Environment for Development

Discussion Paper Series

May 2011 ■ EfD DP 11-06

Conditional Cash Transfers and Payments for Environmental Services

A Conceptual Framework for Explaining and Judging Differences in Outcomes

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Conditional Cash Transfers and Payments for Environmental Services: A Conceptual Framework for Explaining and Judging Differences in Outcomes

U. Martin Persson and Francisco Alpízar

Abstract

Despite the recent popularity of conditional cash transfers (CCT) and payments for environmental services (PES) programs, what determines their success is not well understood. We developed a conceptual framework to give insight into some of the main determinants of CCT and PES program efficiency that hope to increase investments in human and environmental capital. We used a simple agent-based model and validated the results with empirical data from existing programs. We show that 1) the share of participants who meet the program's conditions at baseline is a powerful predictor of program efficiency, (2) and selection bias erodes program efficiency to a large extent. (Selection bias stems from agents who already meet program criteria and who self-select into programs at higher rates than those who do not meet the conditions.) Based on these results, we discuss possibilities for improving efficiency—mainly by targeting applicants or increasing payments—and criteria for evaluating and choosing CCT, PES, or other policy instruments.

Key Words: conditional cash transfer, payment for ecosystem services, program evaluation, additionality

JEL Classification: D04, H53, I38, Q28

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Conditional Cash Transfers and Payments for Environmental Services: A Conceptual Framework for Explaining and Judging Differences in Outcomes

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Introduction

The last two decades have seen the emergence of two innovative and related policy approaches that encourage social and environmental services in developing countries: conditional cash transfers (CCT) and payments for environmental services (PES). What these two mechanisms have in common is that they offer positive incentives (cash or in-kind payment) that are conditional on investments in social or environmental capital. Conditional cash transfers support poor families, contingent on investments in the human capital of their children, mainly by mandating school attendance and/or use of healthcare services. Payments for environmental services compensate natural resource managers (usually land owners), conditional on environmental services or land-use practices that secure that service. Both programs, it has been argued, offer advantages over previous policy approaches (such as unconditional cash transfers, supply-side interventions, integrated conservation and development projects, and sustainable forestry management) that have shown meager results in reducing poverty and conserving ecosystems (Rawlings and Rubio 2006; Pattanayak et al. 2010).

Recent reviews of conditional cash transfers (e.g., Rawlings and Rubio 2005; Handa and Davis 2006; Fiszbein and Schady 2009) and payments for environmental services (e.g., Landell-Mills and Porras 2002; Bulte et al. 2008; Wunder et al. 2008; Pattanayak et al. 2010) highlight the pace at which these policies have spread across the developing world. In 2008, 29 developing countries (mainly in Latin America) had at least one CCT program in place with more planned or already underway (Fiszbein and Schady 2009). In many countries, nationwide CCT programs

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The authors gratefully acknowledge financial support from the MISTRA program, "Biodiversity and Ecosystem Services in a Changing Climate" (BECC) and from SIDA (Swedish International Development Cooperation Agency) via the Environment for Development Initiative (www.efdinitiative.org). We also thank Allen Blackman, Paul Ferraro, Olle Häggström, Juan Robalino, and Laura Villalobos for their valuable comments and insights.

form the backbone of social security policy, such as the Brazilian Bolsa Famila or the Mexican Oportunidades programs. Each of these serves a quarter of their country's population (11 million and 5 million households, respectively) and they have budgets of 0.5 percent of their gross domestic product (Fiszbein and Schady 2009).

Payment for environmental services schemes are even more prolific. An early review by Landell-Mills and Porras (2002) found close to 200 incipient PES schemes in developing countries, and the numbers have only increased since then (Pattanayak et al. 2010). Generally, however, these programs are small in scale (sub-national). Three exceptions are Costa Rica's PSA (Pagos por Servicios Ambientales [Payments for Environmental Services]) program, which since its inception in 1997 has made payments for forest conservation (primarily) on nearly 500,000 hectares of land; China's Sloping Lands Conservation Program (SLCP), which so far has contracted 12 million hectares for reforestation in an attempt to prevent soil erosion; and Mexico's PSAH program (Pago de Servicios Ambientales Hidrológicos [Payments for hydrological environmental services]),which compensates beneficiary communities for preserving 600,000 hectares of forest (Pattanayak et al. 2010).

Many CCT programs incorporate rigorous impact evaluations as part of their implementation, often using experimental designs to create credible counterfactuals against which outcomes can be measured (Rawlings and Rubio 2005; Handa and Davis 2006; Fiszbein and Schady 2009). As a consequence, a large body of evidence shows that CCT schemes have successfully alleviated short-term poverty and increased accumulation of long-term human capital through higher school enrollment rates and greater utilization of public health services (Rawlings and Rubio 2005; Fiszbein and Schady 2009).

Most PES programs, unfortunately, are not evaluated against the same exacting scientific standards as CCT (Ferraro and Pattanayak 2006; Pattanayak et al. 2010). The thorough evaluations that have been conducted, mainly in Costa Rica's PSA system (see reviews in Pattanayak et al. 2010; Davis et al. 2010), found that PES programs generally have a low impact in terms of increasing forest conservation. Consequently, the recent PES review by Pattanayak et al. (2010, 268) concluded that "we do not yet fully understand either the conditions under which PES has positive environmental and socioeconomic impacts or its cost-effectiveness."

Similarly, Filmer and Schady (2009, 2) contended that "despite the popularity of CCTs, little is known about what features of program design…account for the observed outcomes"; and de Janvry and Sadoulet (2006, 2) argued that "almost no analysis has been conducted on the effectiveness of alternative program designs in achieving these results, despite the large sums spent to obtain them."

The objective of this paper is to explore the determinants of additionality of CCT and PES schemes, defined as the programs' capacity to deliver desired outcomes that would not have occurred in their absence. We look at the context (i.e., at the framework of conditions at the baseline) in which payment systems are constructed and explore how, and to what extent, this context determines the programs' capacity to induce more investments in human or environmental capital than without the conditional payments. We also analyze possible ways of increasing the additionality of payments through changes in program design.

We first constructed a simple conceptual model and an associated agent-based model that allows us to generate conceptual scenarios and explore available strategies to increase additionality in light of the asymmetry of information present in all CCT and PES programs. Empirically, we used data from previous studies to test and strengthen the predictions of the agent-based model.

There are two main reasons for focusing on how to increase additionality. The first is simply that low additionality implies that a CCT or PES program does little to contribute to its goal of reducing long-term poverty or increasing (or securing) environmental services. Since all CCT and PES programs operate on a limited budget, increasing additionality is an important way to augment policy impact and use public funds more efficiently.

Second, in the case of conditional cash transfers, the rationale for conditioning payments—rather than relying on unconditional, purely redistributive policies—is that either market failures are causing some families to underinvest in the human capital of their children or attaching conditions may make redistributions more politically palatable (Das et al. 2005; Fiszbein and Schady 2009).Thus, if a large share of payments goes to households that are already making sufficient human capital investments, it weakens both the economic and political cases for CCT. The same argument holds for payments for environmental services, whose main justification is to correct for market failures (externalities) that cause underinvestment in environmental capital.[1]

In both cases, a better understanding of how baseline context (i.e., the ex-ante conditions under which a CCT or PES program is established) potentially affects additionality can help policymakers decide whether CCT or PES programs are the best policy option. Whichever is chosen, this baseline information can point policymakers toward program design features that truly increase the additionality of payments.

We recognize that CCT and PES programs often have multiple objectives (e.g., short-term poverty alleviation on top of using healthcare services or preserving woodlands). In some cases, there are conflicts and tradeoffs between achieving the goals and maximizing additionality (see, e.g., Das et al. 2006). Moreover, some measures to increase the direct additionality of a CCT or PES program may have unintended consequences (spillovers) that offset some or all the gains in efficiency. While the focus of our analysis in this paper is strictly on additionality, we will return to these issues and discuss them at the end of the paper.

This paper proceeds as follows. The first section draws a conceptual framework of CCT and PES additionality to help identify the factors influencing it and ways it can be increased. Based on this conceptual framework, section 2 introduces a stylized multi-agent model of a generic CCT/PES scheme to illustrate the insights gained from the conceptual framework. It also presents the empirical strategy for testing the validity of these insights in explaining the performance of existing CCT or PES programs. Results from the model and the statistical analysis are presented in section 3, which puts some flesh on the bones of the stylized conceptual framework. The paper concludes by discussing the tradeoffs between additionality and other policy goals, and the unintended spillover effects from increasing additionality. It also shows how the framework presented in this paper may help policymakers design CCT or PES programs and choose the most appropriate program—CCT, PES, or other policy instrument.

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[1] One can, of course, argue that all providers of ecosystem services should be rewarded, even if their private optimal level of provision happens to coincide with society's optimal level. Still, if payments do not lead to any change in provision of services, it is questionable whether governments can be motivated to allocate public funds to finance PES. Also, if not all providers can be paid, as is often the case in PES programs, it makes sense to try to direct payments where they have the largest impact on service provision.

1. A Conceptual Framework of CCT and PES Additionality

Before introducing the conceptual framework of CCT and PES additionality, a word on terminology is warranted because the CCT and PES literatures use different terms for similar concepts and sometimes the same term for very different concepts. The benefits awarded to program beneficiaries (cash or in-kind) are commonly called transfers in CCT and payments in PES; here we use the latter term *payments* for both programs.

Both conditional cash transfers and payments for environmental services aim to change behavior in a way that potentially increases social well-being, be it through higher school enrollment or more reforestation. Clearly, even before a CCT or a PES program is in place, some children already attend school and some landowners are already restocking forests. The degree to which program conditions are met—even before the program is implemented—is the *baseline compliance level*. This is a key concept in this paper, so we reiterate that this is an ex-ante measure reflecting exogenous factors that lead landowners or families to meet the conditions, irrespective of the program.

The central concept of our analysis is *additionality,* a measure of the extent to which a program produces outcomes that would not have occurred in its absence.[2] Additionality can be expressed either in relative or absolute terms, in other words, as the share or number, respectively, of program beneficiaries who would not have met the program conditions without the payments. Most of the time, we discuss *relative additionality* because it allows us to compare the efficiency of various CCT and PES programs that vary in scale (number of beneficiaries). However, when discussing the effect of changes that affect the number of beneficiaries in a program (i.e., changing the payment level due to a fixed budget), we instead use *absolute additionality* because this is in that case the relevant measure of program impact.

In the CCT literature, the terms *leakage* and *error of inclusion* commonly denote the share of payments going to households that would have met the program conditions in the absence of payments; in other words, relative additionality as we define it is simply *1 minus the leakage rate*. Finally, we use the term *spillover* to denote effects—positive or negative—of a

[2] Here we are sidestepping the issue of whether the activities or behavior that forms the basis for conditional payments actually lead to the desired outcomes. Although there is evidence that this is not always the case—for example, increased school enrollment does not necessarily lead to better learning outcomes (Fizbein and Schady 2009), and the link between forest cover and water availability is not straightforward (Wunder et al. 2008)—adding this layer of complexity is the subject of a different paper.

CCT or a PES program on condition fulfillment among nonparticipants. (Negative spillovers are called leakage in the PES literature, but not in this paper.)

Implementation of CCT and PES programs varies widely in scale (number of recipients), scope (conditions to be met or the main aim of the program), benefit structure (cash or in-kind payments, payment level and differentiation, choice of payee), targeting methods, and monitoring and enforcement of conditions (see Wunder et al. 2008; Fiszbein and Schady 2009). But, they all share a basic rationale in that they offer positive incentives conditional on a given behavior desired by society as a whole, namely, increased investment in human or environmental capital.

These programs thus identify an activity or behavior on which payments will be conditioned (e.g., school enrollment, prenatal healthcare visits, vaccination schedules, monitoring of children's growth, adoption of predefined agricultural practices, and forest conservation or reforestation, etc.). They define the population eligible for payments, (i.e., potential beneficiaries, such as only poor households or only landowners in priority areas) and then decide who actually will be program beneficiaries, either by negotiating with service providers (small-scale PES schemes) or by choosing applicants[3] (national PES and nearly all CCT schemes).

A central feature of CCT and PES schemes is their voluntary nature: households or land owners can freely choose whether to apply for or accept payments or not.[4] Of course, once an agent receives payments, meeting the conditions is mandatory, although again the extent to which this is monitored (if at all) varies widely in CCT and PES programs (Fiszbein and Schady 2009; Wunder et al. 2008).

Given the voluntary nature of CCT and PES programs, potential beneficiaries can be divided into four categories (see figure 1):

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[3] In a majority of CCT and PES programs, prospective beneficiaries voluntarily apply for payments. However, our results and conclusions also hold for programs where program officials actively seek beneficiaries, who then voluntarily choose to accept the offered payment and conditions or not.

[4] The only exception is the Chinese SLCP, where some involuntary enrollment has been reported (Wunder et al. 2008). Sommerville et al. (2009, 2) argued that, even though participation in a PES scheme is voluntary, "service providers do not necessarily have the choice whether or not to provide the service, such as in cases where land-use change is illegal." However, such restrictions are seldom (if ever) perfectly enforced and land owners may chose to deforest, even if it is not legal. (It is estimated that roughly 85% of all tropical deforestation occurs illegally).

A: Those who apply for payments, but will meet the program conditions with or without them

B: Those who apply for payments and will not fulfill the conditions without payments

C: Those who do not apply for payments, but will meet the conditions regardless

D: Those who do not apply and will not meet the conditions

Assuming that agents maximize their perceived utility,[5] we expect them to end up in category A, B, C, or D, depending on the utility they derive from meeting the conditions (U_C); utility from not meeting conditions (U_{NC}); and the utility from participating in the CCT or PES program (U_{PP}), according to the relations given in figure 1.

Figure 1. Conceptual Categorization of Potential CCT or PES Recipients Based on Their Baseline Compliance and Application Decisions

		Will meet program conditions in absence of payment?	
		Yes	***No***
Applies for payment?	***Yes***	**A:** $\begin{pmatrix} U_C > U_{NC} \\ U_{PP} > 0 \end{pmatrix}$	**B:** $\begin{pmatrix} U_C < U_{NC} \\ U_{PP} > U_{NC} - U_C \end{pmatrix}$
	No	**C:** $\begin{pmatrix} U_C > U_{NC} \\ U_{PP} < 0 \end{pmatrix}$	**D:** $\begin{pmatrix} U_C < U_{NC} \\ U_{PP} < U_{NC} - U_C \end{pmatrix}$

Relations in parentheses describe the conditions under which agents will end up in one of these categories: U_C = utility from meeting the programs conditions, U_{NC} = utility from not doing so, and U_{PP} = utility from participating in the CCT/PES program.

[5] Note that this does not presuppose that these perceptions are rational or that resulting decisions are privately or societally optimal. For example, households may underinvest in children's education because they are not fully informed about future returns to education (due to principal-agent relations in the household—also called "incomplete parental altruism") or they do not account for positive externalities from increased education levels (Fiszbein and Schady 2009, 2).

Based on this conceptual framework, any effort to increase additionality—being equal to the share or total amount of payments going to agents of category B—through design improvements will inevitably be framed at the departure line by the following three factors:

1) The share of the eligible population that would meet program conditions in the absence of payments, or the baseline compliance level (In our model, this is [A+C]/[A+B+C+D].)

2) The degree of selection bias in who applies for payments

3) The extent to which one is able to differentiate between applicants who will meet conditions in absence of payments and those that will not, and to use this information to direct payments to the latter.

That is, the agents applying for payments are simply a sample of the full population and their composition reflects the composition of the overall group, but not perfectly. If participants who already meet program conditions (in absence of payments) self-select into the program at a higher degree than those who do not meet conditions (i.e., if A/[A+C] > B/[B+D]), additionality will potentially be harder to achieve, particularly given limited budgets and imperfect information. This is negative selection bias, which impacts program additionality negatively. If the opposite holds, we have positive selection bias. Put another way, negative selection bias exists if the share of participants not complying at the baseline among all applicants (B/[A+B]) is lower than in the population as a whole ([B+D]/[A+B+C+D]).

If programs allocate payments randomly or if all eligible beneficiaries who apply receive payments, additionality is strictly determined by factors (1) and (2) above, so that the larger the baseline compliance level, the lower the expected additionality; and the higher the degree of negative (positive) selection bias, the lower (higher) the expected additionality. In the limit, if baseline compliance is zero, additionality will naturally be 100 percent and, conversely, if the baseline compliance is 100 percent, then additionality will be zero.

Selection bias can occur if the factors that affect whether agents meet program conditions in the baseline also affect the decision to apply for payments or not. Sometimes this is intentionally exploited—such as in public workfare programs, where a work requirement and low wages induce the poorest to self-select into the program (Coady et al. 2004)—creating positive selection bias. On the other hand, studies of the Costa Rican PSA system have shown that two important features positively affect participation: low agricultural suitability of land and off-farm employment (Zbinden and Lee 2005). These factors simultaneously discourage forest clearing (Angelsen and Kaimowitz 1999) and most likely lead to negative selection bias.

Below we present empirical evidence of the extent to which selection bias impacts additionality, but it is worth noting that there is a natural tendency toward negative selection bias. Agents who already meet program conditions at the baseline (i.e., even before the program is implemented, such as those in categories A and C) will apply for payments as long as the utility derived from doing so is positive ($U_{PP} > 0$); on the other hand, those who do not meet conditions at baseline (categories B and D) will apply only if the benefits from participation outweigh the opportunity cost of compliance ($U_{PP} > U_{NC} – U_C$). The latter, by definition, is larger than zero for those who will not meet conditions in absence of payments (see figure 1). This source of selection bias, however, will be lower as the payment level increases (hence, U_{pp}). Finally, in most cases, we also expect selection bias to be smaller as the application rate increases (i.e., as the share of the population that applies for payments climbs). In the limit, when everybody applies, selection bias will, by definition, be zero.

It follows directly from the three determinants of CCT and PES additionality above that there are three corresponding strategies in which the efficiency of these programs can be increased:

Strategy 1: Restrict program eligibility to a sub-population with a lower baseline compliance level.

Strategy 2: Decrease negative or increase positive selection bias.

Strategy 3: Target payments to category B applicants.[6]

In addition, a fourth strategy (4) uses flexible payments, which allows more agents to be paid out of the same program budget, thereby raising additionality (de Janvry and Sadoulet 2006; Ferraro 2008; Alix-Garcia et al. 2008).

The two first options for increasing additionality both aim at increasing the share of category B applicants in the total number of applicants, so that even if one cannot distinguish between A and B applicants, a random allocation of payments will still increase the share of payments to B applicants. In all four categories, policymakers or program officials need

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[6] Note that since the poor often exhibit lower school enrollment and less healthcare utilization, in practice many CCTs already use a combination of strategies 1 and 3 by successfully targeting the poor. In other words, strategy 1 would geographically target the program at areas with a higher incidence of poverty, and strategy 3 would determine eligibility through proxy means or means testing of program applicants. Still, as we show later, additionality is disappointingly low in many cases.

information on what to base changes in program design. In the first case, obtaining such information (e.g., differences in school enrollment rates between age groups, genders, or communities; or regional deforestation rates) is relatively easy. In the three latter categories, information is highly asymmetric and program officials must rely on limited or imperfect information to figure out the causes of selection bias, to distinguish category B applicants from category A, or to offer payments that are more in line with the opportunity costs of program participation. (For the latter, see Ferraro 2008.)

2. Methods and Material: Numerical Model and Empirical Strategy

In the analysis in this section, we focus primarily on the issues of baseline compliance and selection bias because, as we show, they are essential determinants of program additionality, which so far have received very little attention in the CCT and PES literatures. We include the results of our modeling, outlining the circumstances in which targeting holds the potential to substantially increase additionality, and then briefly discuss the role payment differentiation can play. Our numerical model helps illustrate the insights gained from the conceptual framework and the empirical data we used to test the validity of these insights for real world CCT and PES programs.

2.1 A Stylized Multi-Agent Model of CCT and PES Additionality

The model presented here is simply a numerical representation of the conceptual framework presented above. The model generates a random sample of *n* agents, each representing a household or landowner in the potential population of beneficiaries, and characterized by 1) the opportunity cost of meeting the conditions for payment, denoted U_{OC} (and equal to $U_{NC} – U_C$ above); and 2) the utility derived from participation in CCT or PES, denoted U_{PP} as above. If $U_{OC,i} > 0$, agent *i* will not meet the conditions in absence of payments. Similarly, agent *i* will apply for or accept CCT or PES payments only if the utility derived from doing so is positive and covers the associated opportunity cost; in other words, if $U_{PP,i} > MAX(0, U_{OC,i})$.

U_{OC} and U_{PP} are assumed to be normally distributed[7] with expected means and variances chosen, so that a given level of baseline compliance with the program and share of agents

[7] We also ran the model assuming uniform distributions of U_{OC} and U_{PP}, but this did not change the qualitative insights and so these results are not presented here.

applying for payments is achieved. To model selection bias, U_{OC} and U_{PP} are set to be correlated, with a correlation coefficient *s* in the interval [-1,1], so that if s < 0 there is negative selection bias, and if s > 0 there is positive selection bias.

It is further assumed that $U_{OC,i}$ is an additively separable function of two sets of variables. One set are those observable to program officials, for example, distance to nearest school or parents' literacy that can affect school enrollment decisions or biophysical characteristics, such as slope and soil suitability, that can affect the profitability of land-use change. The other set includes what is unobservable, such as the degree of "parental altruism" and attitudes toward schooling, or the opportunity cost of child labor versus school enrollment. It may also include socioeconomic factors that affect the profitability of land-use change (education, wage, access to credit, agricultural knowledge, etc.) or land-use change decisions (the intrinsic valuation of forests and agriculture). The observable characteristics are denoted $F_{obs,i,}$ and the unobservables $F_{uno,i}$. It is assumed that both are normally distributed and independent, so that $U_{OC,i} = F_{obs,i} + F_{uno,i}$ and $\mathrm{VAR}(U_{OC}) = \mathrm{VAR}(F_{obs}) + \mathrm{VAR}(F_{uno})$. By varying the share of variation in U_{OC} that is due to observable agent characteristics, we can change the amount of information about baseline compliance available to program officials. If the share is zero, they have no information; if the share is 1, they have perfect information.

Similarly, we assume that the utility from program participation $U_{PP,i}$ is fully separable in utility derived, on one hand, from the monetary compensation; and, on the other hand, from participation in the program, per se. Assuming a logarithmic utility function, the former can be expressed as ln(p), where p is payment level; and the latter is assumed to be normally distributed. Notably this term can be negative or positive. The reasons for a negative term include transaction costs, mistrust towards the regulator in general, social stigma from receiving welfare aid (CCT), or fear of losing property rights to land (PES). The reasons for a positive term include support for the program's objective and pride in participating (e.g., being recognized for investing in the future of one's children or for being an environmental steward).

Based on the agent characteristics $U_{OC,I}$ and $U_{PP,i}$ each agent *i* makes an ex-ante decision regarding meeting program conditions (e.g., whether to send one's children to school or to clear one's forest plot) and then another decision whether to apply for payments or not, according to the above decision rules. The regulator then allocates payments among participants until the total PES budget is exhausted. This allocation can be random or targeted. (Targeting simply ranks applicants by the observable variable(s) $F_{obs,i}$ that is known to correlate with the decision to meet the conditions or not.)

Finally, additionality is measured as the share or number of payments going to agents who make an ex-ante decision *not* to meet the conditions in the absence of payments. Note that we assume full compliance once payments have been made and no process or behavioral spillovers (e.g., agents who ex ante decide to comply with the program's conditions in the absence of the CCT or PES program and stand by their decision even if they eventually do not receive payments). All results presented here are the average of 1,000 model runs with a random generation of 10,000 agents in each run.[8]

2.2 Empirical Strategy for Testing the Determinants of CCT and PES Additionality

Our second methodological strategy empirically tests the insights gained from the conceptual framework and the numerical model. We used data from seven CCT programs and one PES program, all of which have sufficient documentation on program implementation and rigorous impact assessments to allow us to estimate program additionality. The data collected is from the following programs and studies:

- Japan Fund for Poverty Reduction, Cambodia (Filmer and Schady 2006)
- Pago por Servicios Ambientales, Costa Rica (Robalino et al. 2008)
- Bono de Desarrollo Humano [Human Development Bonus], Ecuador (Schady and Araujo 2008)
- Programa de Asignación Familiar [Family Support Program], Honduras (Morris et al. 2004)
- Progresa/Oportunidades, Mexico (Schultz 2004; Barham et al. 2007; de Janvry and Sadoulet 2006)
- Atención a Crisis [Crisis Support], Nicaragua (Macours and Vakis 2008; Macours et al. 2008)
- Red de Protección Social [Social Support Net], Nicaragua (Maluccio and Flores 2005; Rawlings and Rubio 2005; Barham and Maluccio 2009)
- Punjab Education Sector Reform Program, Pakistan (Chaudhury and Parajuli 2008)

[8] We can provide the actual coding that generated our simulations upon request.

Based on the estimated program impacts in these evaluations, we calculate 58 measures of program additionality in terms of school enrollment, health care utilization, and forest conservation outcomes. These studies estimate the effect of the program in meeting conditions among program beneficiaries (i.e., the effect of the treatment on the treated), and the resulting impact is taken as a direct measure of additionality. For studies providing estimates of the effect of payments on the whole population of eligible beneficiaries (i.e., the effect of the treatment on all potential beneficiaries, treated or not[9], often termed the intent-to-treat effect), we calculate additionality by dividing the estimated impact by the share of the eligible population that, in the end, enrolled in the program. For example, if school enrollment increases by 10 percent among all eligible beneficiaries due to the program, but only 80 percent actually enrolled in the program, then the additionality is 12.5 percent.

Based on the insights from the conceptual framework, we expect additionality to be influenced by the baseline compliance level and degree of selection bias, and whether payments are targeted or not. (Data on the baseline share of condition fulfillment was available for all additionality observations.[10]) Selection bias is not directly observable, but as discussed above we expect it to be lower the higher the payment level and the larger the share of eligible beneficiaries who apply for payments. Finally, targeting does not differ among programs: all of them target payments based on poverty (CCT) or service provision (PES), and none tries to direct payments to those least likely to meet conditions in absence of payments.

We run a Tobit regression with left and right censoring (at 0 and 100 percent, respectively) to test the significance of three factors in explaining observed program additionality, namely:

1) Percentage of baseline compliance level
2) Percentage of the potential population of beneficiaries that actually applies for payment[11]

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[9] Often termed the “intent-to-treat” effect.

[10] We calculated this by taking the level of condition fulfillment after program implementation minus the impact, or by simply using the pre-program level of condition fulfillment if the former data was not available

[11] For most of the programs, we had data on take-up rates, or the share of the eligible population who became program beneficiaries. Since no applicants in the CCT programs studied were turned down if they were eligible for payments, take-up rates should equal the application rates. However, data on take-up rates were only available as program averages and not as baseline compliance disaggregated by child gender or age, so it would correspond to each program indicator of additionality.

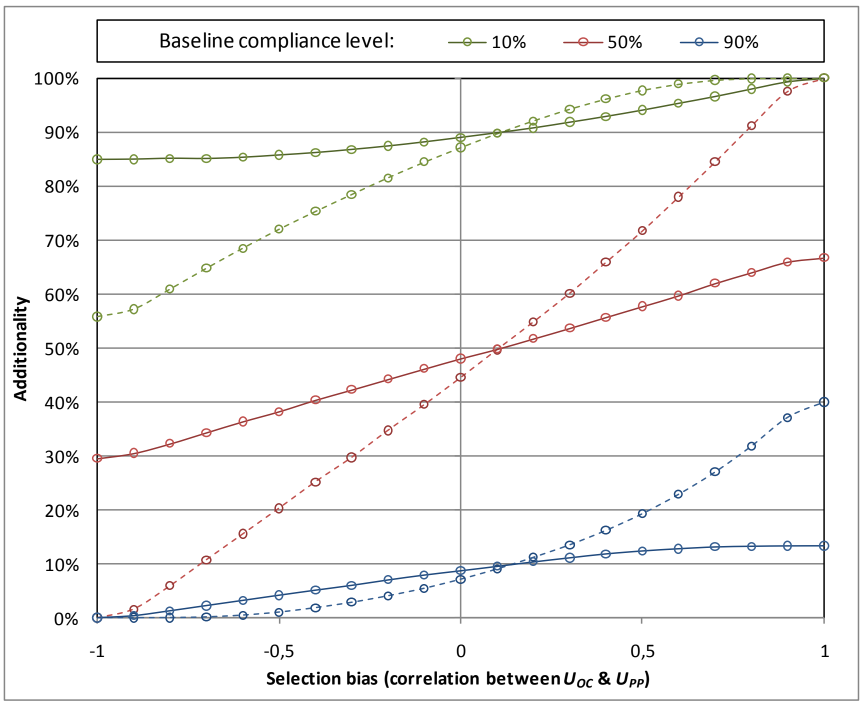
3) Payment level as percentage of average per capita expenditures among program beneficiaries (Data on this factor comes from Fiszbein and Schady 2009.)

Here, we test two models, one with just the baseline compliance level as a dependent variable, and the other a full specification with all three variables. Although we also have alternative constructions for the payment variable (e.g., monthly payment per child enrolled in the program or monthly payment per beneficiary household), we expect the payment variable expressed as share of per capita expenditures to better capture the differences in payment levels across programs. It is a more useful measure of the extent that payments offset opportunity costs of program participation.

3. Determinants of CCT and PES Additionality: Numerical Illustrations and Empirical Evidence

This section presents results from the numerical model, illustrating the determinants of additionality in CCT and PES programs. We complement this with empirical estimates of additionality derived from impact evaluations of both CCT and PES programs, and discuss insights that can be gained from both. Figure 2 displays the basic results from the numerical

Figure 2. Additionality of a CCT/PES Program as a Function of Selection Bias (horizontal axis)



Baseline compliance level is shown in green, red, and blue lines. Program application rates are continuous lines (75%) and dashed lines (25%). See text for further explanation.

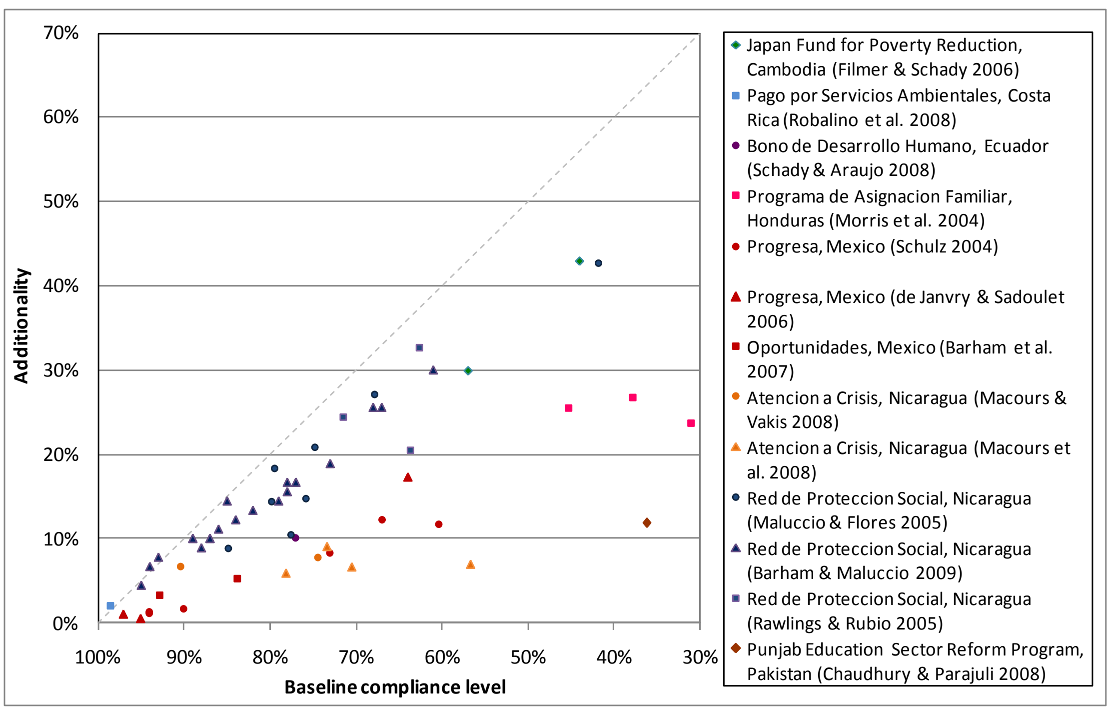
model, in terms of how additionality depends on the two first identified determinants of additionality: baseline compliance level and selection bias (assuming no targeting).

3.1 Baseline Compliance Level and Additionality

The role of the baseline compliance level in determining the potential for additionality of CCT or PES is clearly visible in figure 2, in the differences between the blue, red, and green lines. These lines assume a random allocation of payments to applicants (i.e., no targeting) and are hence a reference bar to eventually judge improvements in program design. As such, it is clear that the bar shifts depending on the baseline; that is, for programs focused on conditions not frequently met at the baseline (green lines), it is much easier to achieve high levels of additionality, even if a random allocation of payments to applicants is used.

Figure 3 displays the results from several empirical estimates of additionality of eight CCT and PES schemes, plotted against the baseline compliance with the program's conditions in the potential population of beneficiaries. First, note that additionality is low in most programs,

Figure 3. Estimates of Additionality in Terms of School Enrollment, Health Care Utilization and Forest Conservation from Eight CCT and PES Programs, Plotted against the Baseline Compliance Level



Deviance from the central dashed line measures the degree of selection bias in who applies for payments, implying that nearly all programs see additionality reduced due to negative selection bias, some by a lot.

averaging only 14.6 percent (median is 12.1 percent and standard deviation is 10.3 percent). Second, this can to a large extent be explained by the high level of baseline compliance in most programs, which is confirmed by the results from the regression analysis in table 1. Baseline compliance level is a highly significant determinant of program additionality in both model specifications. On average, the results suggest that for each percentage point increase in baseline compliance, additionality is reduced by just over one-half a percentage point.

Table 1. Results from the Tobit Regression Analysis of the Determinants of Additionality

Variable	Unit	1*	2*
Baseline compliance level	(%)	-0.353	-0.576
		(0.000)	(0.000)
Application rate in the program	(%)		0.312
			(0.000)
Payment as share of per capita expenditures	(%)		0.637
			(0.000)
Constant	(%)	40.23	16.38
		(0.000)	(0.000)
Number of observations		60	53
Likelihood ratio (χ^2)		32.03	104.8
Probability of null model (χ^2)		0.000	0.000

*p-values are in parentheses.

The level of the baseline service provision helps explain some of the results of CCT and PES impact evaluations, such as the fact that CCT impacts are generally higher among poorer populations with lower school enrollment and health service utilization rates in the baseline (e.g., Fiszbein and Schady 2009, 135). Similarly, the results that puzzled Schady and Araujo (2008)—why Ecuador's Bono de Desarrollo Humano program has a higher impact on school enrollment rates than Mexico's Oportunidades program, despite the fact that payment levels are higher in the latter—may simply be that baseline school enrollment rates are lower among program beneficiaries in Ecuador than in Mexico (77 percent versus more than 95 percent).

Taking a PES example, the role of baseline compliance can explain why many evaluations show that Costa Rica's PSA results in small additionality in reducing forest clearing, but is much more effective in inducing additional reforestation (see, e.g., Daniels et al. 2010).

For reducing forest clearing, the baseline service provision rate is about 98.5 percent (a result of an annual deforestation rate of about 0.3 percent compounded over PSA's five-year contract period), while additional reforestation is around 8 percent, which is the compounded sum of a yearly reforestation rate of 1.5 percent over the same period (MINAET-FONAFIFO 2010).

Although Fiszbein and Schady (2009, 131) noted the relationship between the baseline service-provision rate and program impact, they offer other, more complex explanations for it than the relatively simple mechanism proposed here. Other factors may, of course, also be at play, but we argue that much of the difference in additionality across CCT and PES programs can be attributed to the fact that those applying for payments are simply a representative sample of the overall population—more or less, depending on selection bias—and therefore display a similar level of program compliance in the baseline.

3.2 Selection Bias, Application Rates, Payment Levels, and Additionality

Going back to figure 2, we also note that selection bias (measured in the horizontal axis) can have a large impact on program additionality, especially for a program with low application rates (the difference between continuous and dashed lines). Simply put, a program with low application rates (dashed line) and negative selection bias will find it harder to achieve additionality compared to a program with high application rates (continuous line). Note also that, as explained above, even in absence of selection bias due to correlation between U_{OC} and U_{PP}, there is some negative selection bias from the difference in the threshold for applying, between those complying with program conditions ex ante and those that do not (i.e., with 90 percent baseline compliance, additionality is slightly lower than 10 percent for $s = 0$).

It follows from this that if there is negative selection bias in the first set of applications, then raising the overall application rate will increase additionality. The opposite holds if there is positive selection bias (the difference in moving from the dashed line to the continuous line on the left and right hand sides of the graph in figure 2). This counterintuitive result can be explained using the terminology of the conceptual framework: increasing the application rate in a case where there is already negative selection bias will imply that new applicants, to a larger extent, will be category B (alas, most As will already have applied), thereby increasing additionality. On the other hand, if there is positive selection bias in the first set of applications, additional applicants will mainly be category A.

Figure 3 clearly shows that additionality of the studied CCT and PES programs is indeed highly reduced due negative selection bias. The dashed line in figure 3 represents points at which additionality equals the baseline *noncompliance* level, which (in absence of targeting) is only possible if there is no (zero) selection bias. The fact that most indicators of additionality are located below this line implies that nearly all programs suffer from some degree of negative selection bias, which in some instances substantially erodes the program's effectiveness. On average, selection bias reduces additionality by 38.5 percent within the sample (median is 29.7 percent, standard deviation is 28.2 percent). This may be a slight overestimation, however, because some of the reduction in program impact, related to noncompliance among program beneficiaries, is due to imperfect monitoring and enforcement of conditions that we were not able to filter out.

In many studies of CCT, the existence of selection bias is mainly discussed in relation to short-term poverty reduction goals—whether self-selection increases the share of payments going to less-poor households.[12] However, few studies discuss or try to estimate the role of selection bias as it affects a program's impact. One reason may be that most studies look at the whole group of potential program beneficiaries and not at the subgroup that actually got treated. This implies that they cannot analyze whether program applicants differ systematically from potential beneficiaries who choose not to apply and, hence, are unable to detect self-selection biases. One exception is the study by Schady and Araujo (2008), showing that the enrollment in Ecuador's Bono Desarrollo Humano program was not random with respect to the program outcome in question: children in beneficiary households had a higher rate of school enrollment in the baseline. The fact that the parents of beneficiary children have more years of schooling and are generally more literate than parents of children not part of the program may help explain this pattern.

Similarly, evaluations of the Costa Rican and Mexican PES programs for forest conservation have also revealed negative selection bias, where payments mainly went to land owners with plots at low risk of deforestation (Hartshorn et al. 2005; Pfaff et al. 2008; Muñoz-Piña et al. 2008). In Costa Rica, selection bias occurs because conservation payments cannot compete with alternative land uses. Ortiz et al. (2003) found that PES is only profitable on marginal lands with zero opportunity cost of conservation. Arriagada et al. (2008, 355), through interviews with both PSA participants and nonparticipants, found the most common reason for

[12] See, for example, the analysis by Coady and Parker (2004) on the determinants of self-selection in the Mexican Oportunidades program or the discussion in Fiszbein and Schady (2009, 74). See also Coady et al. (2004) for an overview of how well targeting antipoverty interventions performs in general, when not restricted to CCT.

enrolling land is "lack of more profitable land use alternatives due to land characteristics," while the second-most common reason for not enrolling land—after lack of information—is that payments are too low. In the Mexican case, however, poor program design seems to be the chief reason for negative selection bias, although the land in the two quintiles with the highest estimated deforestation risk constitutes only 18 percent of forest land eligible for conservation payments (Muñoz-Piña et al. 2008).

As discussed in relation to the conceptual framework, we expect negative selection bias to be smaller (i.e., closer to zero) as program application rates and payment levels increase. This intuition is also confirmed by the statistical analysis, where both the application rate and payment level in the program are highly significant determinants of additionality (see table 1). In our simple econometric model, increases in the payment level—when all beneficiaries are paid the same—raise additionality by 0.64 percentage points for each percentage point increase in payments as share of per capita expenditures. Although economic intuition, as formalized in the conceptual model above, holds that higher payment levels should positively affect program outcomes, previous evidence of this effect is scant with mixed results (see, e.g., De Janvry and Sadoulet 2006, Filmer and Schady 2009). Fiszbein and Schady (2009, 133) concluded that "the differences across countries in impacts summarized…suggest that, at current transfer levels, the marginal effect of larger transfers on school enrollment may be modest." However, they did not test this proposition formally. Our results, using cross-country data, strongly suggest that higher payment levels do lead to higher program impacts.

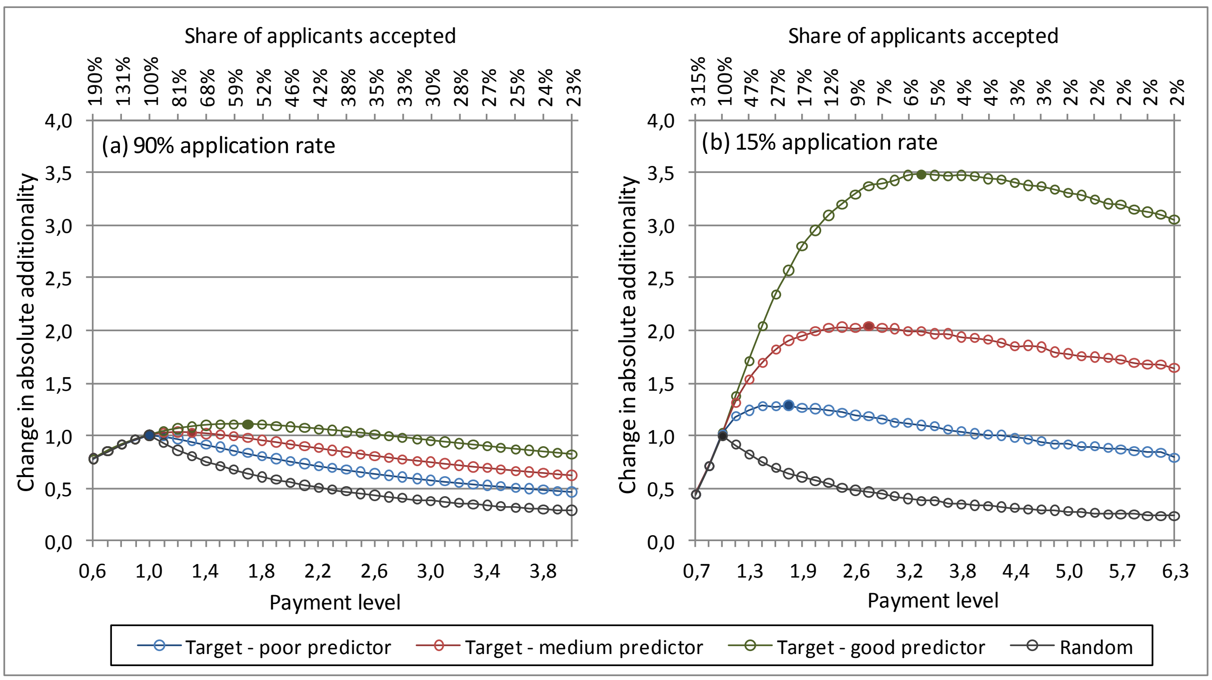
In our model, a percentage point increase in application rate increases additionality by about 0.3 percentage points. Raising additionality by increasing application and take-up rates can be achieved by better dissemination of program information, especially in areas with low levels of baseline compliance with program conditions. As noted above, lack of information is the main reason for not enrolling lands in Costa Rica's PSA program, and same holds for the application rates of poor households in Mexican Oportunidades program (Coady and Parker, 2005).

3.3 Targeting and Additionality

The potential for raising CCT and PES additionality through targeting is inevitably restricted by information asymmetries and the ability of a program to distinguish applicants who comply with program conditions at baseline and those that do not (categories A and B, respectively, in the terminology of our conceptual model). In our numerical model, this is captured by the share of variation in the opportunity cost of program participation (U_{OC}) that is observable to program officials; obviously, the higher this share is, the higher the accuracy of identifying category B applicants and the higher the benefits of targeting.

However, this general statement requires further qualification because other program characteristics are likely to be important in determining the value of information and the potential for increased additionality due to targeting. Figure 4 illustrates this by contrasting two stylized payments schemes where the increases in additionality, which can be achieved by targeting, differ markedly. The first one (on the left) is modeled after the Nicaraguan Red de Protección Social CCT program and has a baseline compliance rate of 78 percent, a very high application rate (90 percent), and a budget that allows all applicants to be paid. Here, the potential to increase additionality via targeting is relatively low.

Figure 4. Changes in Additionality of a CCT/PES Program



These are changes resulting from targeting and changes in the payment level for two stylized programs: (a) a program with a 78% baseline compliance level and high application rate, and (b) a program with a 95% baseline compliance level and a low application rate. The share of the variance in the variable determining baseline compliance decisions (U_{OC}) that is observable is 10%, 30% and 60% in the poor, medium, and good predictor cases, respectively.

The second—based on the Costa Rican and Mexican PES programs—has a very high baseline compliance level (95 percent), a low application rate (15 percent), and a budget that only allows a share of applicants to be paid. In this case, the potential for increased additionality through targeting is much higher. Note that the red, blue, and green curves reflect cases where the shares of the variance in the observable variable that determines baseline compliance decisions (U_{OC}) are 10 percent, 30 percent, and 60 percent, respectively.

To understand why the potential for targeting differs, first note the obvious point that if not all applicants can be paid due to budget constraints, then targeting payments (to pick up category B applicants) will unambiguously raise additionality. However, if all eligible applicants are paid (as in most CCT programs), then there is no possibility of targeting category B applicants because they will have already been paid.

In the latter case, increases in additionality may still be achieved by combining targeting with increases in the payment levels. Increasing payments can have two opposing effects on additionality: on one hand, it will induce more noncompliant applicants to apply (turning category Ds into Bs), which will raise potential additionality; but, on the other hand, it means fewer applicants can be paid (if the budget is fixed), implying lower additionality. Whether the net effect on additionality is positive or negative depends on the relative strengths of these effects and whether the information is available to single out category Bs among the applicants.

In the Nicaraguan CCT case (left graph in figure 4), application rates are high. Consequently, the number of category D applicants is small and higher payments will only minorly increase the number of B applicants. One therefore needs good information about baseline compliance to overcome the loss in additionality due to the reduction in the number of program beneficiaries. And, even if baseline decisions can be predicted with high accuracy, the potential benefits from targeting are small simply because most noncompliers are already being paid.

The situation is very different for the Costa Rican and Mexican PES programs (right graph in figure 4). Here the application rate is small, implying that the number of category B applicants will rise more rapidly as payment levels increase. In such a situation, even relatively poor predictors of baseline compliance can raise additionality substantially. (The value of information is high.) At the point where only about 25–30 percent of applicants are paid, as has been the case in Costa Rica's and Mexico's PES schemes, targeting based on poor, medium, and good predictors of deforestation increases additionality compared to the random allocation of contracts by about 85 percent, 160 percent, and 240 percent, respectively.

In general, we can conclude that the poorer the program performance at the outset, the higher the relative gain from targeting. That is, the relative increase in additionality that can be achieved through targeting is higher:

- the lower the application rate in the program,

- the smaller the share of applicants that can be paid,
- the higher the baseline compliance level, and
- the more negative the selection bias.

However, while the relative gains from targeting can be high in the cases where additionality in the outset is low (e.g., in programs with high baseline compliance and negative selection bias), in absolute terms, additionality may still be very low.

In addition to this, additionality can be further raised by differentiating payments based on the opportunity cost of meeting program conditions (de Janvry and Sadoulet 2006; Alix-Garcia et al. 2008; Ferraro 2008; Wüncher et al. 2008) —although this of course requires more information and may be politically sensitive to implement. In the end, there is no clear-cut answer to the potential of using predictors of baseline noncompliance and matching payment levels to the agent's opportunity cost of compliance. This will differ from case to case depending on program specific characteristics.

In addition to how well noncompliance risks and opportunity costs can be predicted, their variability within the target population will also affect the expected benefits of targeting and differentiating payments. Basically, the greater the variability, the higher the expected benefits (cf. Wüncher et al. 2008). As discussed below, the costs—both economical and political—of payment targeting and differentiation may also differ widely between programs (Fiszbein and Schady 2009).

Finally, even if both baseline compliance behavior and opportunity costs can be predicted with some accuracy (or if that information can be elicited through procurement auctions, for example), CCT and PES efficiency still can be highly constrained by baseline compliance levels and degree of selection bias. For instance, if initial additionality is only a small percent or so—as in the Costa Rican PES system or the primary school enrollment in the Mexican *Oportunidades* scheme—then additionality is still likely to remain poor, even if one is able to predict baseline behavior with a high degree of accuracy.

4. Discussion and Conclusions

We developed a simple conceptual framework for understanding the determinants of CCT and PES program impacts in terms of increasing investments in human and environmental capital. This framework helped us identify two factors that are key to understanding the program efficiency: the level of ex ante compliance with program conditions and the degree of selection bias from who applies for payments.

That selection bias reduces program impact should not come as a surprise, since the prevalence of self-selection biases in public programs has been widely documented in developed countries (Currie 2004). However, the magnitude of this effect is staggering in the programs studied here, reducing average impacts by close to 40 percent. The impacts of CCT and PES schemes should certainly benefit greatly from a deeper understanding of the determinants of applications, take-up rates among eligible households, and reduction of selection biases through better program design. These issues have only received cursory attention in the literature (Currie 2004; Coady and Parker 2005).

The impacts of CCT and PES programs, to a large extent, can be explained by the factors identified by the conceptual framework and validated in the empirical analysis. This suggests that the framework can be used to make ex-ante impact assessments, especially if combined with survey data on participants' baseline behavior and responses to payments. By shedding light on both expected selection bias and information available for targeting, the framework can also help make rough ex-post estimates of a program's effect, when available data does not support rigorous impact assessments (i.e., for most PES schemes). For instance, as already noted, it would be extremely surprising to find that the Costa Rican or Mexican PES systems had much impact on forest clearing, given low baseline noncompliance and ample evidence of selection bias. Under such circumstances, a finer focus on deforestation risk has secondary relevance.

However, because additionality to such a large extent is determined by baseline compliance with program conditions, using achieved additionality as a measure of program success may be unfair. After all, a program implemented to change behavior, which begins with a baseline compliance of 99 percent, will never achieve the results of one where there is little or no compliance (1 percent). A more relevant measure of program design, therefore, is how actual impacts compare with what is expected, given a baseline scenario of random allocations and minimal selection bias (i.e., deviations from the dashed line in figure 3). By this measure, programs in our sample displayed quite a wide variation in impact.

One can, of course, also ask whether it makes sense to allocate public funds to a CCT or PES program, if compliance is already high and the expected policy impact consequently low. The answer depends on the primary goal of the program. If poverty alleviation or general compensation to land owners for environmental service provision is the primary aim, then a CCT or PES may be a reasonable policy choice. However, in such a case, one should also ask whether the benefits of making payments conditional on certain criteria outweigh the costs or whether the stated policy goals can be better achieved in other ways, such as with unconditional payments (cf. discussion in Fiszbein and Schady 2009, 166–72).

In much the same way, the potential of increasing CCT and PES additionality through targeting specific categories of applicants and differentiating payments also has to be weighed against the economic and political costs. Again, if a program's main purpose is to transfer resources to the poor, then increasing payments and targeting applicants (thereby potentially reducing the number of beneficiaries) to achieve higher additionality may not be acceptable. On the other hand, the change in distribution may still be progressive (see, e.g., de Janvry and Sadoulet 2006). If the program budget does not allow all applicants to be paid, or if the main aim of the program is to increase the investment in human and environmental capital, then targeting applicants is much less problematic.

Good examples of the latter—where the low additionality is more worrisome because it compromises the main objective of the program—are the two programs in our sample that aim at closing gender gaps in school enrollment: Japan's Fund for Poverty Reduction in Cambodia and the Punjab Education Sector Reform Program in Pakistan. In both cases, negative selection bias reduces additionality substantially, by around 27 percent and 81 percent, respectively. This indicates that large benefits could be reaped by targeting the applicants better.

An important limitation of our analysis comes from the assumption that there are no process or behavioral spillovers. Both in the choice of CCT, PES, or other policy instrument, and the decision to adopt a targeting strategy in a program, one should take into account possible program spillovers that affect investments in human and environmental capital among nonparticipants. For instance, Costa Rica's PSA payments can lead to relaxed capital constraints for participating farmers, allowing more clearing on non-PSA land (Hartshorn et al. 2005). The introduction of PSA payments can also reduce the intrinsic motivation for forest protection among nonparticipants, making the overall impact of the program negative (given the low additionality on PSA lands). Without a doubt, we need a deeper understanding of behavioral responses to the introduction of payment systems by both beneficiaries and non-beneficiaries, in order to assess the full impacts of different policy designs for the increasingly popular CCT and PES schemes.

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