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A Poverty-Sensitive Scorecard to Prioritize Lending and Grant Allocation

Evidence from Central America

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ABSTRACT

Development projects are generally subject to a potential tradeoff between sustainability and poverty reduction. Grants are also commonly assigned without a standardized criterion. This paper proposes an innovative scoring tool that combines both a risk and poverty scorecard to prioritize lending and grant allocation. We implement and test the instrument through a competitive fund for demand-driven projects in Central America intended to better link smallholder farmers to markets and improve their welfare. The evaluation results show that the highest-ranked projects generally have a larger economic impact on their beneficiaries than lower-ranked projects. We observe a larger effect on income, access to credit, and access to local markets, and the relative differences are stronger over time. The proposed scorecard tool is intended to better ensure the accountability and sustainability of development funds and can be easily adapted to different contexts.

Keywords: poverty scoring, risk scoring, lending, grant allocation, development projects

JEL codes: O16, Q14, C14

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1. INTRODUCTION

The importance of credit in creating and improving economic opportunities in developing markets, particularly for smallholder producers, microenterprises, and small enterprises, is generally recognized by policy makers and has been well documented (for example, Ghosh, Mookherjee, and Ray 2000; Armendariz de Aghion and Morduch 2005; Khandker 2005; Brett 2006).¹ Apart from microcredit and soft loans, financial assistance is generally provided by donors in the form of competitive funds for loans or grants. The optimal use of funds, however, may be subject to a potential tradeoff between sustainability and poverty reduction in the sense that projects that typically target poor or vulnerable populations are not necessarily sustainable in the medium or long term. For example, the provision of subsidized inputs (or equipment) may have an important initial impact on poor smallholder farmers, but it is not usually sustainable over time.² Credit programs such as the so-called agricultural development banks, which were created to provide credit at subsidized interest rates, have also generally failed to achieve their objectives both to serve the rural poor and be sustainable credit institutions (Adams and Graham 1981; Adams and Vogel 1985; Braverman and Guasch 1986; Seibel 2000).³ In addition, the use of scoring algorithms, such as risk-ranking instruments or credit-scoring models, to select development projects for lending or grant allocation is still very limited.

This paper proposes an innovative scoring tool that combines both a risk and poverty scorecard to prioritize development projects. The objective of the tool is to help in selecting projects that not only target the poor but also represent a low risk and are more likely to be continued after the project intervention is over. The proposed scoring tool consists of two stages. A risk scorecard is developed in the first stage to estimate the potential risk of the projects and assess their sustainability. Similar to credit scorecards used to evaluate the creditworthiness of borrowers in the face of adverse selection, a risk score is estimated for each project based on the characteristics of the project and the loan or grant requested. Only those projects that meet a certain risk-level threshold are then assessed in the second stage, in terms of their impact on poverty through a poverty scorecard. Several geographic, employment, and spillover indicators can be used to construct the poverty score, although the variables finally used will also depend on the objectives of the program under consideration.

The improvement of the proposed two-stage scoring tool over existing methods is twofold. First, the risk-scoring algorithm is built based on the latest developments in econometric modeling. In particular, the risk scorecard is constructed using data-driven (semiparametric) scoring models, which can provide a more accurate risk estimate relative to standard (parametric) scoring methods. This is critical in developing markets where reputation is difficult to measure at an initial stage and contracts are hard to enforce; a more precise risk measure can help to mitigate adverse selection problems by preventing the exclusion of potential “good” projects (borrowers) and the inclusion of “bad” projects (borrowers). Second, by combining two scorecards, the proposed instrument goes beyond standard poverty scorecards to prioritize lending or grant allocation. Schreiner (2010), for example, recommends a poverty-targeting approach to prioritize lending based on using household surveys to identify high-poverty areas. The proposed lending or grant allocation criterion in this study goes beyond this: it ranks projects with a poverty reduction potential that also meet a maximum risk level.⁴ Ultimately, the instrument is intended to

¹ The general role of microenterprises and small enterprises in economic development is also well established (McPherson 1996).

² In their recent review of input subsidy programs in Africa south of the Sahara, Jayne and Rashid (2013) find that the costs of such programs usually outweigh their benefits. Even the “smart subsidies” involving vouchers to promote input adoption, which have become popular in Africa in recent years, are not proven to be cost effective (see, for example, Minot and Benson 2009). In Latin America, Bulte, Damania, and Lopez (2007) find evidence that rural subsidies to large farmers tend to be distorting, limiting their development.

³ Seibel (2000) further remarks on the clear need to transform these banks into viable and sustainable providers of financial services.

⁴ To the extent that spatial data and data related to poverty maps are incorporated in the analysis, Schreiner’s scorecard is nested in the second stage of the proposed scoring system. The inclusion of several employment and spillover indicators to

help donors and policy makers choose from a pool of loan or grant applications based on both the chances of project survival and poverty reduction potential. The proposed tool is also flexible enough that it can be easily adapted to other contexts and settings depending on the goals set by stakeholders.

To evaluate the tool, we implemented a pilot program in Central America through a competitive fund for development projects intended to improve the welfare of smallholder farmers in the region. The nature of the program was pro poor, market oriented, and demand driven. All project applications were assessed and ranked using the scorecard tool, and a representative sample of beneficiaries from the selected projects was surveyed over a period of three years to assess changes in different economic indicators. If the tool is effective in identifying (ex ante) sustainable projects with a high poverty reduction potential, we would expect higher-ranked projects to have a larger economic impact on their beneficiaries than lower-ranked projects and those relative differences could be sharper over time. We particularly focus on changes in income (total and per capita), access to formal credit markets, and access to local markets, given also the objective of the pilot program.

The remainder of the paper is organized as follows. Section 2 provides further details about the scorecard methodology and the pilot program implemented. Section 3 presents the data and the methodology to evaluate the tool. Section 4 discusses the evaluation results, and Section 5 concludes.

construct the poverty scoring is also in line with Serrano-Cinca, Gutierrez-Nieto, and Reyes (2013), who recommend a social approach for microfinance credit scoring.

2. THE SCORECARD TOOL

This section briefly describes the components of the proposed scorecard tool and the implementation of the instrument in Central America. For further details on the design and implementation, refer to Hernandez and Torero (2014a).

Components of the Scorecard Tool

The objective of the scorecard tool is to select development projects that are both sustainable and target the poor or vulnerable populations. In this sense, the proposed scoring tool consists of two stages. In the first stage, a risk score is constructed to evaluate the projects' potential risk and assess their sustainability. In the second stage, a poverty scorecard is applied to those projects that meet a certain risk-level threshold to evaluate them in terms of their likely impact on poverty reduction.

The first stage relies on the premise that sustainability is a necessary condition for poverty alleviation in the long run. Similar to the likelihood of defaulting in credit markets, which is usually captured through a credit scorecard, a risk score can be derived by computing a default probability based on the characteristics of the project, including the project developer and beneficiaries, and the characteristics of the loan or grant requested.⁵ The key innovation is to use a robust risk-scoring algorithm that is simple to implement, efficient, and dynamic: simple in the sense that it can be easily implemented using basic information directly collected during the loan or grant application process as well as external information easily available from other sources; more efficient in the sense that employing more flexible, data-driven statistical models permits one to improve the accuracy of risk ranking relative to standard scoring methods (surprisingly, these more flexible methods have not yet been widely used in credit scoring);⁶ and dynamic in the sense that the method can be implemented when there is initially limited information, which is a common characteristic in developing countries, and the algorithm can then be improved across time when new information becomes available.

We particularly use a statistical model that does not impose a specific functional/distributional form in the relationship between the default probability and the project and loan characteristics. Not imposing a specific (and probably erroneous) functional assumption permits us, for example, to capture potential nonlinearities in the relationship between the odds of defaulting and the project or borrower characteristics.⁷ Statistical models in which specific functional forms are not imposed are known as semi- and nonparametric estimation methods. Hernandez and Torero (2014b) provide an extensive discussion of the advantages of using these types of models for risk scoring in developing microcredit markets, relative to standard parametric models. The specific semiparametric model used for the scorecard is the single-index model proposed by Klein and Spady (1993), which involves a relatively faster and less computational burden estimation process compared with other data-driven methods.

The probability of default in this model is given by

$$P(Y = 1 | X) = E(Y | X) = g(X' \beta), \quad (1)$$

where Y is a binary variable associated with the default of the loan (project)—that is, $Y = 1$ for “high”-risk borrowers and $Y = 0$ for “low”-risk borrowers; X is the set of variables that could affect the likelihood of

⁵ Although with a grant there is no repayment obligation (as opposed to a loan), we can still obtain a default probability to assess the risk of the project.

⁶ A plausible explanation for the lack of use of these methods in credit scoring is that several of these alternative data-driven methods are relatively new, while lending institutions are typically more familiar with linear scoring algorithms with multiple variables. Recently, analysts have begun to use psychometric scoring tools (based on logistic models) as an attempt to improve microcredit risk analysis (see, for example, Klinger, Khwaja, and LaMonte 2013).

⁷ For instance, the default probability may decrease with the size (assets) of the institution asking for a loan up to a certain threshold, after which size does not affect the odds of defaulting. A standard (parametric) scoring model will not capture this feature as it assumes a constant linear relationship between the odds of defaulting and each explanatory variable.

default; $g(\cdot)$ is an unknown function; and β is the set of parameters to be estimated. The model is semiparametric in nature since the functional form of the linear index is specified, while $g(\cdot)$ is left unspecified.⁸

The maximum likelihood estimator of β is, in turn, given by

$$\hat{\beta} = \arg \max_{\beta} \ln(\beta, g) = \sum_{i=1}^n \left(y_i \ln g(X_i' \beta) + (1 - y_i) \ln(1 - g(X_i' \beta)) \right) \quad (2)$$

such that $g(\cdot)$ is approximated for each borrower (applicant) i through a leave-one-out nonparametric kernel estimator

$$\hat{g}_{-i}(X_i' \beta) = \frac{\sum_{j \neq i} k\left(\frac{(X_j - X_i)' \beta}{h}\right) y_j}{\sum_{j \neq i} k\left(\frac{(X_j - X_i)' \beta}{h}\right)} \quad (3)$$

where $k(\cdot)$ is a kernel function (for example, Gaussian kernel) and h is the bandwidth, which is jointly estimated with the coefficient vector β when maximizing the leave-one-out log likelihood function.⁹

The risk score estimated for each project (borrower) i is the estimated $\hat{g}_{-i}$ using $\hat{\beta}$. Appendix A.1 provides additional details on the specific steps to calculate the risk score. Note that we initially need past loan/credit information from comparable borrowers/institutions to construct a risk algorithm to be applied to the new loans/grants for development projects that we are interested in evaluating. Only those borrowers (projects) with a risk score below a certain threshold are then assessed in terms of their potential impact on poverty.

In the second stage, we can use different indicators to construct a poverty scorecard for the projects that meet the risk cutoff. For example, projects could be assessed in terms of their labor intensity (for example, proportion of low-skilled workers or female participation) or in terms of their geographical location (for example, projects located in poorer areas are expected to have a greater impact on poverty). Additionally, the impact of a project is likely to vary from one region to another depending on local conditions such as infrastructure and access to external markets; for instance, a project in an area with a high poverty rate and that faces infrastructure constraints is expected to have a higher impact on the poor than a project in an area with fewer poor people and no binding constraints. A value chain perspective is also recommended when assessing a project's poverty effects since there can be spillover effects across the supply chain (for example, direct and indirect labor effects). Overall, we recommend using geographic, employment, and spillover indicators.

To weight these different indicators (variables), we implement a principal component analysis. This statistical method simply creates new variables that are linear combinations (weighted sums) of the original variables. This procedure permits us to avoid assigning arbitrary weights for the different

⁸ In a parametric setting, $g(\cdot)$ is assumed, for example, to be a logistic function, which results in the widely used logit model.

⁹ Single-index models also require two identification conditions under which the unknown parameter vector β and the unknown function $g(\cdot)$ can be sensibly estimated. First, the set of explanatory variables X must contain at least one continuous variable. Second, β cannot be identified without some location and scale restrictions. One convenient location-normalization is to not include a constant in X ; one convenient scale-normalization is to assume that the first component of X has a unit coefficient and that this first component is a continuous variable. See Li and Racine (2006) for further details.

indicators considered. The new variables are referred to as the “principal components” and are uncorrelated (orthogonal) to each other. The number of principal components generated is equal to the number of original variables. The first principal component accounts for most of the variation in the data, the second principal component accounts for most of the variance that has not been accounted for by the first principal component, and so forth.

Generally, one or two principal components are needed to account for more than half of the variation of the data. As a rule of thumb, we suggest using all first principal components necessary to account for at least half of the data variation. As each component is a weighted sum of the variables considered to measure poverty reduction, higher values for a component denote a higher poverty impact. We can then rank projects accordingly on their poverty dimension such that the project ranked first is the project with the highest potential impact on the poor and the project ranked last is the one with the lowest potential. The specific steps to construct the poverty scorecard are presented in Appendix A.2.

Implementation of the Scorecard Tool

To apply and test the scorecard instrument, a pilot was implemented in Central America through a competitive fund for development projects intended to improve the welfare of poor smallholder farmers. The nature of the program was market oriented and demand driven, covering four countries in the region: Guatemala, El Salvador, Honduras, and Nicaragua. In particular, the program was designed to provide funds (up to a maximum of US\$250,000)¹⁰ for projects that involve creating or improving market opportunities for smallholders in the region, especially in areas with high poverty rates. The projects were required to be elaborated by the same farmers’ associations or small enterprises applying for the funds. The program was implemented by the local agency Unidad Regional de Asistencia Técnica with the financial support of the Multilateral Investment Fund of the Inter-American Development Bank and the Austrian Development Agency.

The application and selection process using the scorecard instrument took place between October 2010 and January 2011. To ensure transparency, the entire application process was done through a website specifically created for the pilot program. The applicants had to provide information regarding the association or enterprise applying for the funds, the intended project and its beneficiaries, their credit history, and the project budget and execution plan, as well as any other relevant information. During the diffusion and launching of the program, the scorecard tool was explained to potential applicants in all four countries.¹¹

A total of 58 projects were submitted by different farmers’ associations and small enterprises across the four countries, out of which 39 were eligible for evaluation.¹² The amount requested by all 39 projects summed \$7.1 million, and a total of \$1.7 million was available for grant allocation. The risk score of the 39 projects (applicants) was obtained following the methodology described earlier. Table B.1 in Appendix B lists the 10 specific variables used to construct the risk scorecard, which are generally considered when assessing microcredit loan applications. Those include characteristics of the direct beneficiaries of the project, characteristics of the association or enterprise applying for the loan, and characteristics of the project and grant requested.¹³ Naturally, additional information was collected to validate the information reported by the applicants.

Figure 2.1 shows the results of applying the risk scorecard to the 39 eligible projects. Imposing a maximum risk score of 67 percent, 24 projects qualified for the second stage of the selection process. Recall that the idea of the first stage in the selection process is to identify those projects with a low or

¹⁰ All dollars mentioned in the text are US dollars.

¹¹ Related materials and an explanatory video were also posted on the website.

¹² The projects that did not qualify were those for which the applicants failed to provide all the required information and fill out all the forms indicated in the program guidelines.

¹³ The vector of parameters ($\hat{\beta}$) to construct the risk-scoring algorithm was obtained in this case using previous credit information (that is, performance, loan and borrower characteristics) from other comparable associations and small enterprises in Latin America.

moderate level of risk to ensure (at least to some extent) the sustainability of the project.¹⁴ Note also that the projects were not ranked at this stage.

Figure 2.1 Risk-scoring results

Source: Authors' calculations.

Note: Each diamond in the figure represents a project. The grey diamonds correspond to the projects (grantees) with a risk score below or equal to 67 percent; the black diamonds correspond to the projects with a risk score higher than 67 percent.

The 24 projects were then evaluated in terms of their potential poverty impact. Seven indicators related to the projects' geographic characteristics, employment creation, and spillover effects were considered for the poverty scoring. Table B.2 lists the specific variables used to construct the poverty scorecard. Those indicators include the average poverty rate and distance to the closest major town of the area(s) of the project implementation, total number of jobs created, proportion of low-skill and female labor participation, and number of direct and indirect (intended) beneficiaries per dollar invested. Part of the information to construct these variables was provided by the applicants during the application process, while other information was obtained from external sources.¹⁵

Figure 2.2 plots the combined scoring of the 24 projects. The horizontal axis measures the project scoring using the first principal component, and the vertical axis measures the project scoring using the second principal component. Moving northeast along the 45-degree line implies a higher poverty impact. Given a program fund of \$1.7 million, a total of nine projects were finally selected with a solicited investment of around \$1.6 million. The first eight projects selected were those that obtained the highest poverty score based on the principal component analysis. The ninth project selected was a project from Guatemala (World Wildlife Fund [WWF]), and its selection strictly obeyed the donors' requirement to include at least one project from each of the four countries.¹⁶

¹⁴ The threshold of 67 percent also guaranteed that at least a certain number of projects passed to the second stage.

¹⁵ As in the case of the risk scoring, additional information was requested to validate the information used to construct the indicators.

¹⁶ WWF was actually ranked 16th in the poverty scorecard.

Figure 2.2 Poverty-scoring results

Source: Authors' calculations.

Note: Calculations based on 24 projects that met the risk-scoring threshold. CP1 is the first principal component, which explains 31.70% of the data variation, while CP2 is the second principal component, which explains 19.98% of the data variation. Each circle represents a project. The grey circles correspond to the projects that were finally selected based on the program budget; the black circles correspond to the projects that were not selected.

Table 2.1 lists the selected projects by their ranking in the poverty scorecard, country, number of beneficiaries, and main product produced. Five projects from Honduras were selected, two from Nicaragua, one from El Salvador, and one from Guatemala. We then had to replace Corporacion Technoserve (Honduras), ranked seventh, with Cooperativa CARUCHIL (Honduras), ranked ninth, due to logistical problems with the implementation of their project. The amount invested by project ranged from \$212,500 in Proyecto Aldea Global (Honduras) to \$74,000 in Empresa Agroindustrial del Coco (Honduras). Most of the money was basically used in extension and training activities on organizational aspects and product transformation and commercialization; these activities were similar across the selected projects, but there was some variation in terms of duration and coverage. The beneficiaries of the projects were generally involved in agriculture-related activities, including the production of basic grains, fruits and vegetables, coffee, cacao, and organic chocolate, and all of them belonged to existing farmers' associations.

Table 2.1 List of selected projects

Ranking	Project	Country	Number of beneficiaries	Amount (US dollars)	Main products
1	Fundacion Banhcafe	Honduras	500	212,176	Fruits and vegetables
2	Empresa Agroindustrial del Coco Lemenigi Lomba (ECACOLL)	Honduras	250	74,005	Fruits
3	Cooperativa Multifuncional Las Segovias	Nicaragua	200	212,299	Basic grains
4	Fundacion para el Desarrollo Sostenible	El Salvador	206	187,075	Basic grains
5	Proyecto Aldea Global	Honduras	150	212,500	Fruits and vegetables
6	Asociacion Coordinadora de Mujeres campesinas de La Paz (COMUCAP)	Honduras	256	205,140	Coffee
7	Corporacion Technoserve	Honduras	240	157,043	Coffee
8	Intercooperation-Helvetas	Nicaragua	90	87,460	Organic chocolate
9	World Wildlife Fund (WWF)	Guatemala	98	186,700	Coffee

Source: Authors' calculations.

Note: The ranking is based on the poverty scoring analysis. The number of beneficiaries corresponds to the number of farmers who directly benefit from the project. The amount is the amount of money effectively assigned to each project. World Wildlife Fund (Guatemala) was ranked 16th by the scorecard but was selected because of the donors' requirement to include at least one project from each of the four countries. Corporacion Technoserve (Honduras) was eventually replaced by Cooperativa CARUCHIL (Honduras), the ninth project in the ranking.

3. EVALUATION STRATEGY

Data

We surveyed a representative sample of beneficiaries of the selected projects. The sample maintained the proportion of beneficiaries in each project by gender and location (municipality). We implemented a baseline survey in 2011, prior to the implementation of the extension and training activities, and two follow-up surveys in 2012 and 2013. We exclude from the analysis Corporacion Technoserve (Honduras) since that project had to be replaced by another one, as indicated above. Our working sample is a balanced panel of 554 beneficiaries.¹⁷

The data collected include socioeconomic characteristics of the beneficiaries, household composition, labor activities and income, household assets and expenditure, and access to public services, among others. The information gathered also permits us to construct four economic outcomes of interest to formally evaluate the scorecard instrument: (1) household monthly income; (2) per capita household monthly income; (3) access to credit markets (if beneficiary receives a loan); and (4) access to local markets (if beneficiary sells part of her production in local markets).¹⁸ These indicators are in line with the objectives of the pilot program.

The ranking of the projects permits us to establish different threshold levels to evaluate the tool. According to the instrument, better-ranked projects should have a higher impact on the outcomes of interest than lower-ranked projects. Since we have eight projects, we can establish seven thresholds to compare changes in outcomes over time. In particular, a first threshold (T1) compares changes in outcomes between beneficiaries of the project ranked first (Fundacion Banhcafe) and beneficiaries from projects ranked 2 to 8. A second threshold (T2) compares changes in outcomes between beneficiaries of projects ranked 1 and 2 (Fundacion Banhcafe and ECACOLL) relative to beneficiaries of projects ranked 3 to 8. The other thresholds (T3, T4, T5, T6, and T7) follow the same logic, where the last threshold (T7) compares changes in outcomes between beneficiaries of projects ranked 1 to 7 relative to beneficiaries of the lowest-ranked project (WWF).

Table 3.1 presents some descriptive statistics of all project beneficiaries at the baseline year. The variables include demographic characteristics, household characteristics, access to services, and the four outcomes of interest. The project beneficiaries exhibit a low income level and a limited access to basic services, as most of them live in rural and remote areas. The average per capita income is \$37 per month, and the access to electricity and sanitation is 34 percent and 14 percent, respectively. The average household size is close to six members, and 93 percent of the households own their homes. Similarly, only 16 percent of the beneficiaries report selling part of their production in local markets.

The table also reports average differences at baseline between beneficiaries of higher- and lower-ranked projects.¹⁹ In general, we do not observe major differences at baseline between beneficiaries of higher- versus lower-ranked projects, which provides support for our evaluation strategy discussed below. We find significant differences only in age, gender, and access to water, but still the differences are very small in magnitude. Regarding the outcome variables, we find differences in per capita income and access to local markets, where the beneficiaries of higher-ranked projects generally show a lower income and market access than those of lower ranked projects. This is in some degree expected as projects were not randomly selected and variables like income (poverty rates) and accessibility are used in the scorecard analysis to rank projects.

¹⁷ We had some attrition due to internal migration and other factors. In particular, we lost close to 10 percent of beneficiaries after each survey round. Yet we do not find major differences, at least in observable characteristics, between the individuals that left and those that remained in the sample across years, as Table B.3 shows.

¹⁸ We find very similar results when using household expenditure instead of income. Details are available upon request.

¹⁹ The reported difference is the average of the mean differences when comparing between higher- and lower-ranked projects on a pairwise basis.

Table 3.1 Summary statistics

Variables	Average	Standard deviation	Difference
Age	41	12.66	0.81*
Male	50%	0.50	0.03*
If no education	23%	0.42	-0.02
Access to electricity	34%	0.47	0.00
Access to water	72%	0.45	0.01*
Access to sanitation	14%	0.35	0.00
Home ownership	93%	0.25	0.00
Household size	5.9	2.48	-0.04
Married	82%	0.38	0.00
Ln household monthly income	5.3	1.21	-0.11
Ln household per capita monthly income	3.6	1.25	-0.10*
Access to credit	50%	0.50	-0.01
Access to local markets	16%	0.36	-0.02*

Source: Authors' calculations.

Note: The column "Difference" reports the average difference in means when comparing across higher- and lower-ranked projects on a pairwise basis. The mean differences are obtained from separate least squares regressions of the continuous variable on a dummy variable distinguishing between the higher- and lower-ranked project. For the discrete variables, the reported differences are the marginal effects resulting from a probit model. * indicates the cases where the estimated differences are statistically different from zero (at the 5% level) in half or more of all corresponding pairwise comparisons.

Methodology

The scorecard tool is intended to select projects that are sustainable and promise a high impact on poverty reduction. Hence, the evaluation strategy consists in assessing whether projects with a higher score have a larger economic (welfare) impact on their beneficiaries relative to projects with a lower score. As discussed earlier, based on the project ranking, we can set different threshold levels (up to seven) to compare average changes in outcomes between projects ranked above the threshold (that is, "treatment" group) and projects ranked below the threshold (that is, "comparison" group). This evaluation strategy is also preferred to comparing pairs of projects as our survey sample does not have sufficient statistical power to separately perform the latter.

We follow then a difference-in-difference approach to compare outcome changes between projects above and below each particular threshold. The panel nature of the data permits us to assess variations in different outcomes over time, while controlling for unobserved individual heterogeneity and other individual and household characteristics.

For each threshold $T_k, k = 1, \dots, 7$, we estimate the following equation:

$$Y_{ijt} = \alpha + \beta_1 t_1 + \beta_2 t_2 + \beta_3 T_k + \beta_4 (t_1 * T_k) + \beta_5 (t_2 * T_k) + \beta_6 X_{ijt} + \kappa_i + u_{ijt}, \quad (4)$$

where Y_{ijt} is the outcome of beneficiary i of project j in period t , such as the log of household monthly income (total and per capita), if individual receives a loan and if individual sells parts of her production in local markets; t_1 and t_2 are dummy variables corresponding to the periods one and two years after the baseline period (t_0); T_k is an indicator variable for whether project j is ranked above threshold k ; X_{ijt} is a vector of individual and household characteristics that includes age, gender, level of education, access to electricity, water, and sanitation, home ownership, household size, and marital status of the beneficiary; κ_i is the time-invariant unobserved individual effect; and u_{ijt} is a white noise error.

The parameters of interest are β_4 and β_5 . These parameters are the difference-in-difference estimators that capture average changes in a certain outcome for projects above the threshold relative to projects below the threshold. β_4 measures relative outcome changes between the baseline period (t_0) and one year after (t_1); β_5 measures relative outcome changes between the baseline period (t_0) and two years after (t_2). We are particularly interested in examining whether $\beta_4 > 0$ and $\beta_5 > 0$, and if $\beta_5 > \beta_4$.

Consistent estimation of the parameters in equation 4 requires the elimination of κ_i as this time-invariant individual effect might be correlated with some of the explanatory variables. We accordingly estimate equation 4 following a fixed-effects approach.²⁰ Naturally, any time-invariant control drops from the equation.

Overall, we exploit variations in the ranking of projects to evaluate outcome changes in projects ranked higher versus projects ranked lower. That is, lower-ranked projects serve as the comparison group for higher-ranked projects. If the scorecard is effectively identifying low-risk projects with a higher potential for poverty reduction, we would expect a higher outcome change among higher-ranked projects and those effects should persist (or increase) across time.

²⁰ A Hausman test also indicates the appropriateness of a fixed-effects model over a random-effects model.

4. RESULTS

This section presents and discusses the evaluation results for the four different economic outcomes considered. Table B.4 reports the relevant difference-in-difference estimators over a period of one year (t_1 versus t_0) and two years (t_2 versus t_0) after the implementation of the projects. The estimated coefficients correspond to separate regressions by outcome and considering different comparison thresholds between higher- and lower-ranked projects (T1 through T7).²¹ The standard errors, reported in parentheses, are clustered at the project level to account for the potential correlation of the economic outcomes among same project participants.²²

Figure 4.1 better illustrates the results for variations in total monthly household income. Several interesting patterns emerge. First, the estimated relative changes are generally positive across thresholds, which indicates that beneficiaries of higher-ranked projects show a higher change in income than lower-ranked projects. The estimated income changes are particularly different when comparing the first-ranked project (Fundacion Banhcafe) versus the other projects (threshold 1, or T1), the first-two-ranked projects (Fundacion Banhcafe and ECACOLL) versus the other projects (threshold 2, or T2), and projects ranked 1 to 7 versus the lowest-ranked project (threshold 7, or T7). The estimated differences are generally not statistically significant for the other thresholds considered (T3 through T6). Hence, the two highest-ranked projects exhibit the best performance (in terms of income generation) relative to the other projects, while the lowest-ranked project, which was only selected due to the donors' requirement of a minimum of one project per country (but was actually ranked 16th), exhibits the worst performance; projects ranked third through seventh do not seem, in turn, to show major performance differences between them. In addition, we observe a higher income variation (almost double) in the second year compared with the first year, which also supports the effectiveness of the tool in identifying certain projects that not only have higher effects in the short run but also higher and increasing effects in the medium run.

As shown in the figure, the first-ranked project shows a 44 percent and 84 percent higher increase in income after the first and second year relative to the other selected projects, the first-two-ranked projects exhibit a 38 percent and 75 percent higher income increase, and the lowest-ranked project shows a 49 percent and 93 percent lower increase. The differences across years are also statistically different for each of these thresholds.

We find a very similar pattern for changes in per capita monthly household income, as depicted in Figure 4.2. In this case, the first-ranked project exhibits a 45 percent and 85 percent higher increase in per capita income after the first and second year relative to the lower-ranked projects (T1), the two highest-ranked projects exhibit a 37 percent and 75 percent higher per capita income increase (T2), and the project ranked lowest shows a 49 percent and 91 percent lower per capita income increase (T7).

²¹ The coefficients of the control variables are omitted for clarity of exposition and are available upon request.

²² The statistical significance of the results is not sensitive to clustering following the Cameron, Gelbach, and Miller (2008) wild-bootstrap procedure given the small number of clusters (eight projects).

Figure 4.1 Changes in Ln monthly income by threshold

Source: Authors' calculations.

Note: The horizontal axis indicates the different thresholds considered (T1 through T7). The reported values correspond to the estimated changes between period 1 (t1) and the base period (t0) and between period 2 (t2) and the base period (t0). The analysis controls for individual and time fixed effects as well as for time-varying socioeconomic characteristics. *, **, *** denote significance at the 10%, 5%, and 1% level. The vertical lines represent confidence bands of one standard deviation.

Figure 4.2 Changes in Ln household per capita monthly income by threshold

Source: Authors' calculations.

Note: The horizontal axis indicates the different thresholds considered (T1 through T7). The reported values correspond to the estimated changes between period 1 (t1) and the base period (t0) and between period 2 (t2) and the base period (t0). The analysis controls for individual and time fixed effects as well as for time-varying socioeconomic characteristics. *, **, *** denote significance at the 10%, 5%, and 1% level. The vertical lines represent confidence bands of one standard deviation.

Similar results are obtained when examining variations in access to formal credit markets in Figure 4.3, although the differences across projects are smaller than in the case of income. Again, we observe significant differences in the performance of higher- versus lower-ranked projects for thresholds 1, 2, and 7, and the relative changes are larger in the second year. The likelihood of receiving a loan after the first and second year is 9 and 28 percentage points higher among participants of the first-ranked project relative to participants of the other projects (T1). When using the second threshold (T2), the likelihood of receiving a loan is 11 and 26 percentage points higher among higher-ranked projects, while in the last threshold (T7) the likelihood is 20 and 26 percentage points higher.

Figure 4.3 Changes in credit access by threshold

Source: Authors' calculations.

Note: The horizontal axis indicates the different thresholds considered (T1 through T7). The reported values correspond to the estimated changes between period 1 (t1) and the base period (t0) and between period 2 (t2) and the base period (t0). The analysis controls for individual and time fixed effects as well as for time-varying socioeconomic characteristics. *, **, *** denote significance at the 10%, 5%, and 1% level. The vertical lines represent confidence bands of one standard deviation.

Finally, in the case of access to local markets, Figure 4.4 shows significant differences in the performance of higher- versus lower-ranked projects for the first two thresholds (T1 and T2), but only in the second year. Using the first threshold, the likelihood of selling part of the production in local markets after the second year is 16 percentage points higher among the first-ranked project relative to the other projects, while in the second threshold the likelihood of selling in local markets is 26 percentage points higher among the two highest-ranked projects. Interestingly, beneficiaries of the lowest-ranked project show a higher likelihood of accessing local markets after the first year, relative to the other project participants, but this difference does not persist in the second year.²³

²³ We also modeled access to credit and local markets using a fixed-effects logit model and find qualitatively similar results. This model enables one to account for unobserved individual heterogeneity but mainly exploits within-individual variation in access to credit and local markets across time (that is, individuals without variation in access to credit or access to local markets over time are dropped from the analysis).

Figure 4.4 Changes in access to local markets by threshold

Source: Authors' calculations.

Note: The horizontal axis indicates the different thresholds considered (T1 through T7). The reported values correspond to the estimated changes between period 1 (t1) and the base period (t0) and between period 2 (t2) and the base period (t0). The analysis controls for individual and time fixed effects as well as for time-varying socioeconomic characteristics. *, **, *** denote significance at the 10%, 5%, and 1% level. The vertical lines represent confidence bands of one standard deviation.

In sum, the estimation results indicate that higher-ranked projects show a higher positive effect on their beneficiaries than lower-ranked projects, and the differences are stronger over time. In particular, the two highest-ranked projects generally exhibit a higher performance in terms of the different economic indicators considered than the other projects. Similarly, the lowest-ranked project, selected only due to the donors' requirement, shows the lowest performance in most cases. These results support to some extent the effectivity of the scorecard tool in identifying and ranking projects (ex ante) based on their potential for poverty reduction in both the short and the medium run. At least the two highest-ranked projects (Fundacion Banhcafe and ECACOLL) are the best performing, while the lowest-ranked project (WWF) is the worst performing. The other selected projects, ranked third through seventh, show a better performance than WWF but do not show major differences between them.

In a set of unreported results, we also separately compared the performance of pairs of projects involved in the same production activity. In particular, we compared the first-ranked project (Fundacion Banhcafe) with the fifth-ranked project (Proyecto Aldea Global), both involved in the production of fruits and vegetables, the third-ranked (Cooperativa Multifuncional Las Segovias) with the fourth-ranked (Fundacion para el Desarrollo Sostenible) projects, both involved in the production of basic grains, and the sixth-ranked (COMUCAP) with the last-ranked (WWF) projects, both involved in the production of coffee. We find better performance among the projects ranked higher, especially for income and access to credit, and the differences are sharper after the second year.²⁴ Still, these results should be taken with caution since, as noted above, our sample does not have enough statistical power to perform separate pairwise comparisons.

²⁴ Details are available upon request.

Cost-Benefit Analysis

To better assess the relevance and potential gains of relying on the proposed scorecard tool, we implement a simple cost-benefit analysis. We use the income estimation results when comparing the performance of the seven highest-ranked projects relative to the lowest-ranked project (WWF) to approximate the benefits of the tool. Recall that WWF was only selected to fulfill the donors' requirement; thus, we can compare the results of the top seven projects relative to what would have happened if projects like WWF would have been selected instead (in the absence of the tool).

Based on Figure 4.1, the change in income of the seven highest-ranked projects was, on average, 49 percent and 93 percent higher than that of WWF after the first and second year. We can assume then that each beneficiary of the seven projects experienced this change in income. The total number of beneficiaries and the amount received by each project are also reported in Table 2.1. The net present value (*NPV*) of the benefits generated by each of these seven projects is given by

$$NPV_j = \sum_{t=1}^n \frac{I_{jt}}{(1+k)^t} \times N_j - Cost_j \quad (5)$$

where I_{jt} is the monthly estimated change in income for each beneficiary of project j in period t ; k is the monthly average interest rate in the region (0.67 percent); n is the number of periods (months); N_j is the total number of beneficiaries of the project; and $Cost_j$ is the total amount of money received by the project.

Figure 4.5 reports the total and per beneficiary net present value of benefits. We consider two scenarios with different time horizons. In the first scenario, we assume that the income of the beneficiaries increased for just one year; and in the second scenario, we assume that the income increased for two years.²⁵ This is equivalent to assuming that the impacts of the interventions lasted for one or two years.

Figure 4.5 Net present value of benefits of using the scorecard tool

Source: Authors' calculations.

Note: Estimates based on the performance of the seven highest-ranked projects (in terms of income) relative to the lowest-ranked project (WWF).

²⁵ The assumed income change is 49 percent over the first year and 93 percent over the second year.

If we only consider changes in income for the first year, we obtain a total net benefit of \$1.7 million, or \$1,040 per beneficiary. This is the approximated additional benefit over a period of one year for selecting projects based on the scorecard tool instead of projects like WWF. On the other hand, if we consider changes in income over a period of two years, the net benefit is four times larger (\$7 million in total, or \$4,262 per beneficiary). Overall, this exercise permits us to better quantify the potential gains of using an instrument like the proposed scorecard tool for project selection. Furthermore, it shows that the selected projects are sustainable: after one or two years the projects themselves can additionally generate a sufficient (or larger) amount of money than the amount originally invested to reinvest and keep obtaining additional gains in the following years.

5. CONCLUSION

A common pattern faced by development interventions and projects is the tradeoff between sustainability and poverty reduction. Projects that target poor, vulnerable populations are not necessarily sustainable in the medium or long run. In addition, there are few standardized criteria (if any) to select projects for lending or grant allocation. This paper proposes an innovative scoring tool that combines both a risk and a poverty scorecard intended to ensure both the sustainability of selected projects and their high poverty impact. In the first stage, a risk scorecard is developed to assess the potential risk of projects and evaluate their sustainability. In the second stage, a poverty scorecard is constructed for those projects that meet a certain risk-level threshold to assess their likely impact on poverty reduction. We implement and evaluate the proposed tool through a competitive fund for demand-driven projects in Central America, which aim to better link poor smallholder farmers to markets and improve their welfare.

The evaluation results show that higher-ranked projects have a larger positive effect on project participants than lower-ranked projects, and the differences increase over time. More specifically, the two highest-ranked projects generally show a stronger performance in terms of the different economic indicators considered than the lower-ranked projects. Similarly, the lowest-ranked project, which was selected only because of the donors' requirement, exhibits the worst performance in most cases. These results support the effectiveness of the scorecard instrument in identifying (*ex ante*) particular projects based on their potential for poverty reduction. A cost-benefit analysis also quantifies the important benefits of relying on an instrument like the scorecard tool to select projects, with net benefits per beneficiary of more than \$1,000 after the first year and more than \$4,000 after the second year.

The proposed scorecard tool ultimately intends to help donors and policy makers to better ensure the accountability and sustainability of development funds. The tool should be viewed as a dynamic process, which can be further improved across time, particularly when there is initially limited information for constructing the scoring algorithms. Other pilot programs are critical to provide additional information (based on the *ex post* evaluation of the selected projects) to extend the working database for the scoring assessment and keep refining the scorecard tool. In this study the evaluation of the tool is based on the performance of a limited number of projects, but additional applications and extensions of pilot programs can help to further assess the effectiveness of the tool in other settings. The refinement process can continue until a performance history is well established for a reasonably large portfolio of loans and grants. In the long run, the scoring instrument could operate through a simple, automatized platform. The scorecard tool can also be easily adapted to other contexts depending on the objectives of the competitive funds. Instead of evaluating projects in the second stage in terms of their poverty impact, we could, for example, evaluate projects in terms of their potential to reduce food insecurity and adjust the second-stage scoring indicators appropriately.

APPENDIX A: STEPS TO CONSTRUCT POVERTY-SENSITIVE SCORECARD

Risk Scorecard

Given a pool of applicants applying for a loan or grant to implement a particular development project, the steps to calculate the risk scorecard can be summarized as follows:

1. Gather information from past loans from the same pool of applicants (borrowers) or from other comparable sets of loans from applicants similar to the pool of borrowers. The information collected should allow us to identify the performance of these borrowers/grantees (default or sustainability of their project). The information should also include (at least) some key characteristics of the borrower (project) and loan.
2. Model the performance of these previous loans as a function of the borrower (project) and loan characteristics using the semiparametric single-index model described earlier.
3. Use the resulting estimated vector of parameters $\hat{\beta}$ from step 2 in equation 3 to derive a risk score for the new pool of borrowers (applicants). We only need to provide the same set of characteristics used in the estimation of $\hat{\beta}$ for the new set of loans we are interested in evaluating.
4. Only those projects (borrowers) with a risk score below a certain threshold level are then assessed in terms of their potential impact on poverty.
5. Steps 1 and 2 can be repeated when new information becomes available (that is, when the new selected projects are implemented and evaluated ex post), such that the scoring algorithm ($\hat{\beta}$) can be updated for subsequent assessments.

Poverty Scorecard

Given a set of projects (borrowers) that meet a certain risk threshold, the steps to construct a poverty score can be summarized as follows:

1. Collect all the necessary information from the projects we are interested in evaluating to construct geographic, employment, and spillover indicators (variables).
2. Normalize the indicators by subtracting the mean and dividing by the standard deviation.
3. Obtain the covariance matrix A of the normalized indicators.
4. Calculate the eigenvectors and eigenvalues of the covariance matrix. Let A be an $n \times n$ matrix. The parameter λ is an eigenvalue of A if there exists a nonzero vector v such that $Av = \lambda v$. Vector v is called an eigenvector of A corresponding to eigenvalue λ .
5. Choose the necessary first principal components that account for at least half of the variation in the data. Typically, either the first principal component alone (CP1) or the first two principal components combined (CP1 and CP2) would satisfy this condition.
6. Use the selected principal components in step 5 to rank the projects on the poverty dimension. If more than one principal component is selected, the sum of the two components should be considered for the ranking.

APPENDIX B: SUPPLEMENTARY TABLES

Table B.1 List of variables used in the risk scorecard

Variable	Description
Characteristics of the direct beneficiaries of the project	
Age	Average age of the beneficiaries
Gender	% of men among beneficiaries
Educational level	% of beneficiaries with secondary or higher education
Marital status	% of beneficiaries married or in common-law
Characteristics of the association/enterprise applying for grant	
Age of association	Years of activity
Size of association	Number of employees or partners in association
Assets	If the association owns land or real estate assets
Interest rate	Interest rate of the most recent loan obtained
Characteristics of project and grant requested	
Project duration	Number of months of project duration
Amount	Amount requested

Source: Authors' calculations.

Table B.2 List of variables in the poverty scorecard

Variable	Criteria for evaluation
Geographic indicators	
Poverty rate	Average poverty rate in area(s) where project will be implemented
Access to markets	Average distance, in hours, of area(s) where project will be implemented to closest major town with a population of at least 20,000 people
Employment indicators	
Labor intensity	Number of new jobs generated by the project
Low-skill labor intensity	% of low-skill labor in the project
Female labor intensity	% of female labor in the project
Spillover indicators	
Effects on supply chain participants	Total number of direct beneficiaries from the project (normalized by total amount invested)
Other spillover effects	Total number of indirect beneficiaries from the project (normalized by total amount invested)

Source: Authors' calculations.

Table B.3 Comparison between individuals that leave and those that remain in the sample across survey rounds

Variable	Average differences	
	Round 2	Round 3
Age	-2.29	-1.1
Male	0.09	-0.03
If no education	0.02	0.03
Access to electricity	-0.06	-0.03
Access to water	0.71***	0.08
Access to sanitation	0.15***	-0.1**
Home ownership	-0.01	0.04
Household size	0.25	0.1
Married	0.03	0.06
Ln household monthly income	0.17	-0.1
Ln household per capita monthly income	0.13	-0.18
Access to credit	0.02	0.1
Access to local markets	-0.03	-0.14***

Source: Authors' calculations.

Note: The first column presents the average differences (at baseline) between individuals that left the sample in the second round versus those that remained in the sample in the first two rounds. The second column presents the corresponding differences (at baseline) between individuals that left the sample in the third round versus those that remained in the sample in all three rounds. The reported differences are based on least squares regressions of each continuous variable on a dummy variable distinguishing between the two groups. For the discrete variables, the reported differences are the marginal effects resulting from a probit model. *, **, *** denote significance at the 10%, 5%, and 1% level.

Table B.4 Estimated economic changes by threshold

Outcome	Threshold													
	T1		T2		T3		T4		T5		T6		T7	
	t1 vs t0	t2 vs t0	t1 vs t0	t2 vs t0	t1 vs t0	t2 vs t0	t1 vs t0	t2 vs t0	t1 vs t0	t2 vs t0	t1 vs t0	t2 vs t0	t1 vs t0	t2 vs t0
Ln household monthly income	0.435*** (0.116)	0.838*** (0.173)	0.375** (0.144)	0.754** (0.216)	0.213 (0.202)	0.435 (0.339)	0.123 (0.216)	0.409 (0.327)	0.234 (0.234)	0.614* (0.293)	0.083 (0.333)	0.521 (0.396)	0.491*** (0.114)	0.926*** (0.15)
Ln household per capita monthly income	0.449*** (0.114)	0.846*** (0.171)	0.371** (0.15)	0.749** (0.219)	0.208 (0.202)	0.417 (0.342)	0.117 (0.216)	0.397 (0.327)	0.224 (0.234)	0.602* (0.291)	0.077 (0.333)	0.513 (0.39)	0.485*** (0.114)	0.910*** (0.152)
Access to credit	0.085* (0.044)	0.276*** (0.053)	0.112* (0.048)	0.256*** (0.063)	0.111* (0.048)	0.116 (0.12)	0.086 (0.058)	0.072 (0.111)	0.096 (0.07)	0.084 (0.111)	0.160** (0.049)	0.148 (0.107)	0.199*** (0.018)	0.255*** (0.042)
Access to local markets	0.123 (0.121)	0.157** (0.054)	0.073 (0.138)	0.263** (0.08)	0.001 (0.166)	0.178 (0.096)	-0.168 (0.185)	0.043 (0.109)	-0.153 (0.222)	0.091 (0.085)	-0.303 (0.253)	0.057 (0.081)	-0.587*** (0.06)	-0.014 (0.06)

Source: Authors' calculations.

Note: The reported values correspond to the estimated changes between period 1 (t1) and the base period (t0) and between period 2 (t2) and the base period (t0) for the different thresholds considered. T1, for example, compares the changes between the project ranked first and projects ranked second through seventh, T2 compares the changes between projects ranked first and second versus those ranked third through eighth, while T7 compares the changes between projects ranked first through seventh versus the project ranked eighth. The analysis controls for individual and time fixed effects as well as for time-varying socioeconomic characteristics. Robust standard errors clustered at the project level are shown in parentheses. *, **, *** denote significance at the 10%, 5%, and 1% level.

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