation in meetings are key determinants of which landowners enroll in PSA. Sills *et al*. (forthcoming) also report that PSA participants are more likely not to be from where they own the PSA parcel (that is, not born in the region where they now own a parcel). While education of the respondent does not differ across samples, there is more likely to be someone with university education in the family of a landowner with a PSA contract. Sills *et al.* (forthcoming) also report in their district-level analysis that districts with PSA contracts, on average, are more likely to have a greater percentage of their areas in forest, a greater percentage of their areas in protected areas, a smaller percentage of their area in valuable land-use classes, lower local road densities, lower population densities, a greater percentage of the population born outside where PSA land is located, and a greater percentage of the population that use fuelwood.

Many of the determinants of program participation and technology adoption explained above are directly related with the immediate causes of deforestation. However, there are important confounders that determine program participation that need to be included in the estimation of the propensity score. These confounders include:

Determinants of program participation

- Age: using the census, I calculate the average age per tract
- Educational level: I count the per-tract number of people that have at least secondary education (*secundaria académica* and *secundaria técnica*)
- Distance to MINAE/SINAC regional offices: I calculate the distance of each tract to the nearest MINAE/SINAC regional office
- % population born inside the tract: I count the number of people per tract that were born inside the *canton* (equivalent to a US county) where they live when the census was implemented

Immediate causes of deforestation and determinants of program participation will serve the purpose of estimating the propensity score (i.e. the probability of having at least one PSA forest conservation contract signed between 1998 and 2004 in a rural census tract).

These confounders will constitute the core group of confounders to be used in the estimation of program causal impacts.[23]

Previous studies of tropical deforestation have also identified underlying causes of deforestation that will be included in an extended specification of the propensity score together with the variables that have determined PSA targeting by FONAFIFO and SINAC as explained in previous sections. The extended set of confounders to be included in the estimation of the propensity score are:[24]

Underlying causes of deforestation

- Population: I measure population density at tract-level from the census
- Proportion of immigrants: I measure immigration by counting the per-tract number of people older than 5 years old in 2000 that were not living in Costa Rica in 1995 using the census
- Proportion of households using fuel-wood for cooking: fuel-wood use is a proxy for the use of forest resources by residents, which would affect deforestation (see Ferraro 2007). I count the per-tract number of households that use fuel-wood for cooking purposes

PSA targeting:

- Distance to IDA settlements: I calculate the distance of each tract to the nearest IDA settlement
- Proportion of tracts located in aquifers
- Proportion of tracts located in Ecomarket areas
- Proportion of tracts located in GRUAS areas

[23] This core group of confounders will allow estimating the propensity score using a logit specification referred as *Logit I* in the results section.

[24] This extended set of confounders will allow estimating the propensity score using a logit specification referred as *Logit II* in the results section.

4.5 EMPIRICAL STRATEGY

The causal effect of PSA on forest cover changes was estimated using PSA forest conservation contracts signed between 1998 and 2004 in the whole country. PSA and Non-PSA census tracts were defined and compared after controlling for pre-PSA (i.e. predetermined) observable socio-economic and biophysical characteristics which determined selection into the program and targeting, and are likely to have affected outcomes (i.e. changes in forest cover). First, I generate estimates of program impact with a binary definition of treatment (i.e. PSA tracts vs. non-PSA tracts) and using propensity score matching and mixed methods to improve covariate balance and relax functional form assumptions. Second, I estimate PSA impact using a continuous definition of treatment using the generalized propensity score method.

4.5.1 Propensity score methods

In the context of PSA, the propensity score is the probability of being a PSA census tract, conditional on a number of control variables: $\Pr(D=1|X)$. In that sense, the propensity score is a function of the control variables. Let's imagine a formula where you plug in the values of the covariates (e.g. tract size, tract population, tract soil quality, etc.) to obtain the probability that the tract will be a PSA tract (i.e. a census tract that contains at least one PSA forest conservation contract). Because participation in PSA requires allocation of land to forest, the biophysical and socio economic tract characteristics that determine participation in PSA are also likely to determine land use, including changes in forest cover, which is the program outcome being analyzed in this study. Therefore, in the estimation of propensity scores, it is most important to include variables that influence simultaneously the participation decision and the outcome variable. When estimating the propensity score two choices have to be made. The first one concerns the model to be used for the estimation, and the second one the variables to be included in this model.

Regarding the model choice, little advice is available regarding which functional form to use for the estimation of the propensity score. In principle any discrete choice model can be used. Preference for logit or probit models (compared to linear probability models) derives from the well-known shortcomings of the linear probability model, especially the unlikeness of the functional form when the response variable is highly skewed and predictions that are outside the [0, 1] bounds of probabilities. For the binary treatment case, where we estimate the probability of participation vs. non-participation (e.g. PSA vs. Non-PSA), logit and probit models usually yield similar results. Hence, the choice is not too critical (Caliendo and Kopeinig 2005). I use a maximum likelihood logit model to estimate the probabilities. In the general framework of probability model we have: *Prob*(PSA participation) = *Prob*(D=1) = F[relevant effects, parameters]. In this case, the probability of participation in PSA is a cumulative distribution function F evaluated as a function of a set (X) of explanatory variables that include tract socio-economic and biophysical characteristics, and a vector β of unknown parameters. The probability of participation model can be written as:

$$Prob(D_i = j) = \frac{e^{\beta' x_{ij}}}{e^{\beta' x_{i0}} + e^{\beta' x_{i1}}} \; for \; j = 0, 1. \tag{4.23}$$

For the decision about which variables to include in the model, there is more available advice regarding the inclusion (or exclusion) of covariates in the propensity score model (Caliendo and Kopeinig 2005). Matching on the propensity score strategy builds on the conditional independence assumption, requiring that the outcome variable (i.e. forest cover change) must be independent of treatment (i.e. PSA) conditional on the probability of PSA participation (i.e. the propensity score). Heckman, Ichimura and Todd (1997) show that omitting important variables can seriously increase bias in resulting estimates.

For radius matching, I use a radius of 2.5 standard deviations, meaning that any control unit outside the range of this radius in the space of the distance metric is dropped when the counterfactual mean is calculated.[25] For the case of kernel matching, I use weighted

[25] Reducing the radius size bellow 2.5 standard deviations did not affect the observations dropped for being outside the common support. 2.5 standard deviation was considered appropriate given variation in observable characteristics between PSA and non-PSA tracts (a higher radius would increase the bias of the estimates because more observationally different control tracts would be used in the matching). Note, however, that for the case of forest gain, reducing the radius successively to 2.0, 1.5 and 1 decreases the treatment effect estimates

averages of all census tracts in the control group where the weights depend on the distance between each tract from the control group and the participant tract for which the counterfactual is estimated. The kernel function used in this case corresponds to a Gaussian function which is the specification most used in empirical applications of KM (see Caliendo and Kopeinig 2005; Ferraro *et al.* 2007).

For nearest neighbor propensity score matching, I present results with bootstrap standard errors using 999 repetitions and Abadie-Imbens bias corrected standard errors. For radius and kernel matching, I only use bootstrap standard errors using 999 repetitions.[26]

4.5.2 Implementation of the GPS methodology

The empirical implementation of the GPS methodology entails making a number of decisions and assumptions (e.g. such as parameterizations and functional forms) to sensibly estimate the objects defined above. In this paper, I follow the implementation outlined in Hirano and Imbens (2004) and implemented by (Flores-Lagunes *et al.* 2007; Fryges and Wagner 2007; and Kluve *et al.* 2007).

First, a lognormal distribution is used to model the conditional distribution of the treatment Ti (% of census tract area protected by PSA) given the covariates. That is, we estimate $\ln(Ti)|X_i \sim N(\gamma_0 + \gamma_1 X_i, \sigma^2)$. The lognormal distributional assumption is predicated based on the empirical distribution of the treatment for each of the samples considered (see Figure X). Thus, the estimated GPS based on this model is simply

$$\hat{R}_i = \frac{1}{\sqrt{2\pi\hat{\sigma}^2}} exp\left(-\frac{1}{2\hat{\sigma}^2}(\ln(T_i) - \hat{\gamma}_0 - \hat{\gamma}_1 X_i)^2\right) \tag{4.24}$$

where $\hat{\gamma}_0$, $\hat{\gamma}_1$, and $\hat{\sigma}^2$ are estimated by ordinary least squares (OLS).

making them to look more similar to NN results. For the case of net deforestation, changes in the radius size did not affect much the results.

[26] Abadie and Imbens (2006b) prove that the bootstrap is not valid for the standard nearest-neighbor matching estimator with replacement although empirical applications of the method still use it (see, for example, Ferraro *et al*. 2007). However, if the number of neighbors increases (as it is the case for RM and KM) the matching estimator does become asymptotically linear and sufficiently regular for the bootstrap to be valid.

In the second step, the conditional expectation of the outcome given the observed treatment level (T_i) and the estimated GPS (i.e. $\hat{R}_i$) is modeled with a flexible linear specification and estimated with OLS:

$$E[Y_i|T_i, \hat{R}_i] = \alpha_0 + \alpha_1 T_i + \alpha_2 {T_i}^2 + \alpha_3 \hat{R}_i + \alpha_4 {\hat{R}_i}^2 + \alpha_5 T_i \hat{R}_i. \qquad (4.25)$$

Finally in the third step, we estimate the value of the dose-response function at treatment level *t* by averaging the above regression function over the distribution of the GPS (holding constant the treatment level *t*):

$$E\widehat{[Y(t)]} = \sum_{i=1}^{N} [\hat{\alpha}_0 + \hat{\alpha}_1 t + \hat{\alpha}_2 t^2 + \hat{\alpha}_3 \hat{r}(t, X_i) + \hat{\alpha}_4 \hat{r}(t, X_i)^2 + \hat{\alpha}_5 t \hat{r}(t, X_i) \qquad (4.26)$$

I can estimate values of the DRF corresponding to different values of the treatment repeating this last step.

4.6 RESULTS

4.6.1 Program participants vs. non-participants

The rural census tracts included in this study area characterized in Table 4.6 which reports descriptive statistics for biophysical and socio economic tract characteristics, and for variables that explain PSA targeting efforts. The table compares non-PSA rural census tracts (column 4) (i.e. rural census tracts that do not contain PSA contracts) with PSA tracts (column 5), which represent continuously treated rural census tracts (i.e. % of PSA protection in each tract varies going from 0.06% to 99.28% according with Figure 4.4). Table 4.6 also shows the p-value for the difference in means (column 6). Although these descriptive statistics are descriptive and not inferential, they represent 98.4% of Costa Rican rural census tracts according with the 2000 census. According with Table 4.6 PSA and non-PSA tracts are significantly different on many counts including. Within the group of biophysical tract characteristics, PSA tracts are significantly bigger, with more 1992 forest stock, worst soil quality, more steeper slopes, more precipitation, fewer number of roads, lower road density, more distant to markets and ports, and more distant to MINAE regional offices. These results are consistent with main determinants of tropical deforestation as explained in previous sections and show already an important correlation between deforestation determinants and PSA participation. Within the group of socioeconomic tract characteristics, PSA tracts have significantly less off-farm employment opportunities, are less populated, have fewer immigrants, more educated, and contain more people that use fuelwood. In terms of the variables that explain PSA targeting, PSA tracts contain less non-eligible area for PSA, are more located further from IDA settlements, further from aquifers, and closer to Ecomarket and GRUAS zones.

This initial comparison of PSA vs. non-PSA tracts differences indicate already the extent of biased comparisons of outcomes due to different distributions of observed covariates in both groups. Even in the case of having a balanced group of participant and non-participant tracts, it is also important to keep in mind that continuously treated tracts differ in the degree of PSA protection (i.e. treatment intensity) and also should be considered in the production of unbiased estimates of program impact. In fact, Table 4.6 reports land use changes for PSA and non-PSA tracts. PSA tracts gained more forest between 1997 and 2005; report a more positive forest loss and a more negative net deforestation between 1997 and 2005.

4.6.2 Estimates of program impact using a binary definition of treatment

Table 4.7 shows the marginal effects on the propensity of a rural census tract to have at least one PSA forest conservation contract signed between 1998 and 2004. These results represent what I called the propensity score in previous sections estimated using the participation probability model shown in (4.21). The logit I specification (column 2) includes only the immediate determinants of tropical deforestation as described in section 4.4.2 and logit II includes also underlying determinants of deforestation and explanatory variables associated with PSA targeting (i.e. per-tract hectares of non-eligible area for PSA, distance to IDA settlements, proportion of tract in aquifers, proportion of tracts located in Ecomarket or

GRUAS zones). Logit II specification also includes regional dummies for groups of conservation areas as described in section 4.4.3.

According with logit I, having a higher percent of tract area with soil class I or II, higher percent of tract area with slope 0-30%, more off-farm employment, more number of roads per tract, more hectares of non-eligible land for PSA, and been further from ports significantly reduce the propensity of a census tract to have at least one PSA contract. Having a higher % of tract area with soil class VII or VIII, higher percent of tract area with slope greater than 45%, more precipitation, higher proportion of tracts in very humid (tropical), dry (tropical) and rainy life zones compared with humid ones, more hectares per tract, more forest stock in 1992 and older people significantly increase the propensity. The logit II specification adds to the group of significant positive determinants of propensity of a census tract to have at least one PSA contract the tract-level proportion of immigrants and of household that use fuel-wood for cooking, distance to IDA settlements, and proportion of tracts located in Ecomarket zones. The logit II specification also adds significant negative determinants of propensity of a census tract to have PSA contracts including population density, and proportion of tracts in aquifers. Compared with *Tempisque- Arenal Tilarán-Guanacaste* (Group II), being in Groups III, IV, V or VI significantly reduces the propensity of a census tract to have PSA contracts (this result is consistent with Table 4.5 that shows Group II as the one more active in terms of numbers of tracts with PSA protection, total area under PSA protection and number of PSA contracts). All these results are consistent with literature on tropical deforestation and previous studies of program participation.

Table 4.8 shows the estimates of program impact using propensity score matching (i.e. nearest neighbor, radius, kernel and blocking). All propensity score methods using logit I(II) suggest a positive and significant impact between 17.310(17.658) ha and 31.450(32.055) ha on the sum of hectares that were not forest in 1997 but recovered to forest during 2005. Logit I(II) propensity score methods also show negative and significant impact between -

21.695(-21.166) ha and -38.155(-34.080) ha on net deforestation between 1997 and 2005.[27] For the case of forest loss, only blocking on the propensity score based on logit II found a significant impact at the 10% confidence level of PSA equal to 10.889 ha.

According with Table 4.8, the magnitude of the impact varies according with the matching estimator being used, but the impact goes from 17.7 ha to 32.1 ha more of forest gain on average in the PSA census tracts vs. tracts with no PSA. These numbers represent between 0.92% and 1.67% of the average size of PSA tracts, 6.06% and 10.98% of the average land enrolled in PSA and 2.24% and 4.07% of the average forest cover in 1997 in PSA tracts.

Results of PSA impact using propensity score methods are fairly consistent in terms of size and significance across the methods for the analyzed PSA outcomes presented in Table 4.8. However, in order to properly compare propensity score methods, it is important to consider the percent of non-PSA tracts used during the matching process. For the case of NN, out of the total population of non-PSA rural census tracts, only 8.4% (i.e. 593 non-PSA tracts) and 8.5% (i.e. 594 non-PSA tracts) were used as matches during the matching process for the case of logit I and II respectively. RM uses the controls lying within the defined radius to find the matches for the treated observation, then in that sense uses a restrictive group of non-PSA tracts comparable with NN. KM is not as restrictive as NN and RM because all controls are used as matches during the matching process resulting in a much bigger sample of controls being used as matches (basically all on-support controls are used during the matching). This explains why the magnitudes of the estimates of PSA impact using KM are comparable with NN and RM, but the significance levels tend to be bigger across the logit specifications and the different program outcomes (as a result of the tradeoff between bias and variance made when using more controls as matches). Regarding propensity score blocking, for the estimation of ATT each block is weighted according with

[27] An impact of PSA on net deforestation equals to -21.695 ha means that on average PSA census tracts have 21.695 ha more of forest compared with non-PSA census tracts.

the number of PSA tracts in each block. In order to avoid overweighting the blocks with higher values of propensity, I defined 10 blocks.[28] The tenth block with the highest values of propensity contains 53% of the total number of PSA census tracts and only 5% of the total number of non-PSA tracts. This helps to explain why blocking gives results of PSA impact that lie between RM and KM estimates because blocking uses all the non-PSA census tracts during matching, but it weights more the ones that have higher propensity values which in this case results in a reduced number of non-PSA tracts (i.e. 5% of total non-PSA tracts).

Table 4.8 also shows the estimates of PSA impact using mixed methods. These estimates correspond to the average treatment effect and not to the effect of PSA on census tracts that in fact have at least one PSA contract. However, using logit I and II, estimates of ATE also suggest a positive and significant impact of PSA on sum of hectares that were not forest in 1997 but recovered to forest during 2005, and a negative and significant impact of PSA on net deforestation between 1997 and 2005. Regarding forest loss, between 1997 and 2005, logit I did not find statistically significant estimates of program impact, however logit II found statistically significant impacts (10% confidence level) but that differ in sign depending on the method (positive and significant impact using weighting and regression, and negative and significant impact using matching and regression).

Unconfoundedness refers to the case where (non-parametrically) adjusting for differences in a fixed set of covariates removes biases in comparisons between treated and control units, thus allowing for a causal interpretation of those adjusted differences. Logit I specification of propensity score implies less bias in the estimation of casual effect because I am matching only on the immediate determinants of deforestation, but sacrifice plausibility of unconfoundedness in the treatment assignment because I am not including underlying determinants of deforestation and covariates that explain PSA participation, targeting and regional variation of PSA implementation. Logit II specification of propensity score makes the CIA more plausible, but increase bias given the potential remaining covariate imbalance

[28] Following Cochran (1968) recommendation, I started with five blocks and 79% of PSA tracts were included in the fifth block (i.e. the block with the highest propensity scores) which is the block that would receive the highest weight in the calculation of ATT.

left after the matching because logit II tries the balance all the covariates judged to be important in predicting deforestation, PSA participation, targeting and regional variation of program implementation. Table 4.9 shows the balance after matching using NN, RM and KM. NN using logit II is the method that achieves the best balance, however even in this case 9 covariates remained unbalance after matching. However, in terms of percent of reduction in bias after matching Table 4.9 also shows the % of bias reduction. In general, across the methods the percent is high indicating that although some variables remain unbalance after matching the percent of bias reduction is significant. In fact, using logit II and NN the mean of the distribution of the absolute bias was 42.300 and the mean after matching was 5.874 which indicate a significant gain in reducing bias due to differences in observable characteristics used during the matching. Figure 4.7 shows the distribution of propensity scores between PSA and Non-PSA tracts according with logit I and II specifications. Figure 4.8 shows the overlap of the distribution of propensity scores between PSA and non-PSA tracts using both specifications of propensity score logit I and II. As shown in Table 4.7, most non-PSA tracts have a low propensity to have at least one PSA forest conservation contract signed between 1998 and 2004. There is common support at most levels of the propensity score, but this is based on very limited number of non-PSA tracts especially on propensity values close to one.

Program implementation differs across regions in Costa Rica. Table 4.3 shows the factors that could affect the performance of PSA in each of the groups of conservation areas defined in this paper. Table 4.10 shows the treatment effect estimates by group. A significant impact of PSA on forest gain was found for all the groups and across all the propensity score matching methods (except for *Osa*). However the direction of the impact was not the expected in several groups. A negative and significant impact of PSA on forest gain could indicate that areas outside PSA are attracting the regeneration of new forests which is consistent with the current forest transition in Costa Rica. The negative impact could also indicate the presence of other forest incentives designed specifically for forest regeneration (e.g. PSA reforestation contracts). *Tempisque-Arenal Tilarán-Guanacaste* and *Pacífico*

Central-La Amistad Pacífico show the anticipated direction of PSA impact on forest gain. According with Table 4.4, the first shows the highest area under PSA protection and the second the third highest area protected by PSA. *Osa* was the only conservation area group where not only PSA impact in forest gain is not significant, but also impacts on forest loss and net deforestation. Table 4.4 shows that *Osa* is the group with the smallest area protected by PSA (in terms of number of hectares protected and percent of conservation area under PSA protection). In terms of forest loss, none of the groups show a clear trend for the impact of PSA in terms of impact direction and significance. This result is not surprising given the deforestation rate in Costa Rica in the last two decades. In that sense, PSA does not have much room for contributing some additionality to the current situation that affect more mature natural forest. However, it is interesting to note that *La Amistad Caribe-Tortuguero* is the group that gives more compelling evidence of a positive impact of PSA on forest loss (i.e. more forest is lost in PSA tracts) and, according with Table 4.4, this is the only group with a low land use capacity combined with a middle regional organization and a not well defined land tenure. For the case of net deforestation, there are mixed results given the PSA impacts on forest gain and loss. *Tempisque-Arenal Tilarán-Guanacaste* and *Pacífico Central-La Amistad Pacífico* are again the groups that show the expected direction of PSA impact. These results provided evidence that PSA impact differs across the country. Variations in the implementation of the program explained by factors shown in Table 4.4 may be playing an important role in the estimation of program impact across regions.

4.6.3 Estimates of program impact using a continuous definition of treatment

4.6.3.1 Estimates of the GPS

Table 4.11 presents the estimated coefficients of the conditional distribution of the PSA intensity (i.e. treatment defined as different percent of tract area under PSA protection). The estimated GPS is the basis for controlling for selection bias into different % of protection intensity. The GPS is estimated using least squares under the lognormal distribution assumption as described in section 4.5.2. The column 2 of Table 4.11 includes all rural census tracts and column 3 includes only PSA tracts (i.e. rural census tracts that contain at least one PSA forest conservation contract signed between 1998 and 2004). Covariates used in the estimation of GPS include immediate and underlying causes of tropical deforestation, determinants of PSA participation and targeting and regional dummies that explain variation in the implementation of the program across the country.[29]

Using all census tracts, variables positively related to log (%) of tract area under PSA protection includes percent of tract area with soil class VII or VIII, percent of tract are with slope>45%, precipitation, proportion of tracts in very humid (tropical), dry (tropical), and rainy life zones, tract size, forest stock 1992, tract-level proportion of households using fuel-wood for cooking, distance to IDA settlements, and proportion of tracts located in Ecomarket zones. Variables negatively related to log (%) of tract area under PSA protection includes percent of tract area with soils class I or II, % of tract area with slopes 0-30%, distance to ports, per-tract hectares of non eligible area for PSA, population density, proportion of tracts in aquifers, and being located in groups III, IV, V and VI. The bottom panel shows that the GPS model has an R^2 of 30.8%. When including only PSA tracts, variables positively related to log (%) of tract area under PSA protection includes percent size of forest stock 1992, distance to IDA settlements, proportion of tracts located in Ecomarket zones and being located in Group III (*Cordillera Volcánica Central*). In this case, the bottom panel shows that the GPS model has and R^2 of 8.7%.[30] Given my interest on ATT, these estimates will be used in the remainder of the paper.

4.6.3.2 Balancing properties of the GPS

An important property of the GPS is that it "balances" the covariates within strata defined by the values of the GPS, such that, within strata, the probability that t=T does not depend on the value of X (Flores-Lagunes *et al.* 2007). This balancing property can be employed to empirically assess the adequacy of the chose functional form to estimate the

[29] These covariates were also used in the logit II specification of propensity score shown in Table 4.7.
[30] Given that the GPS will act as a balancing score, obtaining a high predictive power of the GPS function is not critical. In fact, these R^2 is similar to the ones obtained in Flores-Lagunes *et al.* (2007) that study the effects of length of exposure to a training program.

GPS in a similar way it was done for the case of the binary definition of treatment with the propensity score (i.e. PSA vs. non-PSA census tracts), however testing for covariate balance is more difficult with continuous treatment.

Hirano and Imbens (2004) propose blocking on both the treatment variable, i.e. percent of tract area under PSA protection in this case, and on the estimated GPS. I implement this by first dividing the sample into three groups according to the distribution of treatment intensity (see Figures 4.4 and 4.5), cutting at the 30th and 70th percentile of the distribution. Group 1 includes census tracts with a treatment level between 0.06% and 5.45% of segment area under PSA protection, group 2 ranges from 5.45% and 18.36% and group 3 ranges from 18.36% and 99.26%. Within each group, I evaluate the GPS at the median of the treatment variable. For each of the covariates I test whether the difference in means of one group compared to the other two groups is significantly different. In the left part of Table 4.12 the corresponding *p*-values from standard *t*-test are reported. Without adjustment, 47% of the covariates (i.e. fifteen) are unbalanced.

Then, in a second step I evaluate the GPS for each individual at the median of groups 1, 2 and 3, i.e. at the PSA intensity of 2.783%, 9.982% and 28.632 respectively. For each of three groups, I make the GPS discrete by using five blocks evaluated by the quintiles of the GPS within each group of treatment intensity (i.e. groups 1, 2 and 3). In other words, I calculate for the first group, consisting of tracts with a treatment level between 0.06% and 5.45% of segment area under PSA protection, the GPS evaluated at the median of this group 1 (i.e. 2.783%). The distribution of the GPS $r(2.783,X_i)$ is then divided into five blocks using the quintiles of the distribution. For the first group, this leads to the intervals [0.0445, 0.1134], [0.1134, 0.1578], [0.1578, 0.1909], [0.1909, 0.2239] and [0.2239, 0.3490]. This process is repeated with groups 2 and 3 by dividing the distribution of the GPS $r(9.982,X_i)$ and $r(28.632,X_i)$.

Within each of the blocks I calculate the difference-in-means of covariates with respect to census tracts that have a GPS such that they belong to that block, but have a treatment level different from the one being evaluated. This procedure tests if for each of these blocks the covariate means of tracts belonging to the particular treatment-level group are significantly different from those tracts with a different treatment level, but similar GPS. For example, to assess the balancing of the adjusted sample, tracts of the first group with a GPS in the first range (i.e. between 0.0445% and 0.1134%) are compared with tracts that are not from the group 1, i.e. tracts that have a different level of treatment, but who have a GPS lying in the first interval as well. For each group, this implies five mean differences and five standard errors. A weighted by the number of observations average over the five blocks in each treatment-level group can be used to calculate the *t*-statistic of the differences-in-means between the particular treatment-levels. The *p*-values from standard *t*-test reported on the right hand of Table 4.12 correspond to the mean difference for each group. In contrast to the unadjusted sample, no *p*-values smaller than 0.100 are shown in Table 4.12. These results indicate that the balance of the covariates is clearly improved by adjustment for the GPS.

4.6.3.3 Assessing the support overlap condition

In the case of a binary definition of treatment, it is common to gauge the overlap by looking at the distribution of the propensity score among treated and non-treated units, sometime restricting estimation to the common support region. However in the case of multi-valued or continuous treatments it is considerably more difficult to gauge this condition. The main reason for this is that there are many levels of the treatment and consequently multiple parameters of interest, each of them requiring a potentially different support condition (Flores-Lagunes *et al.* 2007).

There are no concrete suggestions in the literature on how to gauge the common support condition in the context of a continuous treatment. However, I followed a test proposed by Peter Mueser and implemented in Flores-Lagunes *et al.* (2007) and Kluve *et al.*

(2007).[31] First, following the procedure for testing for the balancing of covariates explained in the previous section, I use the three groups defined according to the distribution of PSA protection intensity, cutting at the 30^{th} and 70^{th} percentile of the distribution. Then I evaluate the GPS at the group median of the treatment intensity variable. For example, I evaluate the GPS for the whole sample at the median treatment intensity of group 1 (i.e. 2.783%), and after that I plot the distribution of the evaluated GPS for group 1 vs. the distribution of the GPS for the rest of the sample. Like in the case of binary propensity score matching, by inspecting the overlap of these two distributions I am able to examine the common support condition graphically. In the same fashion, I test the common support condition of groups 2 and 3 vs. the rest of the sample.

Figures 4.9 plots the distribution of the evaluated GPS of group 1 and the same distribution of the rest of the sample in the same figure, Figures 4.10 and 4.11 precede similarly for groups 2 and 3 respectively. The three figures show that the common support is satisfied given the good overlap in the support of the GPS for the three groups. Overall, I conclude that the overlap support condition is not a concern in the estimated model.

4.6.3.4 Estimates and plots of the dose response function

Recall that the second step of this empirical analysis consists in the estimation of the conditional mean of the program outcome given the observed PSA protection intensity (T_i) and the estimated GPS ($\hat{R}_i$). Table 4.13 contains the estimation results for the dose-response function following the specification shown in (4.24). Figures 4.12, 4.13 and 4.14 present the entire DRF for the full sample of PSA tracts, providing a general overview of how conservation intensity given by the percent of census tract area protected by PSA affects the program outcomes included in this study. The DRF plots are obtained with 99 different values of the treatment that correspond to the 99 percentiles of the corresponding empirical distribution. Figures 4.12 and 4.14 show that the expected PSA impacts on forest gain and net deforestation (positive on forest gain and net deforestation) reach to a point where more

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intense protection does not increase outcome. Figure 4.12 shows that PSA has a positive impact on forest gain only up to a certain point when the percent of census tract area under PSA protection reaches 30% (same for net deforestation shown in Figure 4.14). The expected negative impact of PSA on forest loss (i.e. less forest loss on PSA tracts) is only seen when the % of census tract under PSA protection reaches 20% (although Table 4.10 shows that forest loss was never significant across methods for any of the conservation area groups). These graphs show the dynamism of the PSA impact on the program outcomes included in this paper. Further research in this area could help to understand conservation threshold effects and determine minimum conservation intensities to obtain significant conservation outcomes.

4.7 CONCLUSIONS

Direct incentives to conserve forests in the form of payments for ecosystem services have become a popular conservation intervention over the past decade (Bulte *et al*. 2008). While economists were instrumental in promoting this approach (Ferraro and Kiss 2002), they are now raising the concern that PES programs are being implemented globally in much the same way previous conservation interventions were implemented: with an unwavering faith in the connection between interventions and outcomes and without a plan to judge the effectiveness of such interventions (Ferraro and Pattanayak 2006).

Currently, the core element of Costa Rican forest policy is PSA, which is the first long-term, nation-wide PES program in the tropics. Since the inception of PSA in 1997, almost 600,000 ha (12% of the national territory) have been enrolled in the program. Almost 532,000 ha (89% of the total land enrolled in PSA) corresponds to forest conservation contracts where landowners, after making a voluntary decision to participate, receive a direct payment for the protection of their forest.

However, PSA was not developed from scratch but grew out of a history of reforestation and forest protection efforts, dating from at least 1969. Whether as a result of these efforts or other changes in the Costa Rican society and economy, deforestation rates started falling in the 1990s, at least several years before the PSA program began. Thus, to evaluate the impact of PSA, the analyst must disentangle the effects of previous government forestry incentives and economy-wide changes that made deforestation less appealing, as well as adjusting for the non-random assignment of contracts.

In this chapter, I applied matching methods using both binary and continuous definitions of treatment (e.g. rural census tracts that contain at least one PSA contract vs. percent of tract area protected by PSA) to evaluate the impact of PSA forest protection contracts signed between 1998 and 2004 on program outcomes. Three program outcomes (i.e. forest gain, forest loss and net deforestation) are considered. These outcomes are all important dimensions of forest cover in Costa Rica, although they have different implications for the bundle of ecosystem services produced and consequently are viewed differently by various stakeholder groups (e.g. stopping loss of existing mature natural forests is the priority of many environmental groups, while others interested in climate change and carbon sequestration are most likely to focus on net change in total forest cover). The effect of temporal and spatial variation in program implementation is also considered by estimating program impact by regions and years. By obtaining and linking census data at the tract level to remote sensing data on land cover, I obtain a large enough sample size (approx. 8,000) to employ both binary and continuous treatment methods. Socioeconomic characteristics at the tract level also provide a more accurate representation of conditions driving decisions about program participation and land use, as compared to previous work that relied on district-level data (which provided only 500 observations for all of Costa Rica). Given that I do not observe all the factors that drive local deforestation rates, the expanded data also permit the inclusion of other fixed effects (e.g. conservation area groups fixed effects) which is a major gain in controlling for the effects of potential unobserved drivers.

With the binary definition of treatment, I find that PSA has different impacts on each dimension of forest cover change. The most robust result is a positive and statistically significant impact on forest gain in the census tracts that contain at least one PSA forest conservation contract signed between 1998 and 2004. This positive and significant effect is robust to all propensity score and mixed methods using the full specification of the probability of having PSA in a tract.

In terms of PSA impact on forest loss, propensity score matching estimates indicate no program impact, although blocking and mixing methods suggest some small impacts. This result is not surprising given the deforestation trend in Costa Rica in the last two decades. Consistent with the recent literature on forest cover in Costa Rica, forest loss is defined here as the sum of all area transitions from natural forest classes (continuous and fragmented) to all other land use classes. Part of the explanation for the lack of impact of PSA on forest loss could be simply that there has not been much transition from natural forest classes to other land uses in the last two decades, due to a wide array of social, economic, and policy factors as well as the location and biophysical characteristics of the forest that remained after the previous half a century of rapid deforestation.

For the case of net deforestation, PSA shows a positive and significant impact across all propensity score and mixed methods. This result indicates that PSA has caused forest gains greater in magnitude than any forest losses in the census tracts that contain at least one PSA forest conservation contract signed between 1998 and 2004. The magnitude of this impact varies according with the matching estimator being used, but the impact goes from 21.2 ha to 34.1 ha more of forest gain on average in the PSA census tracts vs. tracts with no PSA. These numbers represent between 1.10% and 1.71% of the average size of PSA tracts, 2.69% and 4.43% of the average forest cover in 1997 in PSA tracts, and 7.25% and 11.59% of the average land enrolled in PSA.

The estimates of PSA impact using a continuous definition of treatment represent the first attempt in the conservation literature to estimate the causal impacts of direct payments for conservation with matching methods that recognize a gradient in intensity of protection.

Results showed that intensity matters, even for the direction of impact of PSA on forest gain, forest loss and net deforestation beyond a certain threshold of protection intensity. Further research is needed in this direction.

Further insight can be gained by considering regional variation in the implementation of PSA. Program impact was expected to vary across regions defined by how intense the protection has been in a particular region (e.g. by the number of signed PSA contracts), the organizational strength of the implementing agency in the region, among other factors (e.g. presence of active NGOs promoting PSA). Preliminary results on regional program impacts shows that in *Tempisque-Arenal Tilarán-Guanacaste* PSA has a positive and significant impact on forest gain and net deforestation and a negative impact on forest loss (although for this case, results were not significant for all methods). This conservation area group represents the most intensively treated in terms of number of PSA contracts, area under PSA protection and number of PSA tracts. Counterintuitive results (e.g. negative impact on forest gain and net deforestation, and positive impact on forest loss) were obtained in some cases where the intensity of PSA protection is lower. These preliminary results suggest that further research is needed that can take into account treatment intensity and effects of PSA contract distribution (preliminary results using continuous treatment presented in this paper could constitute the first steps on that direction). Future evaluations should also consider other possible confounders that might drive reforestation as well as deforestation, as well as possible interaction effects in policy implementation (e.g. evaluating the impact of different PSA modalities as multiple treatments). Further study of regional variations in PSA implementation and impact could lead to valuable recommendations for development of PES in other countries.

All these results indicate that PSA is having an important impact on the forest transition underway in Costa Rica. It is also important to highlight that this paper presents an analysis of the causal effect of PSA contracts signed for natural forest conservation, and the results indicate significant and positive results in the establishment of new forests. In light of these results, PSA should be evaluated beyond its impact on tropical deforestation per se. There is evidence from many tropical countries that new forests are being established on former agricultural land, even as deforestation of existing mature forest proceeds. However, there is almost no empirical analysis of the impact of PES and in particular of PSA on the forest transition underway in Costa Rica. In that sense, this paper constitutes an important contribution to the literature on the evaluation of causal effect of PES using state-of-the art matching methods, and in particular to the impact that PSA has on the ongoing forest transition in Costa Rica.

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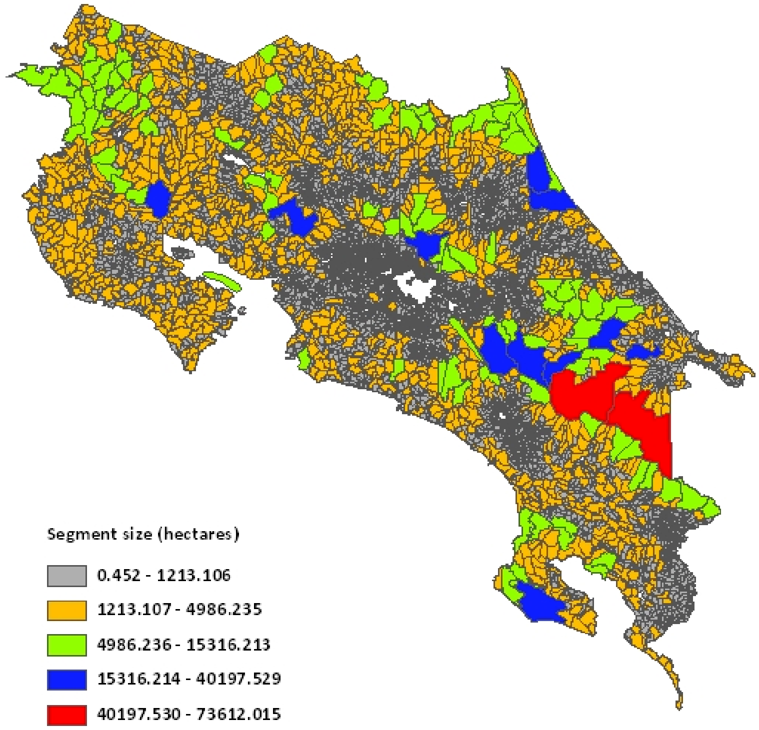


Figure 4.1: Costa Rican rural census tracts classified by size

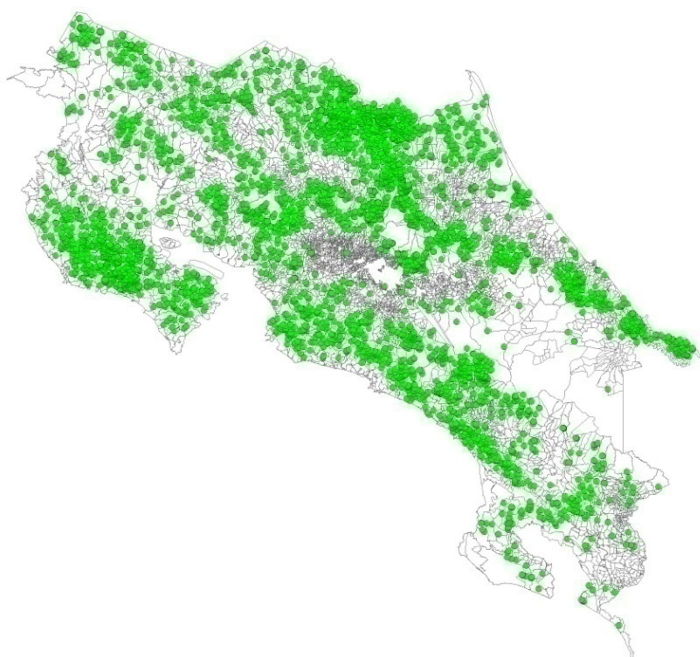


Figure 4.2: Distribution of PSA Protection contracts 1998-2004

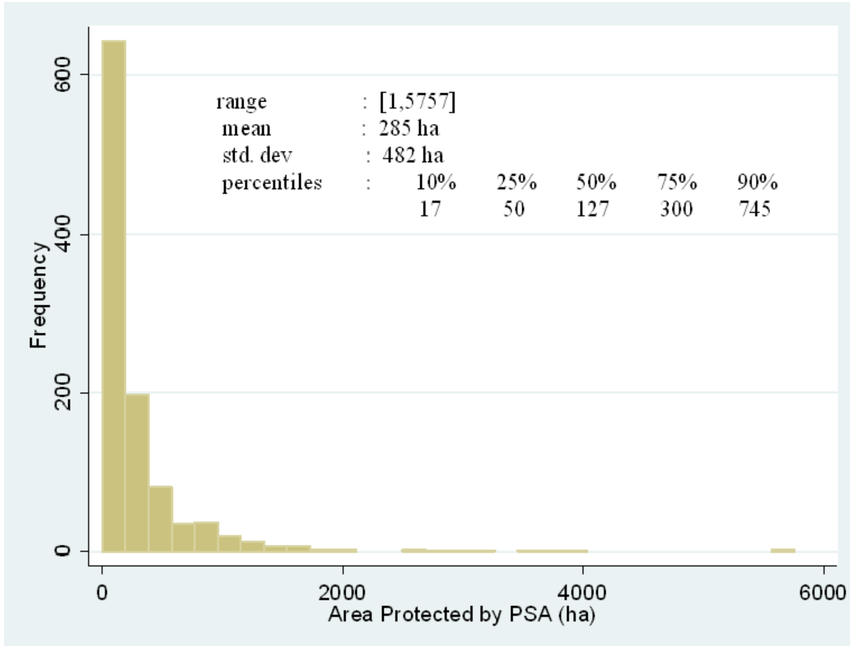


Figure 4.3: Distribution of the area protected by PSA protection 1998-2004 per census tract

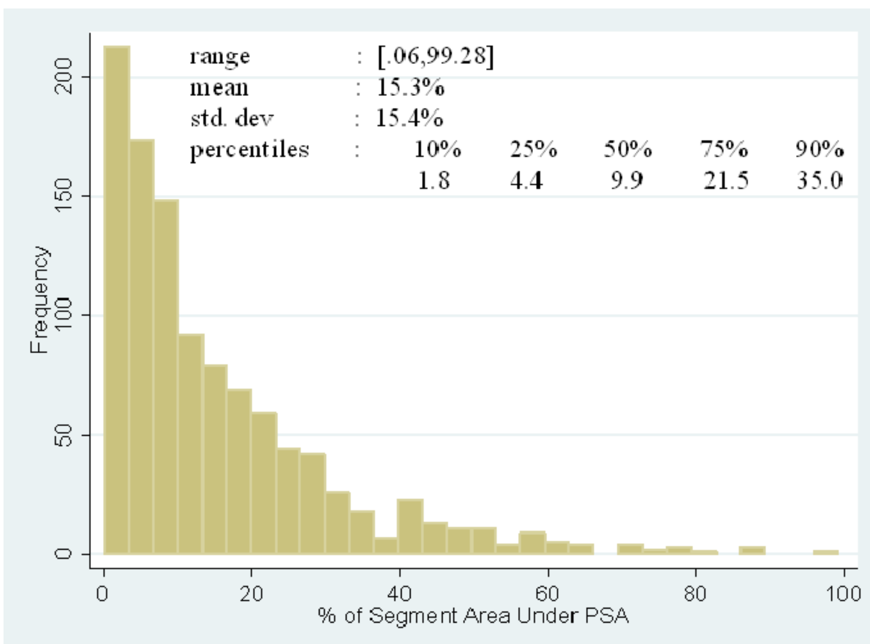


Figure 4.4: Distribution of the percent of census tract area protected by PSA Protection 1998-2004

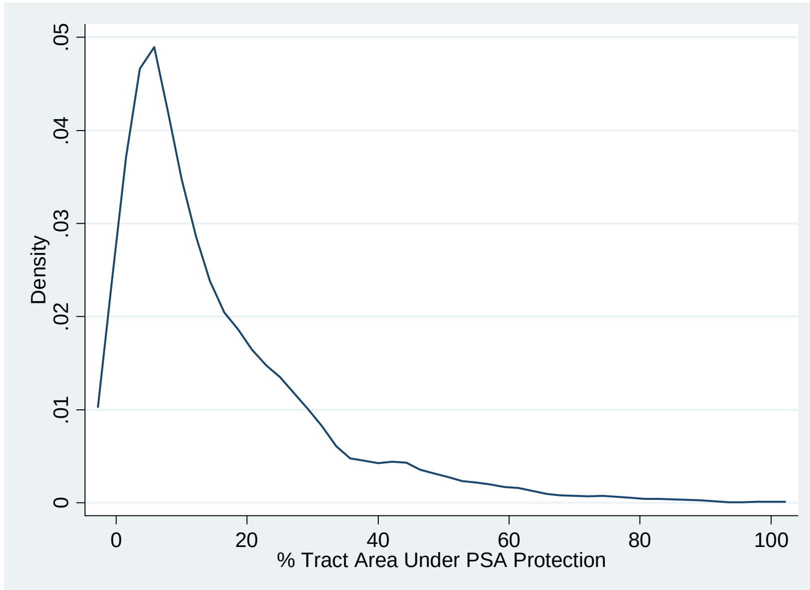


Figure 4.5: Kernel density estimates of the percent of census tract area protected by PSA 1998-2004

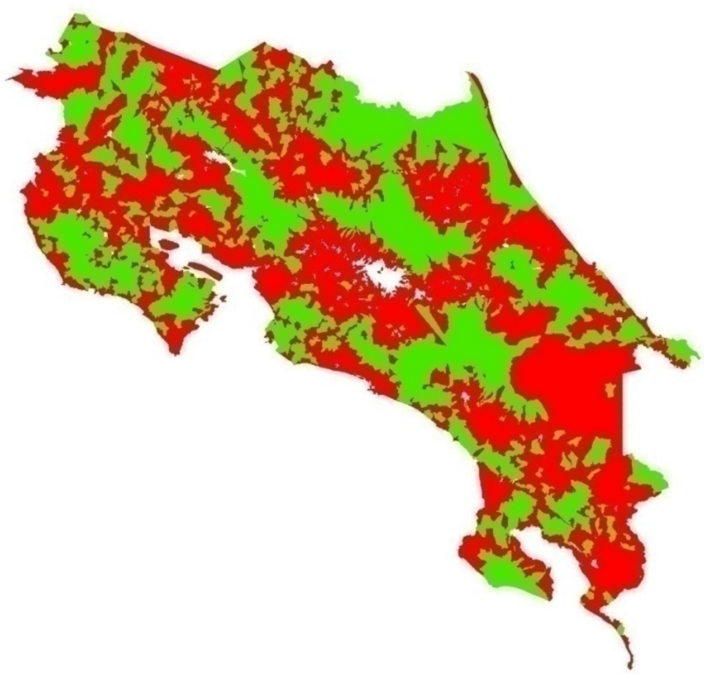


Figure 4.6: Areas containing tracts with PSA protection contracts (green areas) and without PSA protection contracts (red areas)

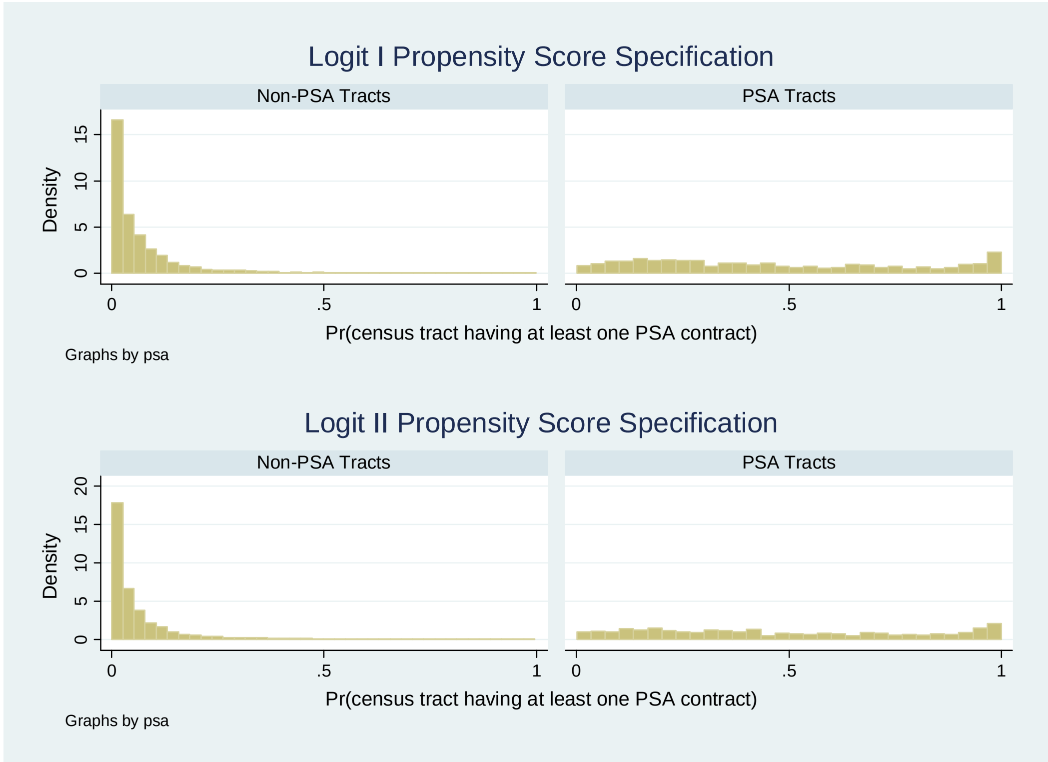


Figure 4.7: Propensity score distribution between PSA and non-PSA tracts

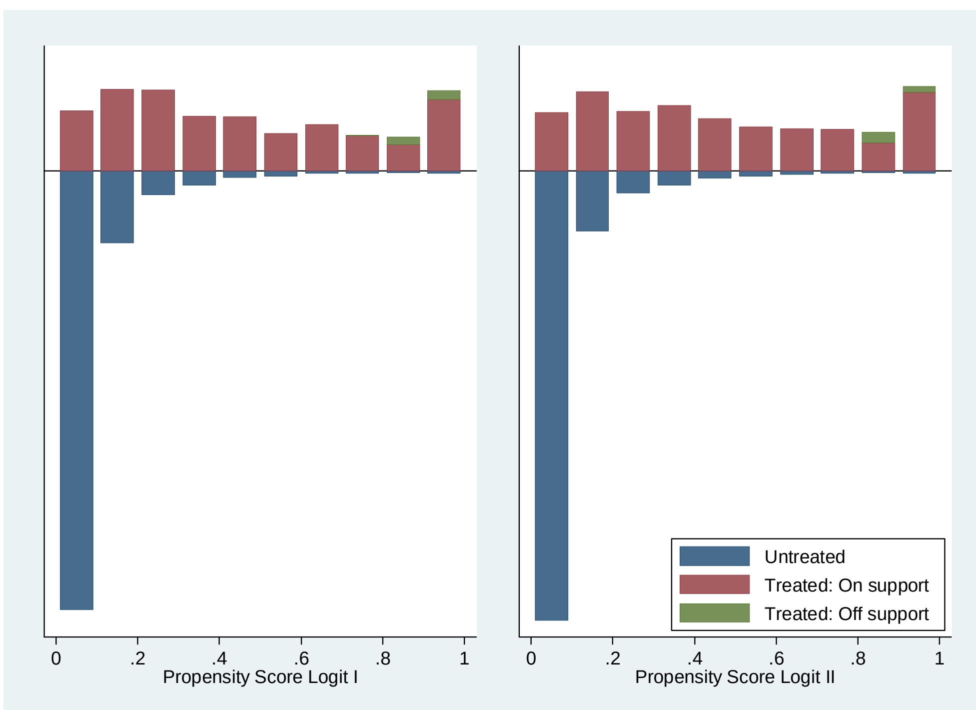


Figure 4.8: Common support graph of propensity scores

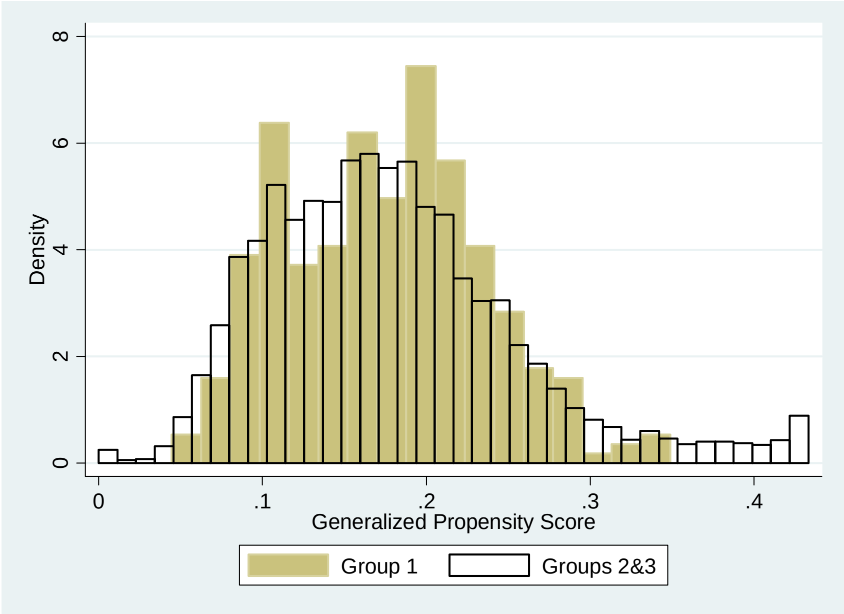


Figure 4.9: GPS common support condition for group 1

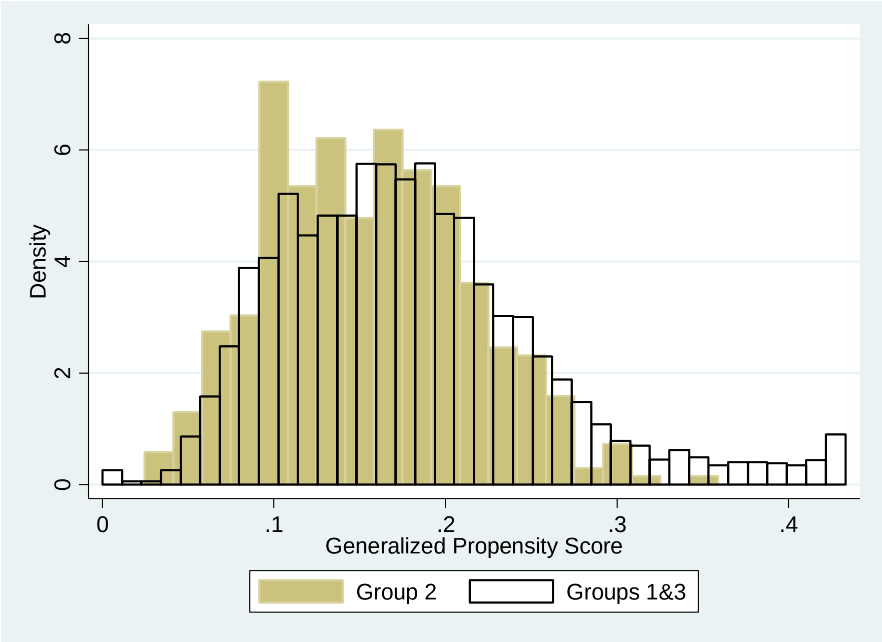


Figure 4.10: GPS common support condition for group 2

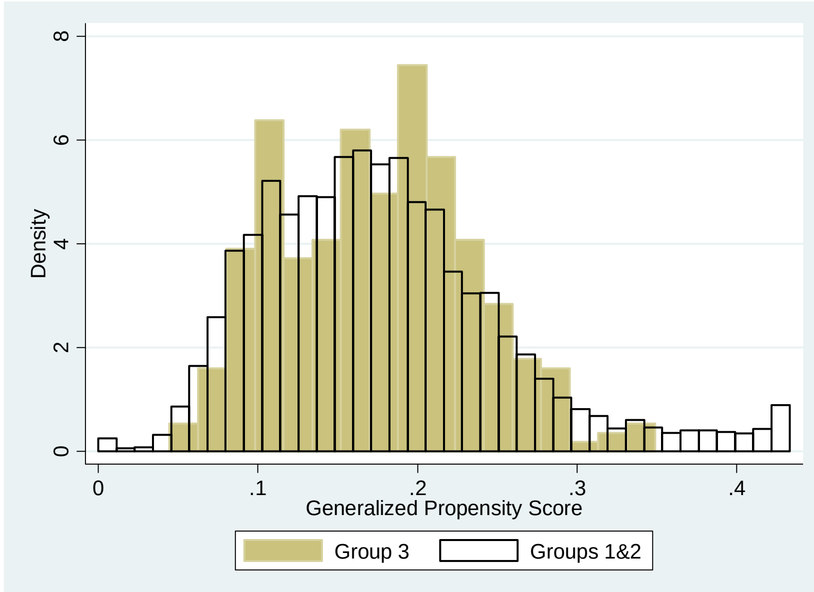


Figure 4.11: GPS common support condition for group 3

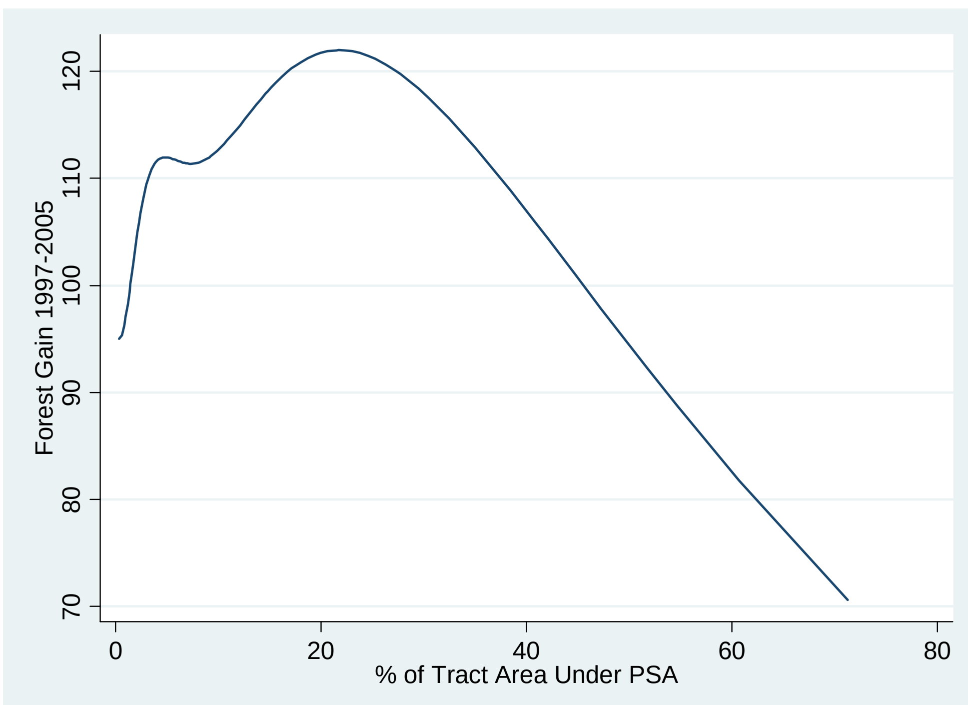


Figure 4.12: Dose response function forest gain 1997-2005

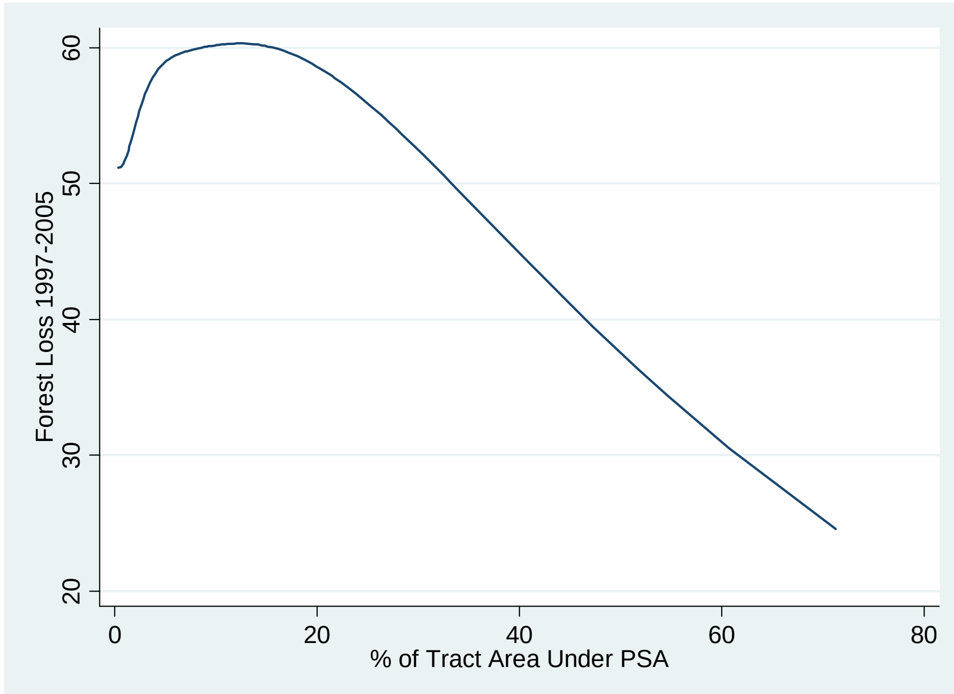


Figure 4.13: Dose response function forest loss 1997-2005

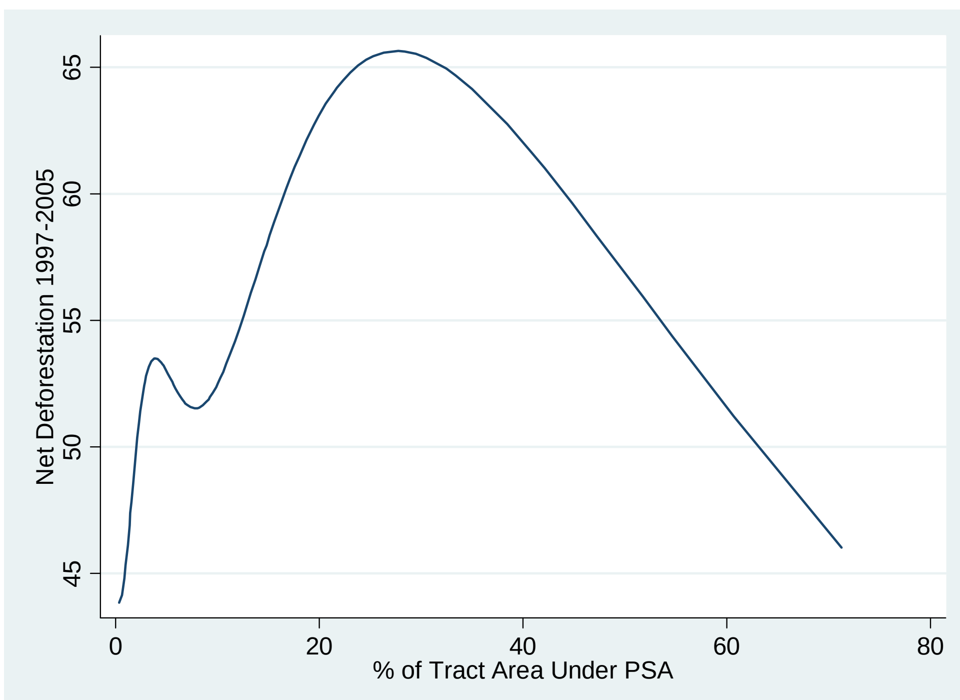


Figure 4.14: Dose response function net deforestation 1997-2005

Table 4.1: Description of PSA modalities during initial years (1997-2008)

Program Option	*Total Payment[a] (Colones)*	*Contract Period (years)*	*Contract Area Min. ha*	*Max. ha*	*Disbursement % of payment per year*
Forest Management	80,225 (1997) 94,000 (1998) 94,000 (1999) 113,300 (2001) 123,540 (2002)	10	2	300	50%, 20%, 10%, 10%, 10%
Forest Conservation	50,000 (1997) 60,000 (1998) 60,000 (1999) 66,000 (2000) 72,600 (2001) 79,160 (2002) 87,100 (2003) 95,800 (2004) 320 (2005-2008)[†]	5+5[††††]	2	300	20%, 20%, 20%, 20%, 20%
Reforestation	120,000 (1997) 154,000 (1998) 154,000 (1999) 169,000 (2000) 185,900 (2001) 202,700 (2002) 223,000 (2003) 245,000 (2004) 816 (2005-2008)[†]	Max 15	1	300	50%, 20%, 15%, 10%, 5%
Natural Regeneration with Productive Potential	816 (2006-2008)[†]	5+5	2	-	20%, 20%, 20%, 20%, 20%
Natural Regeneration in Abandoned Cattle Ranches	205 (2006-2008)[†]	5+5	2	-	20%, 20%, 20%, 20%, 20%
Agroforestry Systems	320 (2003) 352 (2004) 1.30 (2005-2008)[††]	3	3,500[†††]		65%, 20%, 15%

Source: www.fonafifo.com

[a] Payments are in nominal values. Inflation rates are: 11.20(1997), 12.36(1998), 10.11(1999), 10.25(2000), 10.96(2001), 9.68(2002), 9.87(2003), 13.13(2004), 14.07(2005), 9.43(2006), 10.81(2007). Source: www.inec.go.cr.

[†] Payment is established in US Dollars.

[††] Payment is US Dollars per planted tree.

[†††] This corresponds to the maximum number of planted trees.

[††††] 5+5 means that these contracts are initially signed for five years, but then they may be renewed by mutual agreement for another five years

Table 4.2: PSA forest conservation distribution among Costa Rican conservation areas

Conservation Area[a]	*Number of census tracts*	*Mean size census tract (ha)*[b]	*Area under PSA (ha)*	*Number PSA tracts*[c,d]	*Mean size PSA tract (ha)*[b]	*Mean size Non-PSA tract (ha)*[b]
La Amistad Caribe	738	602 (1,047)	40,340	90 (648)	1,649 (1,959)	457 (739)
Arenal-Huetar Norte	819	918 (1,206)	58,719	179 (640)	2,162 (1,830)	570 (613)
La Amistad Pacifico	862	691 (1,272)	23,189	130 (732)	1,980 (2,163)	462 (855)
Arenal Tilarán	489	449 (761)	20,679	62 (427)	1,509 (1,122)	295 (544)
Cordillera Volcánica Central	2,466	249 (836)	42,447	153 (2,313)	1,824 (2,378)	145 (445)
Guanacaste	189	1,987 (2,603)	18,481	62 (127)	3,214 (2,425)	1,388 (2,483)
Osa	386	883 (1,394)	17,639	47 (339)	2,052 (1,754)	721 (1,256)
Pacífico Central	1,088	434 (674)	32,730	119 (969)	1,522 (1,127)	300 (438)
Tempisque	703	915 (995)	45,806	192 (511)	1,611 (990)	654 (863)
Tortuguero	461	476 (1,252)	22,250	31 (430)	3,270 (3,553)	275 (441)

[a] In terms of PSA land compared with total area of each conservation area, PSA in *La Amistad Caribe* represents 6.5%, 8.9% in *Arenal-Huetar Norte*, 3.7% in *La Amistad Pacífico*, 5.2% in *Arenal Tilarán*, 6.6% in *Cordillera Volcánica Central*, 5.3% in *Guanacaste*, 4.1% en *Osa*, 5.8% in *Pacífico Central*, 8.9% in *Tempisque*, and 7.3% in *Tortuguero*.
[b] Standard deviation in parenthesis.
[c] PSA tract refers to rural census tracts with at least one PSA forest conservation contract signed between 1998 and 2004.
[d] Number of non-PSA segments in parenthesis.

Table 4.3: Grouping of conservation areas following four criteria

Group	*Land use capacity*	*Organization*	*Land tenure*	*Future expectative*
Arenal Huetar Norte	High	Very good	Very well defined	Middle
Tempisque- Arenal Tilarán-Guanacaste	Middle/low	Very good	Well defined	High
Cordillera Volcánica Central	High	Very good	Well defined	Middle
La Amistad Caribe-Tortuguero	Low	Middle	Not well defined	Middle/High
Pacífico Central- La Amistad Pacifico	Middle/low	Good	Not well defined	Middle/High
Osa	Middle/High	Bad	Not well defined	High

Table 4.4: PSA protection contracts by implementation period and conservation area group

Conservation area group	***PSA imlementation period***			***Number of PSA Protection contracts per group***	***Number of PSA tracts***[a]	***Total area under PSA protection (ha)***
	1998	***1999-2002***	***2003-2004***			
Arenal Huetar Norte	70	194	355	619 (19%)	179 (17%)	53,755 (18%)
Tempisque- Arenal Tilarán-Guanacaste	151	427	336	914 (28%)	316 (30%)	82,529 (27%)
Cordillera Volcánica Central	49	187	234	470 (14%)	153 (14%)	40,674 (13%)
La Amistad Caribe-Tortuguero	64	253	187	504 (15%)	121 (11%)	57,883 (19%)
Pacífico Central- La Amistad Pacifico	114	310	181	605 (18%)	249 (23%)	54,174 (18%)
Osa	17	133	42	192 (6%)	47 (5%)	17,184 (6%)
Totals	465 (14%)	1,504 (46%)	1,335 (40%)	3,304 (100%)	1,065 (100%)	306,199 (100%)

[a] PSA tract refers to rural census tracts with at least one PSA forest conservation contract signed between 1998 and 2004.

Table 4.5: Descriptive statistics of census tracts included in the PSA analysis

Statistic	***Total segments***	***PSA Segments***[a]	***Non-PSA segments***
Total number	8,203	1,065	7,138
Mean size (ha)	571	1,928	369
Standard deviation (ha)	1,118	1,920	757
Coefficient of variation	196%	100.4%	48.7%
Min (ha)	0.5	7	0.5
Max (ha)	15,316	13,951	15,316

[a] It refers to rural segments with at least one PSA protection contract signed between 1998 and 2004.

Table 4.6: Comparison of pre-matched non-treated and continuously treated census tracts

Variable	*Name*	*Description*	*Non-Treated Mean (SD)[a]*	*Continuously Treated Mean (SD)[b]*	*P value*
Tract size (ha)	TRACT	Size in hectares of each rural census tract as defined in Costa Rican Census 2000	368.62 (756.74)	1,927.63 (1,919.80)	0.000
Size of forest stock 1992	FOREST 92	1992 per tract forest stock size in hectares obtained from Landsat satellite images	72.472 (2.666)	787.92 (1,022.23)	0.000
% of tract area with soil class I or II	CLASS I	Class I: agricultural production. Class II: suitable for agriculture requiring land and crop management practices such as water conservation, fertilization, irrigation, etc.	13.67 (30.46)	5.24 (14.10)	0.000
% of tract area with soil class VII and VIII	CLASS II	Class VII: strong limiting factors on agricultural production; land is only suitable for forest plantations or natural forest management. Class VIII: land is suitable only for watershed protection	10.32 (25.84)	30.10 (37.35)	0.000
% of tract area with slopes 0-30%	SLOPE I	% of tract area with slopes 0-30%	93.67 (37.36)	81.70 (35.66)	0.000
% of tract area with slope > 45%	SLOPE II	% of tract area with slope > 45%	5.58 (11.64)	12.24 (15.81)	0.000
Precipitation (mm)	PP	Average precipitation at the centroid of each tract obtained from Atlas Costa Rica 2004	3,146.37 (1,008.98)	3,430.70 (951.31)	0.000
Proportion of tracts in humid lifezones	GOOD LZ	Proportion of tracts where centroid is in one of the Holdridge (1993) humid life zones: pre-montane, lower montane, montane and tropical	0.35 (0.48)	0.30 (0.46)	0.001
Proportion of tracts in very humid and montane life zones	MEDIUM LZ	Proportion of tracts where centroid is in one of the Holdridge (1993) very humid life zones: pre-montane, lower montane and montane	0.50 (0.50)	0.29 (0.46)	0.000
Proportion of tracts in very humid (tropical), dry (tropical), and rainy lifezones	BAD LZ	Proportion of tracts where centroid is in one of the Holdridge (1993) tropical life zones: very humid, dry and rainy life zones	0.15 (0.35)	0.40 (0.49)	0.000
Off-farm employment	JOB	Number of salaried people (*asalariado*) out of the total labor force per tract	0.41 (0.23)	0.27 (0.26)	0.000
Roads per tract (number/ha)	ROADS	Number of roads from the Atlas Costa Rica 2004	0.20 (0.50)	0.02 (0.041)	0.000
Road density per tract (kms/ha)	DENSITY	Road density from the road network Atlas Costa Rica 2004	72.77 (109.84)	15.71 (13.14)	0.000
Distance to market (kms)	MARKET	Minimum linear distance from the center of the census tract to the nearest major city	9.74 (7.97)	15.81 (9.14)	0.000

Table 4.6: Continued

Variable	*Name*	*Description*	*Non-Treated Mean (SD)*[a]	*Continuously Treated Mean (SD)*[b]	*P value*
Distance to ports (kms)	PORT	Minimum linear distance from the center of the census tract to the nearest port (Puntarenas or Limón)	77.25 (31.36)	81.61 (33.44)	0.000
Population density (number/ha)	POP	Number of inhabitants according to Costa Rican Census 2000 per census tract and per hectare	9.37 (29.64)	0.23 (1.23)	0.000
Tract-level proportion of immigrants	IMMIG	Per tract proportion of people that did not born in Costa Rica according to Costa Rican Census 2000	0.07 (0.09)	0.10 (0.13)	0.000
Tract-level proportion of people with least secondary education	EDUC	Tract-level proportion of people educated at least at the secondary level	0.93 (0.08)	0.96 (0.06)	0.000
Tract-level proportion of households using fuel-wood for cooking	WOOD	Tract-level proportion of households using fuel-wood for cooking	0.27 (0.24)	0.50 (0.26)	0.000
Distance to MINAE offices	MINAE	Minimum linear distance from the center of the census tract to the nearest Ministry of the Environment office	10.15 (6.84)	13.84 (7.53)	0.000
Age	AGE	Per tract population average age in years	26.13 (3.22)	26.31 (3.73)	0.099
Proportion of in tract-residents in 1995	RESID	Per tract proportion of people older than 5 years old that in 1995 lived in the same canton they were living in 2000	0.77 (0.11)	0.77 (0.12)	0.360
Per-tract number of hectares of non-eligible area for PSA	NONELEG	Non-eligible area for PSA includes protected areas and wetlands	70.82 (556.06)	308.49 (1,048.85)	0.000
Distance to IDA settlements	IDA	Minimum linear distance from the center of the census tract to the nearest IDA settlement	14.15 (11.83)	17.19 (12.42)	0.000
Proportion of tracts in aquifers	AQUIFER	Proportion of tracts where centroid is located in an aquifer	0.29 (0.45)	0.15 (0.35)	0.000
Proportion of tracts located in Ecomarket zone	ECOMARKET	Proportion of tracts where centroid is located in an Ecomarket zone	0.07 (0.25)	0.27 (0.44)	0.000
Proportion of tracts located in GRUAS zone	GRUAS	Proportion of tracts where centroid is located in a GRUAS zone	0.06 (0.23)	0.23 (0.42)	0.000
Forest gain 1997-2005	GAIN 9705	Sum of hectares that were not forest in 1997 but recovered to forest during 2005	15.106 (49.902)	111.708 (173.923)	0.000
Forest loss 1997-2005	LOSS 9705	Sum of all hectares transitions from natural forest in 1997 to other classes in 2005	9.646 (40.901)	55.917 (123.173)	0.000
Net deforestation 1997-2005	NETDEF 9705	Sum of all hectares transitions from natural forest in 1997 to other classes in 2005	-5.461 (56.865)	-55.792 (201.843)	0.000

[a] It refers to rural census tracts that do not contain forest conservation PSA contracts signed between 1998 and 2004
[b] It refers to rural census tracts that contain at least one forest conservation PSA contracts signed between 1998 and 2004

Table 4.7: Marginal effects on the propensity of a census tract to have PSA contract (dependent variable = 1 if tracts has at least one PSA contract)

Characteristic	***Marginal Effect***	
	Logit I[a]	***Logit II***[b]
Intercept		-3.971 (1.043)***
CLASS I	-0.011 (0.002)***	-0.010 (0.003)***
CLASS II	0.008 (0.001)***	0.009 (0.001)***
SLOPE I	-0.008 (0.002)***	-0.007 (0.002)***
SLOPE II	0.009 (0.005)**	0.012 (0.005)**
PP	0.000 (0.000)***	0.000 (0.000)***
MEDIUM LZ	-0.130 (0.116)	0.002 (0.122)
BAD LZ	0.456 (0.137)***	0.546 (0.145)***
JOB	-0.014 (0.003)***	-0.006 (0.004)
ROADS	-9.640 (1.158)***	-8.387 (1.141)***
MARKET	0.008 (0.007)	-0.008 (0.007)
PORT	-0.007 (0.001)***	-0.004 (0.002)*
TRACT	0.001 (0.000)***	0.001 (0.000)***
FOREST 92	0.001 (0.000)***	0.001 (0.000)***
NONELEG	-0.001 (0.000)***	-0.001 (0.000)***
MINAE	-0.005 (0.007)	0.001 (0.008)
AGE	0.034 (0.014)**	0.030 (0.015)**
EDUC	0.672 (0.794)	0.531 (0.835)
RESID	0.032 (0.260)	0.219 (0.322)
POP	na	-0.002 (0.001)**
IMMIG	na	1.135 (0.524)**
WOOD	na	0.605 (0.233)***
IDA	na	0.024 (0.004)***
AQUIFER	na	-0.120 (0.118)
ECOMARKET	na	0.601 (0.241)**
GRUAS	na	-0.255 (0.252)
GROUP I	na	-0.233 (0.164)
GROUP III	na	-0.332 (0.172)*
GROUP IV	na	-0.439 (0.217)**
GROUP V	na	-0.967 (0.151)***
GROUP VI	na	-1.440 (0.300)***
Observations	8,073	8,073
Pseudo R-square	0.393	0.412
Log-likelihood	-1,892.647	-1,834.081

Standard errors in parenthesis. *** = 99% confidence, ** = 95%, * = 90%.

[a] Logit I includes the main determinants of tropical deforestation and PSA participation

[b] Logit II adds other determinants of tropical deforestation (POP, IMMIG, WOOD), determinants of PSA targeting (IDA, AQUIFER, ECOMARKET and GRUAS) and dummies for regions (GROUP I, GROUP III, GROUP IV, GROUP V, GROUP VI).

Table 4.8: Treatment effect estimates

PSA Outcome	***Propensity Score Methods (Average Treatment Effect on the Treated)***				***Mixed Methods (Average Treatment Effect)***	
	Nearest Neighbor matching	***Radius matching***	***Kernel matching***	***Blocking***	***Weighting and regression***	***Matching and regression***
			Logit I			
Forest gain 1997-2005	22.989 (0.007)*** [0.019]**	31.450 (0.000)***	17.310 (0.029)**	29.281 (0.000)***	29.814 {0.000}***	20.226 {0.000}***
Forest loss 1997-2005	-15.166 (0.149) [0.122]	7.930 (0.285)	-5.161 (0.605)	7.586 (0.241)	5.658 {0.137}	-5.664 {0.146}
Net deforestation 1997-2005	38.155 (0.011)** [0.009]***	23.519 (0.029)**	22.472 (0.097)*	21.695 (0.027)**	24.831 {0.000}***	25.890 {0.000}***
			Logit II			
Forest gain 1997-2005	19.113 (0.047)** [0.051]*	31.526 (0.000)***	17.658 (0.031)**	32.055 (0.000)***	27.791 {0.000}***	22.367 {0.000}***
Forest loss 1997-2005	-14.967 (0.329) [0.473]	7.206 (0.375)	-5.657 (0.610)	10.889 (0.100)*	7.019 {0.076}*	-7.075 {0.070}*
Net deforestation 1997-2005	34.080 (0.070)* [0.128]	24.320 (0.030)**	23.316 (0.109)	21.166 (0.025)**	21.301 {0.001}***	29.443 {0.000}***
Observations			8,073			
# PSA census tracts			1,050			
# PSA census tracts off common support		31		na	na	na
# PSA census tracts used in matching		1,019		1,050	1,050	1,050
# Non-PSA census tracts used in matching		519		7,138	7,138	7,138

P-values in round brackets using bootstrapped standard errors with 999 repetitions. *P*-values in squared brackets using Abadie-Imbens bias corrected robust standard errors. *P*-values in curly brackets from OLS robust standard errors. Trimming level for common support is 3 percent. *** = 99% confidence, ** = 95%, * = 90%. Five blocks were defined based on propensity score. Propensity score balance was not achieved in two blocks.

Table 4.9: Balance-checking criteria for matching on the propensity score

Characteristic	***Logit I***			***Logit II***		
	Nearest Neighbor	***Radius***	***Kernel***	***Nearest Neighbor***	***Radius***	***Kernel***
CLASS I	0.753 (97.6)	0.000*** (63.9)	0.074* (84.8)	0.298 (91.6)	0.001*** (66.6)	0.073* (84.7)
CLASS II	0.594 (95.5)	0.000*** (69.4)	0.218 (89.7)	0.189 (89.0)	0.000*** (70.0)	0.095* (86.1)
SLOPE I	0.990 (99.8)	0.028** (71.3)	0.443 (90.1)	0.826 (97.1)	0.018** (70.0)	0.211 (84.0)
SLOPE II	0.862 (98.1)	0.001*** (64.9)	0.071* (80.6)	0.563 (93.7)	0.001*** (69.2)	0.037** (78.0)
PP	0.180 (79.0)	0.000*** (38.2)	0.002*** (52.8)	0.021** (64.4)	0.001*** (48.7)	0.017** (63.0)
GOOD LZ	0.319 (60.4)	0.016** (3.4)	0.017** (3.8)	0.000*** (-48.8)	0.030** (12.7)	0.040** (17.5)
MEDIUM LZ	0.627 (95.3)	0.036** (79.0)	0.861 (98.3)	0.407 (91.9)	0.088* (83.0)	0.925 (99.1)
BAD LZ	0.617 (95.8)	0.000*** (63.8)	0.029** (82.0)	0.004*** (76.5)	0.000*** (68.9)	0.054* (84.1)
JOB	0.042** (92.6)	0.000*** (69.1)	0.013** (90.3)	0.443 (97.3)	0.000*** (71.8)	0.010*** (89.8)
ROADS	0.300 (98.9)	0.000*** (66.5)	0.001*** (88.0)	0.789 (99.7)	0.000*** (68.4)	0.001*** (88.1)
MARKET	0.225 (92.0)	0.000*** (72.9)	0.351 (93.9)	0.451 (95.2)	0.001*** (78.3)	0.627 (96.8)
PORT	0.236 (57.0)	0.590 (81.2)	0.134 (46.4)	0.139 (49.7)	0.492 (76.3)	0.083* (39.4)
TRACT	0.496 (96.0)	0.000*** (70.1)	0.097* (91.0)	0.038** (88.4)	0.000*** (77.9)	0.743 (98.3)
FOREST 92	0.176 (91.5)	0.000*** (63.0)	0.002*** (81.1)	0.484 (96.0)	0.000*** (69.4)	0.024** (87.4)
NONELEG	0.296 (78.4)	0.028** (58.4)	0.477 (85.5)	0.090* (63.8)	0.160 (73.2)	0.865 (96.6)
MINAE	0.214 (88.7)	0.003*** (72.0)	0.620 (95.4)	0.438 (93.1)	0.019** (78.1)	0.772 (97.3)
AGE	0.440 (31.0)	0.953 (94.8)	0.852 (83.4)	0.729 (68.9)	0.791 (76.3)	0.944 (93.6)
EDUC	0.471 (94.0)	0.000*** (65.0)	0.062* (83.7)	0.495 (94.1)	0.000*** (64.0)	0.015** (78.2)
RESID	0.055* (-97.9)	0.550 (38.8)	0.574 (42.1)	0.052** (-101.2)	0.529 (34.8)	0.593 (44.5)
POP	0.724† (98.0)	0.000***† (60.5)	0.001***† (79.6)	0.333 (94.5)	0.000*** (67.9)	0.013** (85.4)
IMMIG	0.002***† (47.5)	0.004***† (51.1)	0.023**† (60.8)	0.678 (92.6)	0.312 (81.8)	0.933 (98.5)
WOOD	0.659† (97.8)	0.000***† (67.5)	0.008***† (86.7)	0.200 (93.6)	0.000*** (73.8)	0.110 (91.9)
IDA	0.002***† (45.0)	0.000***† (27.9)	0.002***† (43.8)	0.279 (80.3)	0.084* (68.4)	0.787 (95.0)
AQUIFER	0.073*† (79.5)	0.000***† (52.5)	0.005***† (67.4)	0.229 (86.3)	0.000*** (58.5)	0.016** (71.8)
ECOMARKET	0.000***† (51.4)	0.000***† (39.9)	0.000***† (50.8)	0.038** (80.3)	0.000*** (60.5)	0.017** (77.6)
GRUAS	0.000***† (54.0)	0.000***† (43.2)	0.000***† (54.9)	0.083* (82.0)	0.000*** (60.3)	0.036** (78.4)
GROUP I	0.018**† (52.4)	0.007***† (46.4)	0.063*† (62.3)	0.277 (77.5)	0.036** (57.4)	0.145 (70.1)
GROUP II	0.222† (83.3)	0.010***† (66.5)	0.252† (84.4)	0.004*** (58.7)	0.699 (94.7)	0.165 (80.5)
GROUP III	0.106† (86.4)	0.013**† (76.2)	0.897† (98.9)	0.404 (92.9)	0.005*** (74.0)	0.553 (94.8)
GROUP IV	0.420† (71.1)	0.506† (76.1)	0.154† (49.8)	0.330 (65.9)	0.978 (99.0)	0.493 (75.8)
GROUP V	0.007***† (-1056.0)	0.091*† (-619.4)	0.079*† (-648.7)	0.288 (-336.2)	0.217 (-405.2)	0.072* (-631.7)
GROUP VI	0.000***† (-1243.0)	0.015**† (-648.6)	0.000***† (-1079.7)	0.833 (41.6)	0.094* (-397.3)	0.009*** (-714.1)

Table 4.9: Continued.

% of bias reduction in parenthesis. *P*-values from standard t-test. *** = 99% confidence, ** = 95%, * = 90%. † These covariates were not included in the specification of the propensity score used for the matching.

Table 4.10: Treatment effect estimates by conservation area groups

PSA Outcome	***Propensity Score Matching Logit I***			***Propensity Score Matching Logit II***		
	Nearest Neighbor	***Radius***	***Kernel***	***Nearest Neighbor***	***Radius***	***Kernel***
Arenal Huetar Norte						
Forest gain 1997-2005	-47.375 (0.000)*** [0.000]***	-28.676 (0.001)***	-46.413 (0.000)***	-42.303 (0.004)*** [0.004]***	-32.229 (0.000)***	-47.392 (0.000)***
Forest loss 1997-2005	0.786 (0.964) [0.918]	9.629 (0.374)	-5.749 (0.667)	-2.426 (0.880) [0.956]	2.720 (0.808)	-10.713 (0.459)
Net deforestation 1997-2005	-48.161 (0.030)** [0.014]**	-38.305 (0.000)***	-40.664 (0.005)***	-39.877 (0.080)* [0.069]*	-34.949 (0.003)***	-36.678 (0.019)**
Tempisque - Arenal Tilarán - Guanacaste						
Forest gain 1997-2005	74.916 (0.000)*** [0.000]***	93.469 (0.000)***	78.235 (0.000)***	66.278 (0.000)*** [0.000]***	85.299 (0.000)***	70.184 (0.000)***
Forest loss 1997-2005	-23.421 (0.021)** [0.003]***	-3.648 (0.550)	-14.937 (0.061)*	-48.152 (0.042)** [0.033]**	-9.114 (0.213)	-22.545 (0.043)**
Net deforestation 1997-2005	98.337 (0.000)*** [0.000]***	97.117 (0.000)***	93.172 (0.000)***	114.430 (0.000)*** [0.000]***	94.413 (0.000)***	92.729 (0.000)***
Cordillera Volcánica Central						
Forest gain 1997-2005	-21.597 (0.072)* [0.043]**	-15.759 (0.023)**	-26.994 (0.000)***	-26.705 (0.033)** [0.011]**	-14.783 (0.023)**	-26.919 (0.001)***
Forest loss 1997-2005	-17.422 (0.317) [0.129]	-6.402 (0.522)	-17.694 (0.157)	-42.526 (0.042)** [0.033]**	-4.929 (0.621)	-16.944 (0.181)
Net deforestation 1997-2005	-4.175 (0.852) [0.713]	-9.357 (0.416)	-9.300 (0.504)	15.821 (0.524) [0.543]	-9.854 (0.386)	-9.975 (0.482)
La Amistad Caribe-Tortuguero						
Forest gain 1997-2005	-16.239 (0.139) [0.147]	-23.868 (0.004)***	-37.502 (0.000)***	-27.589 (0.026)** [0.015]**	-27.729 (0.001)***	-42.377 (0.000)***
Forest loss 1997-2005	12.038 (0.628) [0.449]	46.065 (0.004)***	36.835 (0.027)**	33.280 (0.094)* [0.085]*	48.383 (0.005)***	38.104 (0.033)**
Net deforestation 1997-2005	-28.277 (0.337) [0.170]	-69.934 (0.000)***	-74.337 (0.000)***	-60.869 (0.015)** [0.006]***	-76.111 (0.000)***	-80.481 (0.000)***

Table 4.10: Continued.

PSA Outcome	***Propensity Score Matching Logit I***			***Propensity Score Matching Logit II***		
	Nearest Neighbor	***Radius***	***Kernel***	***Nearest Neighbor***	***Radius***	***Kernel***
	Pacífico Central- La Amistad Pacifico					
Forest gain 1997-2005	45.501 (0.020)** [0.009]***	47.623 (0.008)***	35.042 (0.071)*	46.087 (0.023)** [0.010]***	60.136 (0.001)***	46.973 (0.012)**
Forest loss 1997-2005	-44.649 (0.001)*** [0.002]***	-5.710 (0.478)	-20.661 (0.059)*	-1.826 (0.917) [0.989]	1.513 (0.853)	-11.966 (0.274)
Net deforestation 1997-2005	90.150 (0.001)*** [0.000]***	53.333 (0.016)**	55.703 (0.030)**	47.913 (0.076)* [0.124]	58.622 (0.008)***	58.939 (0.020)**
	Osa					
Forest gain 1997-2005	66.237 (0.024)** [0.058]*	45.959 (0.042)**	34.213 (0.147)	59.152 (0.016)** [0.005]***	45.823 (0.046)**	37.166 (0.121)
Forest loss 1997-2005	89.785 (0.144) [0.122]	113.620 (0.032)**	95.793 (0.078)*	74.232 (0.430) [0.292]	115.067 (0.033)**	99.554 (0.081)*
Net deforestation 1997-2005	-23.548 (0.348) [0.702]	-67.661 (0.242)	-61.580 (0.296)	15.079 (0.871) [0.880]	-69.244 (0.225)	-62.388 (0.302)

P-values in round brackets using bootstrapped standard errors with 50 repetitions. *P*-values in squared brackets using Abadie-Imbens bias corrected robust standard errors. Trimming level for common support is 3 percent.
*** = 99% confidence, ** = 95%, * = 90%.

Table 4.11: Estimated GPS: loglinear regression of PSA intensity on covariates

Variable	***GPS coefficient***	
	(1)	***(2)***
Intercept	-0.133 (0.186)	2.389 (0.709)***
CLASS I	-0.001 (0.000)***	-0.002 (0.002)
CLASS II	0.003 (0.000)***	0.001 (0.001)
SLOPE I	-0.001 (0.000)*	0.003 (0.002)*
SLOPE II	0.003 (0.001)**	0.003 (0.003)
PP	0.000 (0.000)***	-0.000 (0.000)
MEDIUM LZ	-0.032 (0.020)	-0.094 (0.093)
BADLZ	0.174 (0.038)***	0.024 (0.100)
JOB	0.000 (0.001)	0.004 (0.004)
ROADS	-0.004 (0.007)	-0.907 (0.773)
MARKET	-0.003 (0.002)	-0.006 (0.005)
PORT	-0.001 (0.000)*	-0.000 (0.001)
TRACT	0.000 (0.000)***	-0.000 (0.000)
FOREST 92	0.000 (0.000)***	0.000 (0.000)**
NONELEG	-0.000 (0.000)***	-0.000 (0.000)
MINAE	0.001 (0.002)	-0.001 (0.005)
AGE	0.004 (0.003)	0.000 (0.010)
EDUC	0.107 (0.125)	-0.368 (0.500)
RESID	-0.035 (0.064)	0.336 (0.209)
POP	-0.001 (0.000)***	-0.001 (0.001)
IMMIG	0.107 (0.127)	0.150 (0.337)
WOOD	0.158 (0.059)***	-0.181 (0.147)
IDA	0.007 (0.001)***	0.008 (0.003)**
AQUIFER	-0.033 (0.019)*	-0.066 (0.088)
ECOMARKET	0.366 (0.106)***	0.233 (0.130)*
GRUAS	-0.082 (0.111)	0.060 (0.134)
GROUP I	-0.076 (0.047)	0.008 (0.114)
GROUP III	-0.071 (0.032)**	0.375 (0.128)***
GROUP IV	-0.114 (0.050)**	0.043 (0.152)
GROUP V	-0.215 (0.035)***	-0.026 (0.114)
GROUP VI	-0.285 (0.061)***	-0.067 (0.183)
Observations	8,073	1,042
R-square	0.308	0.087
Prob>F	0.000	0.000

Robust standard errors in parenthesis. *** = 99% confidence, ** = 95%, * = 90%.
(1) refers to all census tracts and (2) refers to all census tracts that contain at least 1 PSA contract

Table 4.12: Balance in covariates with and without adjustment based on PSA conservation intensity

Covariate	*% of segment area protected by PSA*					
	Unadjusted			*Adjusted*		
	[0.06,5.45]	**[5.45,18.36]**	**[18.36,99.28]**	**[0.06,5.45]**	**[5.45,18.36]**	**[18.36,99.28]**
CLASS I	0.304	0.615	0.117	0.791	0.851	0.691
CLASS II	0.650	0.245	**0.090***	0.875	0.629	0.510
SLOPE I	0.695	0.653	0.929	0.784	0.870	0.973
SLOPE II	0.273	0.581	**0.091***	0.756	0.379	0.661
PP	0.213	0.928	0.250	0.689	0.985	0.846
GOOD LZ	0.220	0.909	0.176	0.757	0.984	0.817
MEDIUM LZ	**0.078***	0.122	0.909	0.695	0.588	0.970
BAD LZ	**0.005*****	0.187	0.170	0.552	0.719	0.850
JOB	0.306	0.849	0.220	0.819	0.926	0.660
ROADS	0.376	0.343	**0.057***	0.582	0.770	0.606
MARKET	0.299	0.148	**0.010*****	0.830	0.637	0.451
PORT	0.466	0.694	0.250	0.878	0.904	0.583
TRACT	0.538	0.848	0.411	0.856	0.957	0.359
FOREST 92	0.235	0.155	**0.007*****	0.677	0.693	0.675
POP	0.145	0.522	0.439	0.637	0.762	0.870
IMMIG	0.574	0.490	0.860	0.853	0.801	0.880
WOOD	**0.091***	0.749	**0.042****	0.738	0.892	0.776
NONELEG	**0.079***	0.692	0.182	0.694	0.873	0.497
MINAE	0.105	0.910	**0.081***	0.735	0.962	0.676
AGE	0.973	0.513	0.506	0.988	0.859	0.779
EDUC	0.491	0.741	0.737	0.840	0.890	0.908
RESID	0.745	0.690	0.452	0.945	0.935	0.850
IDA	0.273	0.742	0.147	0.818	0.849	0.815
AQUIFERS	0.654	0.876	0.778	0.636	0.958	0.941
ECOMARKET	**0.003*****	0.934	**0.002*****	0.704	0.988	0.794
GRUAS	**0.011****	0.857	**0.006*****	0.748	0.963	0.790
GROUP I	**0.030****	0.291	0.298	0.669	0.239	0.843
GROUP II	0.110	0.599	**0.030****	0.616	0.935	0.769
GROUP III	**0.001*****	0.903	**0.000*****	0.458	0.982	0.719
GROUP IV	0.167	0.438	0.578	0.734	0.785	0.926
GROUP V	0.951	0.553	0.566	0.977	0.789	0.787
GROUP VI	0.780	0.325	0.183	0.913	0.709	0.500

P-values from standard t-tests in parentheses. ***= 99% confidence, ** = 95%, * = 90%.

Table 4.13: Estimated parameters of the conditional distribution of program outcomes given percent of tract area under PSA and the GPS

Variable	***Program Outcomes***		
	Forest gain 1997-2005	***Forest loss 1997-2005***	***Net deforestation 1997-2005***
	Coefficient (SE)	***Coefficient (SE)***	***Coefficient (SE)***
Intercept	95.232 (20.102)***	51.385 (14.246)***	-43.847 (23.370)*
% tract area under PSA protection	-0.908 (0.798)	-0.692 (0.565)	0.216 (0.927)
(% tract area under PSA protection)^2	0.003 (0.004)	0.002 (0.003)	-0.000 (0.004)
GPS	143.4811 (185.979)	51.999 (131.801)	-91.481 (216.214)
(GPS)^2	-302.078 (362.314)	-76.241 (256.767)	225.837 (421.216)
GPS × % tract area under PSA protection	4.555 (3.478)**	1.709 (2.465)	-2.846 (4.044)
Observations	1,050	1,050	1,050
Adj R-squared	0.000	0.004	0.002
Prob>F	0.366	0.550	0.882

APPENDICES

Appendix 1: Hectares enrolled in different forest programs created in Costa Rica before PSA

Program	***Hectares Enrolled***	***Period***
Deduction from income tax	35,597	1979-1992
Soft loans	2,802	1985-1995
Certificado de Abono Forestal (CAF)	45,842	1986-2000
Certificado de Abono Forestal por Adelantado (CAFA)	40,747	1988-2000
Fondo para el Desarrollo Forestal (FDF)	12,789	1989-1995
Certificado de Abono Forestal para Manejo (CAFMA)	45,222	1992-1999
Certificado de Protección del Bosque (CPB)	22,200	1995-1996

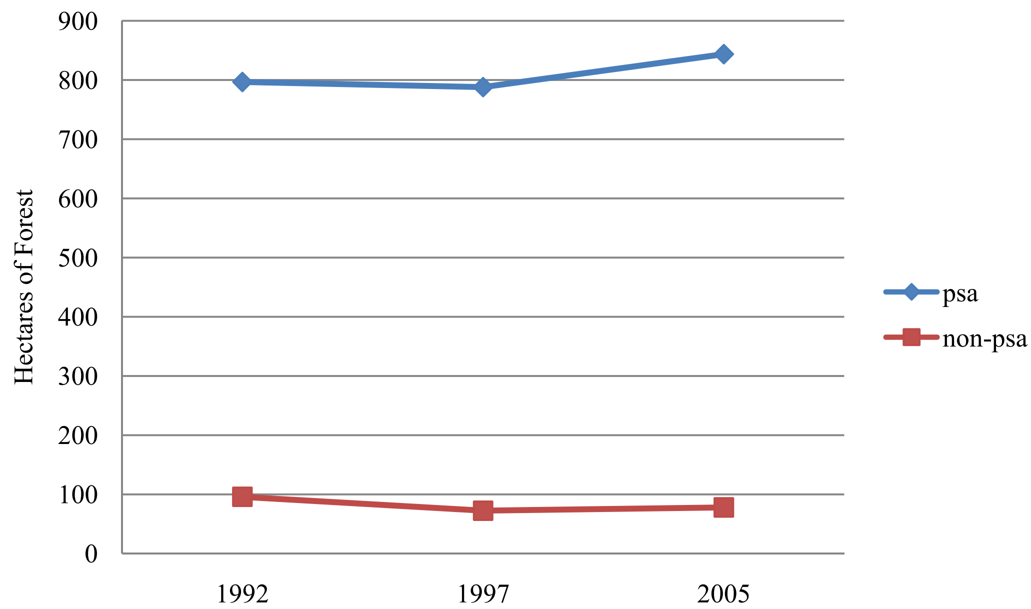
Source: Fonafifo, 2005

Appendix 2: Geographical datasets employed in the Costa Rica LULC analysis

Geographical Dataset	***Source***	***Format and type***	***Description***
Indigenous territories	Ecomarkets Project (The World Bank, 2000)	Vector (shapefile) - polygon	Indigenous territories boundaries. Boundaries were defined with Costa Rican 1:50,000 Topographic Maps
Protected areas	SINAC	Vector (shapefile) - polygon	Protected areas boundaries defined with Costa Rican 1:50,000 Topographic Maps
Costa Rica land cover 1992	Ministerio de Agricultura y Ganaderia	Vector (shapefile) - polygon	Thematic map derived from satellite images at 30 x 30 m of spatial resolution. Sixteen land cover categories defined
Costa Rica land cover 1997-2000	FONAFIFO Earth Observation System Laboratory, University of Alberta Tropical Science Center	Vector (shapefile) - polygon	Thematic map derived from Landsat 7 images at 28.5 x 28.5 mts of spatial resolution. Eight land cover classes defined. The classification was conducted with 1997 images but due to the lack of quality "cloud free" image for a north section of the country a 2000 image classification was added
Costa Rica land cover 2005	FONAFIFO Earth Observation System Laboratory, University of Alberta Tropical Science Center Instituto Tecnológico de Costa Rica	Vector (shapefile) - polygon	Thematic map derived from Landsat ETM + images at 28.5 x 28.5 mts of spatial resolution. Fifteen land cover classes defined
Census tracts	INEC	Vector (shapefile) - polygon	Boundaries of census tracts

Source: Cordero (2008).

Appendix 3: Deforestation trend between PSA and non-PSA census tracts



5. Dissertation summary and conclusions

In this dissertation, I report estimates of the causal effect of PSA on forest cover using state-of-the art program evaluation methods. Participation in PES is by definition a voluntary transaction (Wunder 2007), and thus by definition subject to self-selection bias. Program administrators also may target specific areas that provide more environmental benefits or that face greater threats to those benefits, introducing another form of selection bias. Distinguishing these selection effects from the causal effect of program participation is the central challenge of this dissertation.

Is the Costa Rican program causing participants to preserve ecosystems that they otherwise would not have preserved? Answering this question requires estimating a counterfactual outcome: the area of ecosystem that landowners would have preserved if they had not received payments. This cannot be estimated by directly comparing program participants with non-participants because of selection bias. Matching is one method for addressing the selection bias and estimating the missing counterfactual without imposing strong distributional assumptions or extrapolating beyond a common support. This method is applied in this dissertation using household-level and census tract-level socio-economic data combined with administrative data on the program, secondary spatial data on biophysical characteristics, and measures of forest cover obtained from self reports, satellite images, and aerial photos.

Even given identical PES contracts, it is unlikely that all landowners will respond to PES in precisely the same way. This suggests that there is no single causal effect of PSA on all parcels and census tracts (units). Specifically, the average impact on a unit drawn randomly from the population (the average treatment effect or ATE) is likely to differ from the average impact on units who actually participated (the average effect of treatment on the treated or ATT). These two effects are identical only under the maintained assumption of homogeneous responses to program participation (for example, in an OLS model). Because PSA participation is voluntary, responses are more likely to be heterogeneous: parcels that are voluntarily enrolled in the program, or census tracts where landowners voluntarily enroll parcels, probably differ from the wider eligible population of parcels or tracts in terms of expected gains from the program, which are in turn related to expected land uses. This dissertation focuses on estimating the ATT, which is most relevant to evaluating the impact of the PSA program to date, but does not necessarily predict the impact of a major expansion of the program in the future.

It is also possible that the impact of PES varies with its intensity, e.g., the size of payment or percent of a parcel or tract under contract. This dissertation also includes the analysis of PSA impact using a continuous definition of treatment (i.e. % of census tract area under PSA protection). By estimating a dose-response function, PSA protection thresholds are calculated that indicate the maximum level of protection per tract in order to observe expected program impacts (e.g. positive impact on forest gain and net deforestation and negative impact on forest loss).

Propensity score matching, originally proposed by Rosenbaum and Rubin (1983), is perhaps the most popular matching method used in a range of fields. However, there are still proponents of multivariate – or covariate - matching, because in cases where there is a firm understanding, based on theory and past empirical evidence, of the determinants of program participation and the outcomes of interest, them matching on these determinants will give unbiased estimates of program impact. I compared propensity score to multivariate matching in the parcel-level evaluation of PSA and found broadly consistent results but somewhat better balance with propensity score matching. In the census tract level analysis, I used only propensity score matching, with both binary and continuous definitions of treatment.

There are several reasons for evaluating the PSA program at two different scales. First, the conceptual framework based on the real options literature suggests that spill-over effects of PSA contracts may be significant because landowners near contracts will be reminded that they can keep open their option to apply for a contract by maintaining forest.

This spill-over may occur within the boundaries of a farm, or across neighboring farms. Matching analysis excludes any spill-over effects from impact estimates, because of the fundamental assumption of “Stable-Unit-Treatment-Value” or SUTVA. This requires that the potential outcomes of units be unaffected by potential changes in the treatment exposures of other units. Intuitively, this assumption is more defensible at the tract level than the parcel level, which motivated our complex sampling scheme for parcels. Development of this sampling frame, the household survey itself, and the acquisition of remote sensing data on parcel land cover (using aerial photos rather than pre-processed land cover maps because of the small size of most farms) were all expensive and time consuming. Thus, the second motivation for the two scales of analysis was to explore less expensive methods for obtaining rigorous and general results on program impacts at the national scale.

The parcel-level analysis focused on the initial years of the PSA program (1997-1998), when the responsible government agencies sought to minimize transactions costs and program delays by not targeting payments. Both the in-depth interviews and the survey in Sarapiquí suggest that landowners responded by enrolling forest that they would not have converted in any case (mainly due to low returns to alternative uses). However, Sarapiquí is also unique in that most PSA contracts were facilitated by a well-established NGO, FUNDECOR. The leaders of this organization did try to target PSA contracts to ‘critical areas’ associated with high deforestation risks. This may explain why the matching identifies a small but statistically significant positive impact on both gross and net deforestation on farms with contracts. This result is reasonably robust to specification of the propensity score and use of multivariate matching as well as mixed methods. The estimation results from the propensity score model also identify differences between participants and non-participants in important aspects that affect program participation and land use, confirming the importance of addressing selection bias to obtain an unbiased estimate of program impact.

The farm-level analysis developed in this dissertation represents an empirical test of the feasibility of applying matching to evaluate PES systems that are being promoted in many tropical forest regions. Because matching relies on the assumption that all characteristics that affect program participation and program outcome are observable and are controlled during the matching, results are highly dependent on the quantity and quality of available data. This suggests an important policy recommendation for new PES programs. The ideal database for a rigorous empirical evaluation of PES would include observations on land use and characteristics of both participant and non-participant landowners and their properties both before and after the program. Collection of these data should be integrated into program operations when rigorous evaluation is a program goal but building experiments (random allocation of contracts) into the program is not politically feasible. The data should be sufficient to fully characterize program participants and feed this information into the matching process in order to select the most appropriate non-participants for estimating the missing counterfactual.[1] Design of the database should be supported by qualitative studies of participants in PES systems to identify key determinants of program participation and program outcomes. Equally important is collecting high-quality time series data on those program outcomes, which in the case of land cover in the tropics, may be significantly constrained by cloud cover that interferes with remote sensing.

The results from different matching estimators suggest that no single method gives the best result but rather, there is always a tradeoff between bias and variance. Nearest neighbor matching achieves the best covariate balance at the cost of higher variance; radius and kernel matching include more controls, reducing variance but increasing bias. The empirical results obtained in this dissertation confirm the common suggestion that different methods should be compared in order to test the robustness of the results. Another important methodological lesson is that OLS, the most traditional evaluation method, can produce reliable estimates of program impact when the dependent variable is change in outcome (i.e., change in forest cover during the program, rather than current levels of forest cover) and the appropriate covariates are included in the regression. However, one needs to be careful in the

[1] With programs that attract significantly more applicants than can be accepted (as is the case with PSA in recent years), one option might be also to maintain better records on rejected and waitlisted applicants.

interpretation of these results. In OLS, the ATE is equal to ATT, but in matching these can differ. For example, in the Sarapiquí case, the OLS results are similar to the ATT estimated through propensity score matching, but both are larger than the ATE.[2]

The two comparative advantages of matching are that it forces consideration of the common support and avoids assumptions of functional form. The similarity of OLS and matching results in Sarapiquí is perhaps not that surprising given that only a few farms with PSA contracts were "off-support" (i.e., had no matches). The same variables were used in the propensity score model and as covariate in the OLS, based on the same assumption that these variables capture all of the factors that affect both participation and forest cover. In this study, data were not available to compare results of other methods, such as instrumental variable or selection models. However, the consistency of OLS and matching estimation results confirms that the estimated causal impacts are robust and defensible.

It is also useful to put the impacts in context of the scale of payments relative to other household income sources. We first calculate the present value of a PSA conservation contract on one hectare in the year 2000 ($66,000 *Colones* distributed over five years) in the equivalent of 2008 US dollars.[3] This is US$120 total, or US$2 per month. On average, 84.5 ha are protected per PSA contract in Sarapiquí, which means that the average PSA payment is US$169 per month. The minimum wage in Costa Rica in 2008 is US$176 per month. Considering that there are on average 4.24 adults in a household receiving PSA payments,

[2] Using nearest neighbor propensity score matching and a parsimonious specification of propensity score, the ATT on changes in self-reported mature native forest cover is 8.4 ha (significant at the 85%) while the ATE is 2.4 ha (non-significant). For the case of changes in total native forest cover from aerial photos, ATT is 6.5 ha (significant at the 85%) while ATE is 3.4 ha (non-significant). Using a full specification of propensity score, the ATT on changes in self-reported mature native forest cover is 16.4 ha (significant at the 85%) while the ATE is 6.7 ha (significant at the 85%). For the case of changes in total native forest cover from aerial photos, ATT is 12.7 ha (significant at the 99%) while ATE is 5.5 ha (significant at the 85%).

[3] This payment was estimated by calculating first the present value of the PSA payment spread over five years using a 12% discount rate, then each present value was expressed in 2008 *Colones* using the Costa Rican CPI between 2000 and 2008 published by the Costa Rican Central Bank (http://indicadoreseconomicos.bccr.fi.cr/indicadoreseconomicos/). Finally the present value of the PSA payments expressed in 2008 *Colones* was converted to 2008 US Dollars (http://www.oanda.com/convert/classic).

the minimum wage for that household is US$746 per month. Thus, PSA payments are a substantial source of income, representing 23% of the minimum wage in the study region. This is consistent with finding a significant impact of the payments on forest cover.

The national analysis of PSA represents the first attempt in the conservation literature to address the causal effect of PES using a continuous – as well as binary - definition of treatment. Results of the national analysis using a binary treatment definition suggest a robust positive and significant PSA impact on both forest gain and net deforestation. As with the household-level analysis, the results are verified by using different specifications of the propensity score and different matching methods. The positive impact of PSA on forest gain and net deforestation and its lack of impact on gross deforestation can be interpreted in light of the on-going forest transition in Costa Rica. “Forest transition” is the label typically applied to the historical period when deforestation slows and expansion of forest area begins, as has occurred in North America, Europe, and parts of Asia. The estimation results suggest that PSA contracts are encouraging this transition in Costa Rica. The impact of PSA contracting on forest gain can also be interpreted as an externality given that this dissertation only included forest conservation contracts.

Tempisque-Arenal Tilarán-Guanacaste, and *Pacífico Central-La Amistad Pacífico* are the two regions (groups of conservation areas) where PSA has had more impact. They are characterized by middle to low land use capacity and good or excellent organization of the relevant conservation agencies. In terms of their characteristics associated with PSA, they have the greatest number of PSA contracts, the most tracts with at least one contract, and the largest area under contract. Counterintuitive results obtained in some other regions suggest that a binary definition may not be appropriate for estimating program impact at the regional scale given the low intensity of treatment in some places. This has important implications for the empirical application of matching in the sense that when scaling-up the analysis, the appropriate definition of treatment may have to be re-considered.

Estimates of program impact at the national level also provide the opportunity to compare program costs with amount of forest conserved. If we consider the PSA payment per hectare (US$120 per ha), administration costs (assumed to be 40% of the payment) and the average number of hectares under protection per segment (293 ha) relative to the impact in terms of number of additional hectares conserved (e.g. 32.1 ha on forest gain according to the method of blocking on the propensity score using a full specification of propensity), then the program costs US$1,528 per hectare of additional forest conserved. This estimate can be compared with the costs of other policies (e.g. increased enforcement of laws against forest conversion, purchasing and protecting land) in order to judge the cost effectiveness of PSA relative to policy alternatives.

Results of continuous treatment suggest that intensity matters and may explain the counterintuitive results obtained in some regions using a binary treatment. PSA impact on forest gain and net deforestation follow the hypothesized pattern only up to a certain percentage of tract area under PSA protection, but after reaching that threshold the effect starts to dissipate. To understand this pattern, recall that forest under PSA contracts are generally well-enforced, so forest cover does not change in the portion of the tract under contract. If there is only a small portion of the tract not under contract, then there is very little room for PSA contracts to have an impact. Clearly, these results require further sensitivity testing and validity checks, precisely because they represent the first attempt to estimate a dose-response function in the context of PES. However, taking the results at face value, they suggest that PSA administrators might want to set a maximum percentage of a region (i.e., census tract) that can be put under PSA contract.[4]

Table 5.1 summarizes the results of the analyses at the farm and census tract levels in a parallel fashion. In the national analysis, OLS, matching and mixed methods failed to reject the null hypothesis of a positive PSA impact on forest gain and net deforestation. Less

[4] Using the dose-response obtained for forest gain, if more than 25% of the census tract area is protected by PSA, then the PSA impact starts to dissipate as more area is brought under protection.

robust results were obtained from the analysis in Sarapiquí, but more than half of the methods (OLS, matching and mixed methods) failed to reject the null hypothesis of a positive PSA impact on net forest change from aerial photos.

The significance of forest transitions in creating more sustainable societies depends on the effects of the transitions on the environmental services that forests provide. According to Chazdon (2008), regardless of the actions taken to promote forest restoration and regeneration, the new forests emerging in human-impacted landscapes will not match the original old-growth forest in species composition and biodiversity. On the other hand, regenerated forests are likely to be just as effective at sequestering and storing carbon as the original forest cover. This has important implications for PSA considering that biodiversity and carbon are two of the ecosystem services targeted by the program.

Thus, this dissertation's findings on PSA's contribution to the forest transition in Costa Rica suggests that the program may be meeting some but not all of its objectives in terms of increasing the provision of ecosystem services. Specifically, the additional services provided by the PSA program are mainly from newly regenerated forests. While these forests may not be equal to the original forest in terms of biodiversity, they do sequester carbon and stabilize soil. The United Nations Framework Convention on Climate Change (UNFCCC) is considering the introduction of a financial mechanism to reduce emissions from deforestation and forest degradation. However, there is ongoing debate and hence much uncertainty about the form of the mechanism, including issues such as the appropriate deforestation baseline, the role of developing countries that have recently lowered their deforestation rates, and the protocols for measurement and validation of emissions reductions (Miles and Kapos 2008). The results of this dissertation bring all of these issues into sharp focus in Costa Rica. They also demonstrate the applicability of state-of-the-art evaluation methods for quantifying the causal effects of direct payments for forest conservation even when facing complex evaluation scenarios. While there are enormous challenges (Canadell and Raupach 2008), there is also potential for payments for ecosystem services from tropical forests to contribute to new sustainable development pathways.

5.1 Bibliography

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Table 5.1: Summary of results using OLS, matching and mixed methods

	National Analysis			*Regional Analysis*	
	Forest Gain	***Forest Loss***	***Net Deforestation***	***Net Forest Change from Self-Reports***	***Net Forest Change from photos***
Ho:	+	−	+	+	+
OLS	2/2	0/2	2/2	1/4	1/4
Covariate Matching	na	na	na	1/6	4/6
PSM	8/8	0/8	8/8	1/6	4/6
Mixed methods	4/4	1/4	4/4	na	na
Total	***14/14***	***1/14***	***14/14***	***3/16***	***9/16***

Null hypotheses (H_0) is the relationship between presence of a PSA contract and change in forest cover.
The total is calculated as number of times the null is not rejected (numerator) divided by number of different specifications and matching methods (denominator).