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Assessing the relative sustainability of smallholder farming systems in Ethiopian highlands

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ABSTRACT

Global population growth will require substantial increases in agricultural production worldwide. Yet, despite growing concern about the environmental and social impacts of increased agricultural productivity, no consensus exists on the appropriate method for assessing the appropriate tradeoffs for sustainability. To address this need, this paper proposes the use of Data Envelope Analysis to create an index that permits assessment of the relative sustainability of smallholder farms in a given region, with minimal external interpretation about how individual farmers weight tradeoffs on their own farms. The method is applied to the Ethiopian highlands to explore the determinants of economic, social and environmental sustainability in the region's agricultural sector. Econometric model results suggest that farmers felt that farm size, market access, access to off farm income, agricultural loans, and access to agricultural extension and demonstration plots are key drivers of agricultural sustainability at the farm-level. Differences in agro-ecological conditions and region-specific factors were also significant determinants of relative farm sustainability. This underscores the importance of geographical targeting and tailoring of interventions to increase farm sustainability.

1. Introduction

The global food system faces a daunting task to meet growing food demands for a burgeoning population. Global population is projected to reach nine billion people by 2050, which requires a 70% increase in food production (Food and Agriculture Organization of the United Nations (FAO, 2009). Achieving such growth without exacerbating environmental problems in already fragile farming systems is a major concern (Tilman et al., 2002). Technological innovations through investments in high yielding crop varieties, chemical fertilizers, resilient technologies to water stress, pests and diseases have provided massive productivity gains in developing and developed countries alike (Binswanger, 1986; Nin-Pratt and McBride, 2014). However, agricultural intensification often has been associated with adverse environmental and social effects, especially under the flagship “Green Revolution” (Ali, 2007; Lee et al., 2001; Li et al., 2013; Tilman et al., 2002). The general concept of sustainability has emerged as a way to think about diverse impacts from farming. Broadly speaking, sustainable farms address three important pillars, namely economic, social and environmental dimensions (Kuhlman and Farrington, 2010; Robert et al., 2005).

The goals for farm sustainability are more clearly understood than our ability to measure and monitor our success at achieving them. Being able to know how sustainable a farm is constitutes an important and necessary step towards designing policies and interventions for bolstering the sustainability of current production systems. The multi-dimensional nature of sustainability, however, makes it difficult to both operationalize (Rigby and Cáceres, 2001) and to develop appropriate indicators that can be applied to diverse spatial and temporal scales and socio-economic contexts (Dantsis et al., 2010; Hayati et al., 2011; Rigby et al., 2001; Speelman et al., 2007). Developing appropriate indices is further complicated by embedded social values (Lele and Norgaard, 1996), conflicting goals and multiple interactions between sustainability dimensions (Morse et al., 2001), as well as general heterogeneity in societal preferences (Garnett and Godfray, 2012; Loos et al., 2014; Robinson et al., 2015). The complexity and uniqueness of farming systems also implies that indicators can be meaningful in one system, but irrelevant in another (Speelman et al., 2007). Therefore, it is often appropriate to use local farming, system-specific indicators and to consider the farm as the basic unit for sustainability assessment (Rigby

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Table 1
Indicators for assessing the economic sustainability of smallholder agriculture.

Notation	Indicators	Description	Mean	Std. Dev.
e1	Agricultural income (AGINCOME)	Total income from crop and livestock sales (ETB/ha).	6729.98	8408.35
e2	Labor productivity (LABORPRODT)	Farm gross value added per labor input (ETB/man-day).	214.72	212.10
e3	Capital productivity (CAPITALPRODT)	Ratio of gross value added to capital inputs (ETB).	6.76	6.28
e4	Crop diversification (CROPDIV)	An index of crop diversification (score).	0.57	0.20
e5	Diversity of income (*INCOMEDIV*)	An index of income diversification, showing the diversity of income sources for the households.	0.17	0.22

et al., 2001; Van Der Werf and Petit, 2002).

Sustainability assessments typically involve many indicator variables across economic, social and environmental sustainability dimensions. The methods used to integrate and aggregate indicators into composite indices are of paramount importance so that they reflect social and individual values (Dong et al., 2015). Composite indices allow for the comparison of relative sustainability between farms (Gómez-Limón and Sanchez-Fernandez, 2010; Rigby et al., 2001), but cannot avoid subjectivity in how they weight indicators (Cherchye et al., 2008; López-Ridaura et al., 2002; Nardo et al., 2005; Shen et al., 2013). Subjectivity is assured in studies that use expert judgements to assign indicator weights (Zhou et al., 2007). Therefore many studies have turned to data-based methods such as Data Envelopment Analysis (DEA), Principal Component Analysis (PCA) and Factor Analysis (FA) to add more structure to how weights are assigned and to rely more on the survey participants to reveal the weights they place on specific dimensions of sustainability (Perišić, 2015).

The primary goal of this study is to construct composite relative farm sustainability indices (FSIs) on nearly 600 Ethiopian farms using DEA. A secondary goal is to examine different factors that drive the relative sustainability of smallholder farmers, thus helping explore potential policies, interventions and institutional innovations for improving sustainability of the farming sector. The applicability of the DEA approach in construction of composite indices has been explored in several studies, including the human development index (Despotis, 2005), the technology achievement index (Cherchye et al., 2008), and the sustainable energy index (Zhou et al., 2007). Recently, it has also been applied to the development of composite indices of agricultural sustainability (Dong et al., 2015; Gerdessen and Pascucci, 2013; Gomes et al., 2009; Reig-Martinez et al., 2011). Our contribution to the literature is to further explore the ability of the DEA method to develop individual farmer and aggregate weights for specific dimensions of sustainability. This exercise reveals how producers would perceive sustainability policies oriented towards a range of objectives. Furthermore, we make these estimations for an Ethiopian region where that information can provide policymakers with the information to support farm sustainability that aligns with the revealed preferences of local constituents.

The structure of this paper is as follows: Section 2 describes the methodological aspects of the study, including the selection of indicators, normalization, weighting and aggregation techniques. Section 3 presents the empirical application of the model. Section 4 presents the study results. Finally, Section 5 provides a discussion and conclusion of the study results, highlighting the policy implications.

2. Methodology

This section begins with a presentation of the DEA framework for computing composite indices. We outline how DEA can be used to compute measures of relative farm sustainability in cases where several indicators of economic, social and environmental sustainability are considered and the challenge is to select objective weights for aggregating the indicators. This is followed by a presentation of a fractional response econometric model, which is used to explain the predictors of relative sustainability performance. Finally, the section provides a conceptual overview of the key variables used in the study.

2.1. Adapting DEA to compute a composite relative farm sustainability index

DEA is a mathematical programming technique generally used to measure the relative efficiency of decision-making units (DMUs) (Banker et al., 1984; Charnes et al., 1979). In the DEA framework, efficiency is defined as the ratio of weighted sum of the outputs to the weighted sum of the inputs (Charnes et al., 1979). The weights that a particular DMU assigns to various inputs and outputs are the decision variables. The DEA model then chooses weights in such a way that efficiency of the DMU is maximized (Gerdessen and Pascucci, 2013). For instance, with production data for a group of farms, DEA could be used to examine the relative technical efficiency of these farms by creating a nonparametric production frontier, from which it identifies the most efficient farms, which are assigned a score of unity. The efficiency scores for the remaining farms can be taken as relative measures, benchmarked against the most efficient farms (Cooper et al., 2007).

In this study, indicators of economic, social and environmental sustainability are developed from cross-sectional data of over 500 households (Table 1). The study then adapts a DEA model, helping to aggregate the indicators into a composite measure of agricultural sustainability at the farm-level. Consistent with the common DEA terminology, the various indicators are treated as "outputs", and a set of weights are selected to compute a "benefit-of-the-doubt" composite indices of relative farm sustainability (Cherchye et al., 2008; Despotis, 2005). The objective is to maximize the weighted sum of the indicators, by choosing the weights assigned to each indicator. The weights derived by the DEA model thus reflect the relative importance of each indicator (Adler et al., 2010), such that greater weight is given to components revealed to be more important by the DMUs under consideration. (Cherchye et al., 2008). The basic assumption in this model is that each farm maximizes its composite sustainability subject to the level of priority given to each of the sustainability indicators.

Based on extensive interviews and literature review in our study region, we consider a set of m (=15) indicators of the economic, social and environmental dimensions of agricultural sustainability for each of n (=600) farming households (discussed in the next section). Our objective is to aggregate these individual sub-indicators into a single-valued composite index, which represents the weighted average of the m sub-indicators. Denoting w_i as the weight of the i^{th} sub-indicator of sustainability of farmer j, the DEA-based composite indicators of farm-level sustainability are obtained by solving the following constrained optimization problem:

$$FSI_i = \max_{w_{ij}} \sum_{j=1}^{m} y_{ij} w_{ij} \tag{1}$$

Subject to:

$$\sum_{j=1}^{m} y_{ij} w_{ij} \leq 1 \ \forall \ i = 1, \ \ldots, n \text{ (normalization constraint)} \tag{2}$$

$$w_{ij} \geq 0 \ \forall \ j = 1, \ \ldots, m \text{ (non} - \text{negativity constraint)} \tag{3}$$

where FSI_i is the Farm Sustainability Index for farm i, y_{ij} is the value of indicator j for individual farm i, and w_{ij} is the weight of the sub-indicator j on the farm i.