



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 between the highest ranked projects and the lower rank ones. The proposed scorecard tool is intended to better ensure the accountability and sustainability of development funds and can be easily adapted to different contexts.

1. Introduction

The importance of credit in creating and improving economic opportunities in developing markets, particularly for smallholder producers and micro and small enterprises, is generally recognized by policymakers and has been well documented (e.g., Ghosh et al., 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 which 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

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

² In their recent review of input subsidy programs in sub-Saharan Africa, 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, e.g., Minot and Benson, 2009). In Latin America, Bulte et al. (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.

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 (semi-parametric) 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 help donors and policymakers 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 estimation results provide supportive evidence that selecting projects using the proposed scorecard tool can deliver better outcomes in terms of impact and sustainability than, for instance, selecting projects without a standardized criterion, selecting projects relying on a parametric approach in the first stage, or selecting projects only relying on a poverty criterion. Still, we acknowledge that we do not formally test the scorecard tool relative to other specific selection methods (or combination of methods), which could provide similar (or better) outcomes in other settings.

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.

2. The scorecard tool

This section briefly describes the components of the proposed

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 construct the poverty scoring is also in line with Serrano-Cinca et al. (2013) who recommend a social approach for microfinance credit scoring.

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).

2.1. 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 permit 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 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 non-parametric 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 semi-parametric 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), i.e. $Y = 1$ 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, psychometric scoring tools have been started to be implemented (based on logistic models) as an attempt to improve microcredit risk analysis (see, e.g., Klinger et al. (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.

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