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EFFECT OF CREDIT CONSTRAINT ON PRODUCTION EFFICIENCY OF FARM HOUSEHOLDS IN SOUTHEASTERN ETHIOPIA[1]

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Abstract

Credit constraint in agriculture affects not only the purchasing power of producers to procure farm inputs and to cover operating costs in the short run, but also their capacity to make farm-related investments as well as risk behavior in technology choice and adoption. These, in turn, influence technical efficiencies of the farmers. Although credit constraint problem has been recognized in economics literature, especially in those dealing with developing countries, little emphasis has been given to its effect on productive efficiency of farmers. In light of this, explicitly considering credit constraint, this paper estimated technical efficiency of credit-constrained (CCFHs) and unconstrained farm households (CUFHs) by employing a stochastic frontier technique on farm household survey data from Southeastern Ethiopia. The CCFHs had mean technical efficiency score of 12% less than that of the CUFHs. Given the largest proportion of CCFHs in Ethiopian farming population, this gap implies considerable potential loss in output due to inefficient production. Improving technical efficiency of all farm households in general but more of particularly the CCFHs is desirable. Additional sources of inefficiency differential between the two groups were also identified, and education level of household heads, land fragmentation and loan size significantly affected technical efficiencies of both groups. Besides, wealth and experience affected the CCFHs, and household size affected the CUFHs. In general, the results have important implications for credit, education and land policies in developing countries.

Keywords: Credit market, stochastic frontier, technical efficiency, smallholders.
JEL classification: C21, C24, Q12, Q14

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1. Introduction

One of important policy concerns in developing countries in general and particularly in Ethiopia is raising agricultural production, given limited resources, to meet the ever-increasing demand for food due to increasing human population. However, attaining maximum possible output using a given level of inputs, in which relative variation among farm households in resource endowments and access to credit results in efficiency differential, requires careful studies.

Recently, there has been a growing interest in understanding the impact of financial structure on production (e.g., Blancard et al., 2006; Petrick, 2005; Barry & Robinson, 2001). In some technical efficiency studies, production inputs and corresponding prices are assumed to be constant, which means that technical efficiency is independent of input use (Alvarez & Arias, 2004; Färe et al., 1990; Lee & Chambers, 1986; Farrell, 1957). This unrealistic assumption precludes, among others, the effect of technical efficiency on input demands (Alvarez & Arias, 2004), for it assumes away relative differences among producers in terms of resource endowments and possible constraints in acquiring additional inputs, which indirectly affect the capacity of producers to attain desired level of technical efficiency. Also, short-term efficiency indices are estimated within a framework of a given production technology. This also ignores the fact that the capacity of farmers to choose appropriate and more efficient technologies can be constrained by bounds of their resources (e.g. Alene and Hassan, 2006), one of such bounds being credit constraint.

Farmers in developing countries, including Ethiopia, have limited internal capacity to finance their farm operations due to meager resources they command. Under such condition, credit facilities are vital to their farm operations (Dicken, 2007). In farm production, credit constraint can have direct and indirect effects. Directly, it can affect the purchasing power of producers to procure farm inputs and finance operating expenses in the short run and to make farm-related investments in the long run. Indirectly, it can affect risk behavior of producers, which can also affect technology choice and adoption by farmers (Guirkinger & Boucher, 2005; Eswaran & Kotwal, 1990). As Binswanger & Deininger (1997) argue, an unequal distribution of initial endowments in environments where financial markets are imperfect and credit is rationed can prevent a large proportion of the population from making productive investments. Thus, a credit-constrained farmer is more likely to invest in less risky and less productive rather than in more risky and more productive technologies (Dercon, 1996). Such risk behavior limits the effort of the farmer in attaining maximum possible output.

Although the notion that a credit constraint influences agricultural production has recently been recognized in the literature (e.g., Blancard et al., 2006; Petrick, 2005; Barry & Robinson, 2001; Färe et al., 1990; Lee & Chambers, 1986), empirical studies focusing on the influence of credit constraint on production efficiency are generally scanty in most developing countries. In Ethiopia, although there have been several efficiency studies carried out (Haji, 2007; Haji & Andersson, 2006; Alene & Hassan, 2006; Gavian & Ehui, 1999; Admassie, 1999; Hailu et al., 1998), since they have used pooled sample data aggregating all sample farmers, irrespective of their credit constraint status, they have not explicitly considered the effect of credit constraint on production efficiency. Often they use a dummy variable for access to credit, measuring whether or not farmers have access to credit. This implicitly assumes that farmers who obtain loans would have their effective credit demand satisfied and would become credit-unconstrained. Clearly, this will not disentangle the difference between borrowing status and credit constraint condition (Diagne & Zeller, 2001; Freeman *et al*., 1998).

The use of dummy variable in this way can only allow one to know whether or not the farmer has access to a credit facility and whether or not credit is obtained. It does not allow one to know whether or not access to credit satisfies the borrower farmers' effective credit demand and alleviates their binding credit constraints. In this connection, for instance, Freeman et al. (1998) noted that significant proportion of farmers in central highlands of Ethiopia, who borrowed for dairy production, remained credit constrained even after taking credit. Thus, one needs to look into credit transactions and directly elicit from the farmers about their credit constraint status (Boucher et al., 2005; Iqbal, 1986).

To this end, this paper has three main objectives: (1) to determine whether the sample farm households were credit constrained or not; (2) to estimate technical efficiency of credit-constrained and unconstrained farm households and compare their efficiency scores; and (3) to identify factors, other than the credit-constraint, contributing to technical efficiency differential between credit-constrained and unconstrained farm households.

Results indicate that there is statistically significant difference among farm households in their credit-constraint status. The mean technical efficiency score of the credit-constrained farm households (CCFHs) was found to be less than that of the credit-unconstrained farm households (CUFHs) by about 12 percent. The study also identified that education level, household size, wealth, farm experience, land fragmentation and loan size had significant and varying effects on CCFHs and CUFHs.

The rest of the paper is organized as follows. Related theoretical and empirical literature is briefly reviewed in section two. Section three contains the analytical framework. Describing the method of data collection in section four, results and discussion are presented in section five. Finally, conclusions and policy implications are presented in the last section.

2. Review of related literature

2.1 Credit markets in developing countries

Credit markets in developing countries are inefficient due to market imperfections such as interest rate ceilings imposed by governments, monopoly power often exercised by informal lenders (Bell *et al*., 1997), large transaction costs incurred by borrowers in loan acquisition, and moral hazard problems (Carter, 1988; Carter & Weibe, 1990). Asymmetric information and incentive compatibility problems also lead to capital market imperfections, which in turn bring about credit constraints faced by borrowers (Blancard *et al*., 2006; Stiglitz & Weiss, 1981). Underdeveloped infrastructure, inadequate institutional environment, and less competitive market situation in developing countries also reflect credit market imperfection. Credit constraint is not only a problem of developing countries. As evidence from various studies (e.g., Blancard *et al*., 2006; Gloy et al., 2005; Jappelli, 1990; Tauer & Kaiser, 1988; Lee & Chambers, 1986) shows, farmers in developed countries, especially small farmers, also face credit constraints, since developed countries' credit markets are not yet as perfect as often assumed in standard economic theories. For example, Blancard et al. (2006) observed that 67% of the farmers in their sample of 178 French farmers were financially constrained in the short run.

In light of this, the presence of credit constraints is less debatable than its extent in the literature (e.g., Pal, 2002; Bali Swain, 2002; Kochar, 1997). This is mainly because access to credit market may not be translated automatically into one's participation in the credit market, given considerable information asymmetry and incentive compatibility problems (Diagne & Zeller, 2001; Barry and Robinson, 2001), and taking loans may not also lead to automatic solution to credit constraints (Guirkinger & Boucher, 2005; Freeman et al., 1998). For example, Barry & Robinson (2001) argue that access to external financing resources being limited, farmers' operations and investments heavily depend on internal financing.

The asymmetries of information in credit market imply that first-best credit allocation is not possible, and this leads to the need for partial or full collateral. Then, inadequate collateral or lack of it implies that some individuals will be denied credit, being otherwise identical to those who have the collateral and obtain the credits. In this connection, Banerjee (2001) argues that high-income individuals can borrow large amounts at low costs whereas low-income ones are able to borrow a small amount at high cost. This suggests that income or wealth level of borrowers has a direct relationship with the amount of available credit and an inverse relationship with cost of credit.

Moreover, lenders may not be legally allowed to charge interest rates on loans above certain limits, although informal lenders in practice may do so, as Emana et al. (2005) noted in Ethiopia, for example. If there is no interest rate allowed for the lender to charge at which the expected return is positive, then there will be credit rationing. Even if allowed to do so, lenders may be affected by adverse selection and/or incentive problems so that the expected return on a loan may not monotonically increase with interest rate. That is, lenders may try to avoid selection and incentive problems by rationing credit. Credit rationing refers to a situation in which, among observationally identical borrowers, some get loans and others are denied, whereas excluding certain observationally distinct groups from credit markets, rather than offering them a contract that require higher interest payments and collateral guarantee, refers to redlining (Stiglitz & Weiss, 1992).

2.2 Access to credit market and credit market participation

Credit market literature distinguishes between access to credit and participation in credit markets (e.g., Diagne & Zeller, 2001). A farm household has access to credit from a particular source if it is able to borrow from that source, whereas it is said to participate in the credit market if it actually borrows from that source of credit. This implies that lack of access to credit can be a constraint externally imposed on the farm households, while participation in a credit market is a choice made by a farm household. Thus, a household can have access but may choose not to participate in the credit market for such reasons as expected rate of return of the loan and/or risk consideration.

In this connection, Eswaran & Kotwal (1990) argue that a non-participating household that has access to credit will still benefit if the knowledge of access increases its ability to bear risk, as it can be encouraged to experiment with riskier, but potentially high-yielding technology. The ability to borrow will also alleviate the need for accumulation of assets that mainly serve as precautionary savings, yielding poor or negative returns (Deaton, 1991).

2.3 Credit constraint

Conceptually, a farm household is credit constrained only when it would like to borrow more than lenders allow or if its preferred demand for credit exceeds the amount lenders are willing to supply (Duca & Rosenthal, 1993). This may occur due to factors on both supply and demand sides of the credit market. On the supply side, lenders assess creditworthiness of their clients based on observable characteristics (Bigsten et al., 2003), and extend loans at certain interest rate. This means that borrowers are credit-constrained if, at specific interest rate, they would have liked to borrow larger amount than the lender supplied. In this case, the borrower exhausts this supply and then looks for another lender.

However, the fact that a borrower exhausts its supply from one source, at specific interest rate, makes it a risky borrower for another lender. Thus, farm households are credit-constrained if they face a binding supply constraint as limited by lenders' considerations (e.g., Feder, 1985; Foltz, 2004). In this case, the farm households may be completely denied access to the credit market or they may be quantity-rationed.

On the demand side, farm households may be constrained due to high transaction costs associated with accessing the loans and risks associated with the credit-financed projects (Feder, 1985). That is, as lenders pass on transaction costs associated with screening, monitoring, and enforcing loan contracts to borrowers, as in the case of group lending scheme (Besley & Coate, 1995), farmers with investments profitable when evaluated at the contractual interest rate may not be profitable when transaction costs are factored in and thus decide not to borrow but remain credit-constrained.

For households with access to credit, risk may reduce loan demand. In this connection, Boucher *et al*. (2005) analytically show that in the presence of moral hazard lenders require borrowers to bear some contractual risk, and if this risk is sufficiently large, farmers will prefer not to borrow even though the loan would raise their productivity and expected income.

As the credit literature suggests, the credit market may consist of four different groups: voluntary non-borrowers, involuntary non-borrowers, rationed borrowers and non-rationed borrowers (e.g. Zeller *et al*., 1997). Voluntary non-borrowers are those who decline to borrow at will either because they have strong risk aversion and fear of getting into debt or because they are prudent and only would like to consume up to what they earn. Involuntary non-borrowers are non-borrowers with no access to credit, or those who perceive that they are highly unlikely to get credit, so that the perceived borrowing costs outweigh the expected benefits of the loan. Non-rationed borrowers are those who want to borrow less than their combined available credit lines from all lenders, whereas rationed borrowers are those who want to borrow more than their available credit limit at a particular point in time.

2.4 Some empirical evidence on effects of credit constraint

Empirical evidence, generally, suggests that credit constraint affects *resource allocations* (e.g. Guirkinger & Boucher, 2005; Parikh et al., 1995), *risk behavior* (e.g., Holden & Bekele, 2004; Eswaran and Kotwal, 1990), *technology choice* and *adoption* (e.g., Alene and Hassan, 2006), *productivity, income* and *profitability* (e.g., Foltz, 2004; Hazarika & Alwang, 2003; Freeman et al., 1998; Adesina & Djato, 1996; Feder et al., 1989, 1990), *efficiency* (e.g. Blancard et al., 2006; Ali & Flinn,1989) and *welfare outcomes* (e.g., Khandker & Faruqee, 2003; Pitt and Khandker, 1996) of farm households. Some of these are highlighted in the following paragraphs.

Significant difference in productivities of credit-constrained and unconstrained households was observed in China (Feder et al., 1989, 1990). It was also found that formal credit increased rural income and productivity and that overall benefits exceeded costs of the formal credit system by about 13 percent in India (Binswanger & Khandker, 1995). Studying the effect of credit constraint in Peruvian agriculture, Guirkinger & Boucher (2005) also found that productivity of credit-constrained households depended on their endowments of productive assets and the credit they obtained from informal lenders.

Better access to and participation in credit market were observed to have resulted in higher income and consumption in Bangladesh (Diagne & Zeller, 2001) and in higher farm profitability in Cote d'Voire (Adesina & Djato, 1996), in Malawi (Hazarika & Alwang, 2003) and in Tunisia (Foltz, 2004). Examining sources of efficiency differentials among basmati rice producers in the Punjab province of Pakistan, Ali & Flinn (1989) found significant effect of farmers' access to credit and later Parikh et al. (1995) also found that farmers with greater loan uptake were less cost inefficient than those with smaller loan size. In Bangladesh, Pitt and Khandker (1996) examined the impact of credit from the Grameen Bank and other two targeted credit programs and found significant effects on household welfare, including education, labor supply and asset holding. Another study in Pakistan by Khandker & Faruqee (2003) also reported formal credit's positive impact on household welfare outcomes.

In Ethiopia, Alene and Hassan (2006), for instance, studying the efficiency of traditional and hybrid maize production in eastern Ethiopia, found significant difference in farmers' technical efficiency due to differences in technology choice. That is, the hybrid maize technology required adoption of a package of improved seed, chemical fertilizers, and cultural practices that farmers did not equally adopt, resulting in low technical efficiency. Part of the reason for the farmers' differential adoption of modern technology could be the credit constraints they face. In the livestock sector, in a study carried out in East Africa, including Ethiopia, Freeman *et al*. (1998) found that the marginal contribution of credit to milk productivity was different among credit-constrained and unconstrained dairy farmers. Again in Ethiopia, Holden & Bekele (2004) observed that households with access to credit compensated for increasing risk of drought by reallocating their production in such a way that crop sales were lower in good years to reduce the need to buy the crops in bad years, and they argued that the households would be less able to do so without access to credit.

In general, the reviewed theoretical and empirical studies suggest that credit market failures give rise to heterogeneous resource allocation and different outcomes among farm households with varying characteristics. A farm household facing binding credit constraint is more likely to misallocate its resources and under-invest than its unconstrained peer. Thus, availability of finance and its accessibility crucially affect production start-up and subsequent performances of the farmers.

In the literature, although credit constraint is identified as an important factor affecting different aspects of farm households, only few studies have directly focused on the effect of credit constraint on technical efficiencies of farm households. The limited availability of studies explicitly addressing the effect of credit constraint on technical efficiency thus calls for more studies.

3. Analytical framework

3.1 Economic model

In economic theory it is often assumed that producers maximize revenue, minimize cost or maximize profit. However, producers are heterogeneous in this optimization process. Given the same inputs and technology, some produce more outputs, more efficiently than others. In the literature, there are different methods of estimating efficiency. At a broader level, one can find parametric, semi-parametric and nonparametric methods based on whether or not one can assume a functional form for an underlying technology and a specific distribution for the error terms. In the parametric family, one can also find deterministic and stochastic efficiency measures depending on whether or not random terms are accounted for. The stochastic estimation techniques take into account the fact that deviations of observed choices from optimal ones are due to failure to optimize (i.e., inefficiency) and random errors, while in deterministic models deviations from optimal levels are attributed solely to inefficiencies, despite that random errors are present.

Moreover, productive efficiency literature (Farrell, 1957; Aigner *et al*., 1977; Bravo-Ureta & Pinheiro, 1993; Sharma *et al*., 1999; Wadud, 2003) distinguishes between technical, allocative and economic efficiencies. In this paper we focus on technical efficiency, taking into account the credit-constraint status of the farm households affecting input use as given. Technical efficiency is defined as the ability to avoid waste by producing as much output as input usage allows, or by using as little input as output production allows (Farrell, 1957).

This study makes use of stochastic frontier analysis (SFA)[**], which requires a parametric representation of the production technology and incorporates stochastic output variability by means of a composite (two-part) error term. In particular, we estimate technical efficiencies of the sample farm households, given their difference in credit constraint status. Based on stochastic efficiency method, a general stochastic frontier model is defined as:

$$y_i = f(\mathbf{x}_i;\boldsymbol{\beta})exp(v_i - u_i); \qquad (i = 1, 2, \cdots, n) \tag{1}$$

where y_i represents the output of the i^{th} farm household, *n* being the sample size, $\mathbf{x}_i$ is a vector of variable inputs, $\boldsymbol{\beta}$ is a vector of technology parameters, $f(\mathbf{x}_i;\boldsymbol{\beta})$ is the production frontier. The symmetric random error v_i accounts for random variations in output, which is assumed to be independently and identically distributed as $N(0,\sigma_v^2)$ independent of the u_i s; the u_i s are non-negative random variables, associated with technical inefficiency in production, which are assumed to be independently and identically distributed and truncations at zero of the normal distribution with mean μ and variance σ_u^2 (i.e., $|N(\mu,\sigma_u^2)|$). The variance parameters of the model are parameterized as $\sigma^2 = \sigma_v^2 + \sigma_u^2$; $\lambda = \sigma_u^2/\sigma^2$ and $0 \le \lambda \le 1$. Given the distributional assumptions of v_i and u_i, the estimate of u_i can

[**]Empirical efficiency studies usually utilize either Data Envelopment Analysis (DEA) or SFA. DEA is a nonparametric approach employing linear programming to construct a piecewise-linear, best-practice frontier for each economic unit (Färe *et al*., 1985). Although, it does not impose a functional form on the data, it attributes all off-frontier deviations to inefficiency by assuming away the possibility of noisy data. SFA explicitly accounts for random shocks and is thus more appropriate in an environment such as our study area, where data can be noisy.

be derived from its conditional expectation, given the composite $\varepsilon_i (= v_i - u_i)$, applying the standard integrals (Jondrow *et al.*, 1982).

$$E(u_i \mid \varepsilon_i) = \mu_i^* + \sigma_i^* \left[\frac{\phi(-\mu_i / \sigma_i^*)}{1 - \Phi(-\mu_i / \sigma_i^*)} \right] \tag{2}$$

where $\mu_i^* = \dfrac{\mu\sigma_v^2 - \varepsilon_i \sigma_u^2}{\sigma_v^2 + \sigma_u^2}$, $\sigma_i^{*2} \equiv \dfrac{\sigma_v^2 \sigma_u^2}{\sigma_v^2 + \sigma_u^2}$ and $\Phi(.)$ and $\phi(.)$ represent cumulative distribution and probability density functions, respectively. Therefore (1) provides estimates for v_i and u_i after replacing ε_i, σ_ε and λ by their estimates. That is, the output-oriented technical efficiency of the i^{th} farm household (TE_i), given the levels of inputs, is defined as the ratio of observed output to maximum feasible output in a state of nature depicted by $exp(-v_i)$ (Battese *et al.*, 1996) as follows.

$$TE_i = \frac{y_i}{f(\mathbf{x}_i; \boldsymbol{\beta}) exp(v_i)} = exp\{-(u_i \mid \varepsilon_i)\} \tag{3}$$

The distribution of u_i limits the estimated technical efficiency of a farm household i between 0 and 1, which is inversely related to inefficiency. The inefficiency scores (IE_i) of credit-constrained and unconstrained farm households are defined as $1 - exp\{(-u_i \mid \varepsilon_i)\}$ and are used as dependent variables in the inefficiency effects models.

3.2 Econometric model

3.2.1 Specification of econometric model

To assess farm household-specific technical efficiencies using parametric approach, the log-linear Cobb-Douglas stochastic production frontier[††] is specified as

$$ln Y_i = \beta_0 + \sum_{k=1}^{6} \beta_{ik} \, ln \, x_{ik} + v_i - u_i \tag{4}$$

[††] The log-linear Cobb-Douglas specification was preferred to other alternatives such as the translog due to its convenience to readily interpret the estimates.

where y_i is the aggregated value of farm outputs of the i^{th} farm household in the sample, measured in Ethiopian Birr[‡‡] and x_{ik} are the input variables, i.e., land, human labour, fertilizer, seed, herbicides and pesticides; the β s are parameters to be estimated; and v_i and u_i are as defined earlier in equation (1). To compare technical efficiencies of credit-constrained and unconstrained farm households, equation (4) is estimated using maximum likelihood estimator (MLE) separately for the two sub-samples, identified by a variable indicating their credit constraint status.

To investigate the effect of farm households' demographic, socioeconomic and institutional factors on technical efficiency, the following inefficiency effects model is separately estimated for the two groups of farm households using least squares method.

$$IE_i = \delta \mathbf{Z}_i + \eta_i \qquad \textbf{(5)}$$

where IE_i is inefficiency scores defined earlier; $\mathbf{Z}_i$ is a vector of proposed household demographic, socioeconomic and institutional variables affecting efficiency; and η_i is a random error term, assumed to be normally and independently distributed with mean zero and variance, σ_η^2.

3.2.2 Model variables and hypotheses

Dependent variable

It was hypothesized that CUFHs would be more efficient than CCFHs. To test this, data were collected from farm households classified as credit-constrained and unconstrained as self-reported by the sample farm household heads. Farm output was measured as annual farm revenues, by accounting for the value of unsold and home-consumed outputs. Assuming same average output price in a season at which the farm households could sell their outputs, the used revenues allowed aggregation of multiple outputs (Parikh *et al*., 1995. This farm revenue per hectare was used as dependent variable in the estimation of the stochastic frontier production function, as used by other researchers (e.g., Alene & Hassan, 2006; Wadud & White, 2000; Feder *et al*., 1990). Assuming that production technologies are homogeneous within the sample and output prices are the same in a season, the difference in per-hectare

[‡‡] The exchange rate was at 9.45 Birr =1US$ in March 2008.

revenue is believed to capture technical efficiency differential among credit-constrained and unconstrained farm households. In the inefficiency effects model of equation (5), the dependent variable is the inefficiency score defined earlier.

Explanatory variables and hypotheses

The explanatory variables for both the stochastic frontier production function and the inefficiency effects models are explained and their effects hypothesized as follows.

Production inputs

Land, labour, seed, fertilizer, herbicide and pesticide are inputs in the stochastic frontier production function specified in equation (4). The inputs are expected to have positive effect on the value of outputs in the production function. However, suboptimal use of some inputs may result in negative output effect and inefficient production. Land (*LAND)* is the total land area operated by the household, including that owned, rented in, contracted in and obtained through gift, and measured in hectare (ha). Labour (*LABOR*) is family labour force and external labour supply (hired, exchanged, or gift), measured in man-days. Fertilizer (*FERT*) is the quantity of chemical fertilizers called UREA and DAP applied to the crop, measured in kilograms (Kg). Seed (*SEED)* is the measure of improved and local seed varieties used by farm households, measured in Kg. Pesticides (PEST) and herbicides (HERB) are measures of the quantities of pesticides and herbicides, respectively, used by the sample farm households, both measured in millilitres (ml). The quantities and qualities of the inputs, and the technical skills of the farm households to properly use the inputs determine technical efficiency of the farm households.

Land is an important input to agricultural production affecting farm output (Wadud, 2003), but the effect of farm size on efficiency is mixed (e.g., Pender & Fafchamps, 2005). Some studies suggest that small farms are more efficient than large ones, but others oppose this. However, undoubtedly, one can see that use of external inputs increases with farm size, and economies of size may be attained as farm size increases. Moreover, larger farms may positively affect lenders' valuation of borrowers' creditworthiness (Khandker & Faruqee, 2003), as do farm outputs and income. Here, it is expected that farm households with larger farms would allocate resources more efficiently than smaller farmers, since they would have better access to credit and can better finance farm operations and on-farm investments.

Agricultural production in developing countries is a highly labour-intensive economic activity. In addition to its direct effect, farm labour supply may also have indirect effect on efficiency since it is complementary to other farm inputs. However, all farm households are not equally endowed with family labour. A farm household with inadequate family labour may wish to satisfy its farm labour demand externally, and to pay for this, will demand credit. Therefore, if the farm household is constrained in the credit market, it may also be constrained in the labour market.

The other variable inputs are often not family supplied, except SEED where farmers may use from their own outputs; they are rather purchased from the market. Credit constraint will have direct effect on their use (Demeke *et al*., 1998) and their suboptimal use in turn will affect the use of land and labour inputs, and thus production efficiency. Farmers who are unconstrained in the credit market are more likely to choose optimal levels of these inputs than their credit-constrained counterpart.

Inefficiency factors

After technical efficiencies are estimated for the two groups of farm households, sources of inefficiency differentials among farm households, besides credit constraint, are estimated using inefficiency scores as a dependent variable. As referred to earlier, the efficiency studies in Ethiopia and elsewhere (e.g. Coelli & Battese, 1996) show that several household demographic, socio-economic and institutional factors affect efficiency differentials among farmers. However, the effect of these factors varies in time and space, depending on specific situations in the study countries, making it imperative to test their effects also in this study area.

Demographic factors

Traditional farming has evolved over years through farmers' own experience of continuous experimentation and learning. Farmers develop and accumulate experiences including farm financing over time, and learn about farm technologies and subsequent productivity effects, market behaviours, and general physical and economic environments to make choices. Farmers may enhance their productive efficiencies, as they get more experienced, learn how to increase income-generating capacities and become able to use cost-effective strategies to cope with adverse shocks. For example, experience in borrowing may help farmers to effectively use external sources to smooth output and income fluctuations. Controlling for this, the age of the farm household head (*AGEH)* is hypothesized to increase productive efficiency. Previous studies (Kalirajan & Shand, 1985; Stefanou & Saxena, 1988; Battese *et al*., 1996) also indicate positive effect of experience on farmer efficiency.

Education is also expected to increase labour productivity by influencing managerial skills of farm operators, as skilled farmers are more likely to allocate resources more efficiently. Hence, education level *(EDUCL)*, measured in farm household head's years of schooling, is included with expected positive effect. Nevertheless, results from previous empirical studies are mixed. For example, while Bravo-Ureta & Pinheiro (1993), Ali & Flinn (1989), Parikh *et al*. (1995) and Battese *et al*. (1996) show that education has a positive effect on farmer's efficiency, others such as Kalirajan & Shand (1985) and Adesina and Djato (1996) found no significant effect.

Another factor possibly affecting technical efficiency of farm households is household size *(HHSZ).* Family labour is often an important source of labour supply in farm households in developing countries. In a situation where rural labour market is underdeveloped, which is also the case in the study area, coupled with credit constraint, farm households with inadequate family labour will experience farm labour deficit, whereas others may experience idle labour surplus. *HHSZ* is thus expected to have a positive effect.

Socioeconomic factors

Here, household wealth and land fragmentation are included. Household wealth (*WEALTH*) captures the market value of total household physical properties such as farm implements, machineries and other stocks. Household wealth is expected to ease credit constraint in two ways. On the one hand, wealthier farmers are expected to own more assets, and will thus have more potential for equity financing, which in turn will generate more income. On the other hand, if equity finance falls short of total financial requirement, since wealthier farmers own more farm assets, this will increase their probability of obtaining external finance through its positive influence on lenders' valuation of creditworthiness. Thus, wealth is expected to have a positive effect on efficiency of particularly credit-constrained group, who often have smaller wealth.

Fragmentation of landholdings (*LANDFRAG*) is commonly regarded as a major obstacle to growth in agricultural production in developing countries (Tan *et al*., 2006). The more the number of plots per total land a farm household operates and the smaller the plot size, the higher the degree of land fragmentation and the less likely is the opportunity to apply new technologies (especially indivisible ones) such as irrigation facilities. Therefore, a negative effect is expected for *LANDFRAG*.

Institutional factors

Institutional factors are important determinants of productive efficiency (Fulginiti et al. 2004). One such factor is access to extension service (*EXACSS*). In this service, farm households often obtain information on improved crop varieties and breeds of animals. However, individual variations among farm households in accessing, searching and utilizing extension services are expected. To the extent technology adoption depends on this service, those with access are expected to be more efficient than those without it. Based on results from previous studies (e.g. Bravo-Ureta & Pinheiro, 1993; Bindlish & Evenson, 1993; Parikh *et al*., 1995), a positive effect is hypothesized.

Efficiency may also be affected by farm households' access to credit information. A farm household cannot apply for loan without any information. Those with access to credit information (*CREDINFO*) will be in a better position to optimally decide in view of external financing and become more efficient than others, hence a positive effect is expected. A farm household may be quantity (loan size) rationed as the amount of credit obtained becomes inadequate for optimal choice of other variable factors of production, for desirable economies of scale require proportionate change in all factors of production. To see this, loan size *(CREDSZ)* is controlled for and a positive effect is hypothesized.

Interest rate is a cost of capital to borrower farm households, and depending on choice of lenders they may incur higher costs inefficiently. In this connection, for example, Gloy *et al*. (2005), studying the costs and returns of agricultural credit delivery in U.S., concluded that many of the largest borrowers have access to credit at more favourable rates than their smaller peers. So, we expect interest rate (*INTEREST)* to have negative effect on production efficiency. In Ethiopia, in general, and in the study areas, in particular, since communication and transportation infrastructure are less developed, access to available credit may be affected by physical proximity of the borrower to the location of the lender. To control for temporal and monetary costs of transportation, which are transaction costs to an individual borrower, distance to a credit facility *(DISCREDF)* is controlled for with expected negative effect.

4. Method of data collection and the data

The data used in this paper were obtained in a survey of farm households conducted during September 2004 to January 2005 in Merti and Adamitullu-Jido-Kombolcha (AJK) districts of Oromia region, Ethiopia. These study areas are located at about 200 km and 160 km, respectively, to the southeast of the capital, Addis Ababa (Finfinnee). The farm households were selected randomly from six Farmers Associations (FAs) in the two districts – four from Merti and two from AJK. Using FA-level list of farm households as a sampling frame, 240 sample farm households were randomly selected. Survey enumerators administered the questionnaire to heads of sample households visiting them at their farmsteads. As shown in Table 1, large fractions of the sample farm households grow several crops such as maize (61%), onion (38%), barley (36%), wheat (31%), *teff*[§§] (30%), haricot beans (25%), sorghum (19%), and faba beans (15%) while relatively smaller proportions also grow other crops such as rapeseed, tomatoes and green beans. The farm households grow multiple crops to diversify their outputs in light of minimizing risks in yields and prices.

In addition to the usual demographic and socioeconomic variables, farm household heads were interviewed on whether or not they had information about lenders, whether or not they applied for credit from any external source in the last 12 months prior to the survey, whether or not their applications were accepted, and if so, the amount they obtained and whether or not they were constrained after receiving it. Moreover, information on location of the lender, interest rates charged, type of credit obtained and repayments were collected.

Table 1: Proportion of farm households growing different crops

Crop	Grower farmers (%)[a]	Crop	Grower farmers (%)[a]
Maize	61	Sorghum	19
Onion	38	Faba beans	15
Barley	36	Rapeseed	9
Wheat	31	Tomatoes	8
Teff	30	Peas	8
Haricot beans	25	Green beans	3

[a] Percentages are sample proportions of farmers growing a particular crop and do not add up to 100%, as most farmers diversify by producing multiple crops. Source: Own survey, 2004/05

5. Results and discussion

5.1 Characteristics of credit-constrained and unconstrained farm households

As descriptive results shown in Table 2 indicate, the overwhelming majority of the sample farm households (70%) reported as credit constrained, which is not surprising, given the low level of rural credit market development in the study areas.

[§§] *teff* (*Eragrostis tef*) is an annual cereal crop of grass family often used in production of *injera*, a major staple food in Ethiopia.

Table 2: Sample descriptive statistics by credit constraint status

Variable name	Variable definition and measurement unit	Unconstrained	Constrained	Full sample	Mean difference test
		Mean§	Mean§	Mean§	t-ratio
AGEH	Age of household head (years)	42.23 (14.95)	43.69 (13.76)	43.25 (14.12)	-.734
HHSZ	Household size (No. of members)	7.58 (3.01)	8.02 (3.97)	7.89 (3.70)	-.863
EDUCL	Household head's education (years)	4.04 (4.13)	3.13 (3.44)	3.41 (3.68)	-.717
LANDWN	Total land owned (ha)	1.62 (1.17)	1.89 (1.34)	1.81 (1.29)	-9.615***
SEED	Crop seed used (kg)	141.10 (192.78)	137.63 (138.51)	138.68 (156.60)	-9.070***
FERT	Chemical fertilizer used (kg)	165.58 (259.40)	129.42 (217.19)	140.42 (230.90)	10.077***
PEST	Pesticides used (100ml)	66.64 (69.05)	6.49 (18.03)	24.79 (49.31)	10.491***
HERB	Herbicides used (100ml)	1.69 (3.86)	0.10 (0.23)	1.18 (3.31)	-3.750***
LABOR	Total labour worked (man-days)	127.45 (75.82)	132.62 (97.81)	131.05 (91.55)	2.449***
LANDSZ	Total land operated (ha)	1.73 (1.35)	1.83 (1.18)	1.80 (1.23)	-9.266***
OUTPVAL	Value of total farm output (100 Birr)	66.27 (82.03)	60.83 (83.62)	62.49 (83.01)	7.319***
WEALTH	Household wealth (1000 Birr)	26.23 (17.23)	9.56 (6.93)	14.63 (13.48)	6.705***
LANDFRAG	Land fragmentation (No. of plots)	2.65 (1.58)	3.13 (1.70)	2.98 (1.67)	-2.003**
CREDSZ	Size of credit obtained (Birr)	323.71 (596.22)	299.71 (573.88)	307.01 (579.62)	-1.529
CREDINFO	% of households with credit information	90	84	86	1.344
CREDAPPL	% of households applied for credit	71	65	67	-2.916***
CREDAPPR	% of households who obtained credit	60	53	55	-4.527***
EXACSS	% of households with extension visit	29	44	40	-8.432***

§Standard deviation of the means in brackets; sample means for dummy variables indicate fractions taking value 1 in the sub-sample. *** and ** indicate 1% and 5% significance levels, respectively, for test of mean difference between the two groups. Credit-constrained and unconstrained groups have sample sizes of 167 and 73, respectively.

Source: Own survey, 2004/05

Although there is no statistically significant difference between credit-constrained and unconstrained farm households in terms of average age, household size and level of education, the two groups have significant differences in other characteristics, as can be seen from the value of the mean difference t-test statistics[***], which are reported in the last column of Table 2. The credit-constrained farm households operate more fragmented farmland, as measured in the number of plots. The proportion of credit-constrained farm households that applied for credit (65%) is significantly smaller than that of the credit-unconstrained farm households (71%).

Since there is no significant difference in terms of access to credit information, this suggests that some credit-constrained farm households did not apply for credit for reasons other than lack of credit information. This can possibly be due to farm households' expected rejection or transaction costs considerations in application decisions. However, the absence of significant difference between the two groups' access to credit information does not imply that they both had adequate information. About 60% and 53%, respectively, of credit-unconstrained and constrained farm households had obtained loans and the difference is also statistically significant, as the mean difference test confirms (Table 2). However, the evidence of quantity rationing is not strong as the difference in credit size between the two groups of farm households is statistically different from zero at only unconventional 11% level of significance.

In terms of production inputs, there is clear statistically significant difference between the two groups of farm households. The credit-constrained farm households operated more land and used more labour but applied lower levels of seeds, fertilizers, pesticides and herbicides than their credit-unconstrained peers. In Ethiopia, land is government-distributed to the farm households based on household size, although there are possibilities of informal land markets, which can result in different holdings among households with same size. In light of this, more land operated by the credit-constrained farm households are more likely due to larger household size, which is also the source of household labour supply. The variable inputs require more capital to purchase and it was observed that the credit-constrained group applied them in lower levels than their credit-unconstrained peers.

As a result, on the output side, the credit-constrained farm households obtained less revenue per hectare of land than the credit-unconstrained farm households. This pattern is similar to the finding by Feder *et al*. (1989), where credit-constrained farmers in China were observed to have used lower levels of inputs and obtained lower outputs than unconstrained farmers. Moreover, credit-constrained farm households had less wealth than their credit-unconstrained peers. This result also

[***] Independent t-test was used to test the null hypothesis of no difference between the means of the two groups, where the reported t-ratios were derived as $t = (\bar{x}_u - \bar{x}_c) / SE(\bar{x}_u - \bar{x}_c)$, and $\bar{x}_u$ and $\bar{x}_c$ are sample means of the variables for credit-unconstrained and constrained groups, respectively.

conforms with Banerjee's (2001) theoretical claim that wealthier farm households get more access to credit because they can afford fixed transaction costs, bear more risk and are less risky to lenders than less wealthy farm households.

Nevertheless, these summary statistics are unconditional means and little can be learned to compare the relative efficiency of credit-constrained and unconstrained farm households. To obtain a better insight, the average figures need to be evaluated conditional on relevant demographic, socioeconomic and institutional characteristics of the farm households, which is the focus of the econometric estimation in the next section.

5.2 Estimated technical efficiencies

Maximum likelihood estimates of the parameters of the stochastic frontier production function specified in equation (4) are obtained using LIMDEP version 7.0 software (Greene, 1995). The estimated values for the variance parameters, λ, in the stochastic frontier production model are significant, which indicate that technical inefficiency affects outputs of the two groups of farm households. The estimates for CCFHs and CUFHs are presented in Table 3. In the case of credit-unconstrained farm households, all input variables but the herbicide and land variables turned out to be statistically significant and all but the land and seed variables showed the expected positive signs. The labour variable has the highest input elasticity of production and herbicide has the lowest, although the effect of herbicide is not statistically significant. This implies that more farm revenue can be obtained by using more labour on the farm, as the production system in the study area is labour intensive.

For credit-constrained farm households, all variables except herbicides are statistically significant and all but land and seed variables have the expected positive signs. The relatively more capital-intensive inputs such as fertilizer, pesticide and herbicide have higher output elasticities for this group of farm households. It is intuitive to see a credit-constrained group to use lower levels of capital-intensive inputs due to binding financial constraint.

The dependent variable is the natural logarithm (ln) of the value of total farm output per hectare (in Birr). Sample size for credit-constrained and unconstrained groups is 167 and 73, respectively.

The relatively higher marginal effects of the limited capital inputs suggest that the credit-unconstrained farm households could choose variable inputs more proportionally than their credit-constrained peers, yielding higher mean productive efficiency.

Table 3: MLE estimates of stochastic production frontier

Variable	Credit-constrained	Credit-unconstrained
	Coefficient, (t-ratio)[a]	Coefficient, (t-ratio)[a]
Intercept	6.95 (12.51)***	5.61 (11.78)***
LnLAND	-0.34 (-1.66)*	-0.11 (-0.86)
LnFERT	0.13 (2.02)**	0.13 (4.47)***
LnSEED	-0.27 (-1.87)*	-0.19 (-2.77)**
LnHERB	0.04 (0.72)	0.02 (0.70)
LnPEST	0.07 (1.70)*	0.05 (2.24)**
LnLABOR	0.58 (4.15)***	0.69 (9.13)***
λ	0.76 (12.82)***	0.67 (11.16)***
σ	1.48 (11.43)***	0.90 (10.98)***
Log Likelihood	-351.15	-259.16

[a] Values in brackets are t-ratios and ***, ** and * indicate 1% , 5% and 10% significance levels, respectively.

Policymakers are often interested in ranking firms in terms of their efficiencies to devise appropriate policies (Dorfman & Koop, 2005). In view of this, frequency distributions of the farm household-specific productive efficiencies for both credit-constrained and unconstrained farm households are reported in Table 4 and Figure 1. It can be observed that productive efficiency varies widely among sample farm households in both groups. The mean technical efficiency score of credit-unconstrained farm households (67%) is higher than that of credit-constrained ones (55%), suggesting a significant deterrent effect of access to credit on the efficiency of the farm households.

The two groups, which mainly differ in their credit constraint status, have a difference in average technical efficiency of about 12%, and given the largest proportion of credit-constrained group, narrowing this gap by improving the credit access will have considerable effect on output growth, a result which is also related to other empirical studies (e.g., Blancard *et al*., 2006).

Table 4: Frequency distribution of efficiency estimates

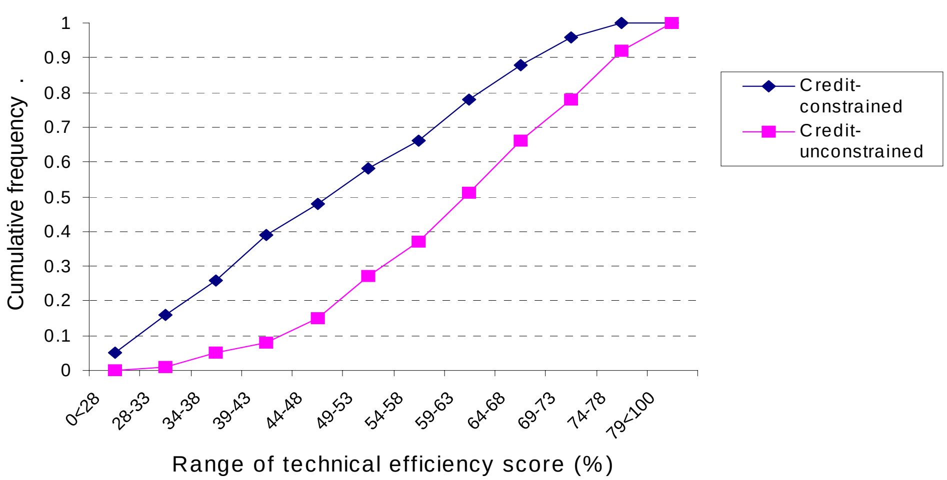
Efficiency Score (%)[§]	Credit-constrained		Credit-unconstrained	
	No. of farm households	Percent	No. of farm households	Percent
0<28	8	5	0	0
28-33	18	11	1	1
34-38	17	10	3	4
39-43	21	13	2	3
44-48	15	9	5	7
49-53	16	10	9	12
54-58	13	8	7	10
59-63	20	12	10	14
64-68	16	10	11	15
69-73	14	8	9	12
74-78	8	5	10	14
79<100	0	0	6	8
Mean	55		67	
Min	20		28	
Max	75		85	
SD	13		11	

[§]The mean, minimum, maximum and standard deviation of the efficiency scores are in percentages. Sample size for credit constrained and unconstrained are 167 and 73 respectively.

The average inefficiency scores for credit-unconstrained and credit-constrained farm households, respectively, are 33% and 45%, indicating the presence of significant difference in the average inefficiency between the two groups of farm households. While the credit-unconstrained farm households, on average, have a loss of 33% of potential maximum farm revenue due to their technical inefficiency, the credit-constrained ones have a corresponding value of about 45%.

The estimated technical efficiencies for the two groups of farm households also revealed different spreads. While the minimum and maximum technical efficiency scores, respectively, are 28% and 85% for the credit-unconstrained farm households, the corresponding scores for credit-constrained farm households are 20% and 75%, respectively. Comparing the minimum and maximum efficiency scores, the two groups have a difference of about 10% in both measures. About 65% of the credit-constrained farm households have 58% and less productive efficiencies while only about 30% of the credit-unconstrained farm households have equivalent efficiencies, indicating bigger loss in potential farm revenue due to inefficiency of the credit-constrained than the unconstrained farm households (Figure 1). Moreover, the distribution of the efficiency scores for credit-unconstrained farm households is concentrated near the highest scores while they are concentrated towards lower scores for the credit-constrained ones.

Figure 1: Cumulative frequency of farm households in technical efficiency score range



Knowing efficiency scores is not an end by itself, and, therefore, next we will see additional factors contributing to the differences.

5.3 Factors affecting inefficiency

The parameter estimates of the relationship between technical inefficiency and farm households' demographic, socioeconomic and institutional factors are reported in Table 5. In this table, the equations have high R-squared values, showing higher explanatory power of the covariates and thereby strong goodness-of-fit of the model to the data. The F-test for joint hypothesis that all non-intercept coefficients in the model are jointly equal to zero was also rejected, indicating that the observed inefficiency differential among credit-constrained and unconstrained farm households is not due to chance but explained by the included covariates.

The fourth column of Table 5 shows estimates for the full sample, where a dummy variable indicating whether or not a farm household has obtained a credit is included for comparison. However, the effect of this dummy turned out to be statistically insignificant, although the positive sign of the coefficient may be taken as indication of the presence of more efficiency for those who borrowed than those who did not. But, as argued before, since this variable does not show the credit-constraint status of a borrower, we cannot rely on the estimated coefficient of this variable.

Now focusing on the second and third columns of Table 5, we will look at the specific variables of the models. In passing, it should be noted that technical inefficiency scores were used in the regression, and therefore when we interpret the coefficients a negative effect of the estimate on technical inefficiency simply means a positive effect on efficiency. Contrary to the hypothesis, the age of the farm household head showed a positive effect on technical inefficiency of the credit-constrained farm households. For credit-unconstrained farm households, age had not significant effect. A positive effect of age for the credit-constrained group of farmers suggests that older farmers were less efficient than younger ones. A possible explanation could be that the older farmers, although more experienced, might be more conservative and less receptive to modern technologies and farm practices enhancing technical efficiency than their younger peers. In Eastern Hararghe zone of Ethiopia, Seyoum *et al*. (1998) also observed a similar result in a study that compared technical efficiencies of farmers within and outside SG-2000 project, a pilot extension project later widely adopted in most agricultural regions of the country.

Household size had significant negative effect on the inefficiency of credit-unconstrained farm households, whereas it had insignificant effect on that of credit-constrained farm households. It means that inefficiency decreases with household size of the credit-unconstrained group. This is possibly because the credit-unconstrained group could choose optimal levels of labor, since they were not financially constrained to do so. For the credit-constrained ones, labour supply did not matter for their optimal choice because they could not proportionally choose optimal levels of other inputs due to their financial constraints.

Table 5: Parameter estimates of inefficiency effects model

Variable	Credit-constrained	Credit-unconstrained	Full sample
	Coefficient (t-ratio)	Coefficient (t-ratio)	Coefficient (t-ratio)
Constant	0.53 (1.82)**	0.73 (1.88)**	0.59 (3.55)***
AGEH	0.09 (2.25)**	0.05 (0.63)	0.06 (3.06)**
HHSZ	-0.05 (-0.61)	-0.07 (-2.33)**	-0.04 (-2.12)**
EDUC	-0.06 (-2.04)**	-0.03 (-2.04)**	-0.05 (-2.56)**
LANDFRAG	0.09 (3.11)***	0.07 (3.50)***	0.08 (3.17)***
EXACSS	-0.08 (-0.73)	-0.12 (-0.55)	-0.12 (-0.68)
CREDSZ	-0.10 (-2.11)**	-0.05 (-2.11)**	-0.07 (-2.32)**
WEALTH	-0.03 (-3.00)***	0.02 (0.44)	-0.03 (-2.71)**
CREDINFO	-0.07 (-0.44)	-0.04 (-0.27)	-0.05 (-0.93)
INTEREST	0.06 (1.20)	0.03 (0.90)	0.07 (0.67)
DISCREDF	0.07 (0.70)	0.05 (0.53)	0.05 (1.30)
CREDAPPR§			-0.24 (-1.56)
Number of observation	167	73	240
R^2	0.89	0.86	0.83

Note: *** and ** indicate 1% and 5% significance levels, respectively. The dependent variable is inefficiency score (IE_i) as defined in the methodology part.

§This is a dummy variable taking value of 1 if the household obtained credit and 0 otherwise, included in the model using the full sample.

As expected, education level of the heads of farm households showed significant positive effect on technical efficiency of both groups of farm households but with higher effect for the credit-constrained group. It indicates that technical efficiency increases with formal schooling of the farm household heads. Moreover, education, as a human capital factor, is also expected to have multiple effects on the performance of the farm households, including acquisition, processing and utilization of information and farm managerial skills. It will improve the quality of decision-making capacities and hence their productive efficiency. This suggests that public policy facilitating investment in farmers' education can also decrease farmers' technical inefficiency. This result supports the effort Ethiopia is currently putting on establishing farmers' technical training centres at the levels of Farmers' Associations, the lowest rural administrative units in rural areas.

Land fragmentation exhibited statistically significant positive effect on technical inefficiency of both groups of farm households, as expected. It means that efficiency decreases with number of farm plots. That is, fragmentation of a given fixed size of total farmland has inverse relationship with efficiency. Two possible explanations can be offered. First, land fragmentation can deter optimal use of indivisible technologies, such as irrigation equipment. Second, considerable amount of time and effort can be lost in coordinating farm operations at different plots, especially with increased distance between the plots. This result suggests that for improved technical efficiency of the farmers, plots of farmland allocated to a household need to be aligned to each other. For Ethiopia, where the farm households are being certified to use farmlands, plots of land allocated to a farm household need to be aligned to each other as close as possible. In a country where land markets function well, farmers may be advised to consider such effects on their efficiency in deciding locations of their land purchases.

The amount of loan obtained significantly and negatively influenced technical inefficiency of both groups of farm households, which means that efficiency increases with loan size. This effect is more pronounced in the case of CCFH. The negative effect of the loan size can be seen in two ways. First, as the loan size increases, the unit cost of borrowing, including transaction costs, decreases because some of these costs are fixed regardless of the amount of loans and with increased loan size, the total cost thinly spreads over large loan size and reduces average unit costs. Second, as the amount of loan increases, farm households could be less constrained to acquire improved technologies and choose optimal levels of inputs, making them less inefficient than others.

The result suggests that for the loan to bring about significant impact on the technical efficiency of a farm household, credit suppliers need to increase the amount of loan per farm household to the extent it can meet its effective credit demand. A larger loan size will also have a cost reduction implication for lenders in that with increased loan size per borrower farm household, unit cost of credit delivery will fall, which can also make the lender more profitable. Ultimately, this can also create an incentive for the lender to reduce the lending interest rate in view of increased loan volume.

The wealth variable had a negative and significant effect on the technical inefficiency of CCFH but no significant effect on that of the CUFH. This means that for CCFH, technical efficiency increases with their wealth. Intuitively, as wealth increases, credit constraint tends to ease both from the demand and supply sides. That is, farmers' capacity to self-finance internally may increase as they get wealthier, and demand for credit may decrease, and if, however, there is demand for credit as the wealthier expands their farm operations requiring additional external finance, wealthier farmers will be less rationed out in the credit market due to their relatively higher creditworthiness than their less wealthy peers. The insignificant effect of wealth on that of CUFH implies that their inefficiency was independent of their wealth, because they could still attain desired efficiency levels since they can optimally choose input levels, for they were not credit constrained. The significant effect of wealth on the productive efficiency of CCFH implies that because this group has financial constraints, their efficiency depends on their wealth levels. It means that within the CCFH, relatively wealthier farm households are more efficient than less wealthy ones.

The effects of the variables extension visit, credit information, interest rate and distance to a lender turned out to be statistically insignificant, which suggests that these variables did not matter for both groups' technical inefficiency. However, we can also suggest some possible reasons for their insignificance. Extension visit and credit information might be insignificant perhaps because farmers had only a few visits to extension offices and had only limited credit information that perhaps did not add much to his/her existing information base. It may also be the case that farmers' technical efficiency may not improve by mere increase in farmers' extension visit and credit information. In this connection, for example, Alene & Hassan (2006) argue that poor communication skills of extension agents and low extension-agent-to-farmer ratio would pose a limit to the number of beneficiary farmers in extension service. Similarly, lack of organized credit market information and farmers' lack of it can also contribute to the insignificant effect of the variable. This in turn implies that better qualities, rather than mere presence, of these services can have more relevance.

As regards the variable *distance to lenders*, perhaps it was insignificant because there was no considerable variation among farmers to equally inaccessible lenders. If not, it suggests that distance may not matter if other components of the transaction costs (such as paper works, speed of loan processing and disbursement) can be significantly reduced. Similarly, costs or some barriers other than the interest rates might be more important to improve the credit constraint situation and its subsequent efficiency effects.

6. Conclusions and policy implications

In this paper, we first tested for statistical difference between credit-constrained (CCFHs) and unconstrained farm households (CUFHs). We found that the group of farm households were statistically different in their credit-constraint status. Based on this result, we then estimated technical efficiencies of CCFUs and CUFHs using parametric stochastic frontier technique. We found that the mean technical efficiency scores for CCFHs and CUFHs were estimated at 55% and 67%, respectively, which means that the two groups of farm households, on average, had technical efficiency difference of 12 percent. Although the credit constraint was the main focus of this study, additional factors were also controlled for. It was found that the technical efficiencies of both groups of farm households were significantly affected by farmers' education, land fragmentation and loan size. Besides, the efficiency of the CCFHs was influenced by their farm experience and wealth, and that of the CUFHs was affected by household size, as related to family labor supply.

The results suggest that credit availability and loan size, farmers' education and landholding structure need to be improved for all farmers. Moreover, especially for CCFHs, farm experience (as related to farm management skills) and household wealth (e.g., through better facilities and incentives to increase saving and capital accumulation) require improvement. In general, the study demonstrated that farmers are not homogenous in their demand for credit and subsequently in their credit constraints, and this has important effect on their technical efficiency.

Agricultural credit policies generally aim at alleviating credit constraints of farmers in order for farmers to be able to increase their output production by producing at maximum possible technical efficiency. In light of this, the results of this study suggest that for a loan to result in higher technical efficiency, it needs to adequately satisfy the effective credit demand of the farmers.

Given the largest proportion of the CCFHs in the Ethiopian farming population, the 12% gap in technical efficiencies of CCFHs and CUFHs suggests that there is considerable potential loss in output due to inefficiency, which calls for a policy measure that would address credit constraint problem of both groups of farm households in general, and those of the credit-constrained group, in particular.

On the one hand, a "blanket supply" of credit to all farm households without considering their difference in effective credit demand and constraint status would not guarantee that such a credit supply would result in alleviation of farmers' credit constraints. On the other hand, and more importantly, the credit-constrained group would be less efficient than the unconstrained ones, resulting in low level of outputs. This, in turn, will adversely affect the capacity of farmers to repay the debt. At the aggregate, this will also affect the effectiveness of credit supply.

The fact that the CUFHs are more technically efficient than the CCFHs suggests that a credit supply that is responsive to effective credit demand of farm households would result in higher outputs, which would also increase creditworthiness of the farmers. An increase in farmers' creditworthiness can raise lenders' incentive to extend more loans to the extent that the effective credit demand of the farmers is met. In other words, adequate credit would solve credit constraint and can increase technical efficiency, farm outputs and creditworthiness of borrowers to repay the debt.

On the contrary, it would be economically unattractive for farmers to receive loans that cannot meet their effective credit demand, as they will remain credit-constrained and cannot increase their efficiency. The implication of this result for lenders is that the farmers' effective demand for credit needs to be identified for different types of farmers before determining the size of loans to the farmers, since farmers are not homogeneous in their demand for credit. In developing countries, government intervention in a credit system, especially in agricultural inputs credit, spurred by credit market failure, often becomes ineffective, mainly because it is often delivered based on the implicit assumption that the farmers have similar demands for credit, thereby ending up in one-fits-all credit supply. This often does not tally with effective credit demand of some farmers. This is evident from the fact that a considerable proportion of respondents who received credit also reported being credit-constrained.

More often, significant credit defaults are reported in the formal credit sectors in developing countries. One possible cause could be that farmers might not attain the necessary technical efficiency that allows debt repayment if the loans could not meet their effective credit demand. However, ability to repay a credit, as related to higher output, could only be a necessary, but not a sufficient, condition for debt repayment. Besides one's ability to repay, factors affecting repayment incentives, in view of possible credit risk, also need to be assessed. This can be one area of future research.

Another important implication of the results for credit policy is related to the cost of credit supply. The insignificant effect of interest rates on the efficiency of farmers suggests that factors other than the direct cost of borrowing may be important to consider. For example, some farmers may find monetary and non-monetary transaction costs (such as paper works, loan processing speed and speed of loan disbursement) higher than the interest rates. In this case, lenders need to consider the effect of such costs on the demand for credit and devise strategies to reduce such costs, by using, for example, information technology (IT), which can lower costs of credit transaction, monitoring and evaluation. In the absence of IT facility, lenders need to consider proximity of branches of financial institutions to borrowers.

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ESTIMATING WEALTH EFFECTS WITHOUT EXPENDITURE DATA: EVIDENCE FROM RURAL ETHIOPIA

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Abstract

In economic studies, household economic status is usually proxied by measures of consumption or income. In recent years, several studies have advanced an asset-based index as an alternative measure of wealth status. In most studies, the asset-based wealth index is constructed with a standard list of assets comprising household ownership of consumer durables, the characteristics of the household's dwelling and sometimes household landownership.

Although a standard list may be useful when comparing households across countries or urban and rural residents in one country, the assets included may not always be relevant for studies focussing on rural areas or a particular rural area only. This paper addresses the question what assets should be included in the wealth index to the best reflect long-term economic status in rural Ethiopia. We use data from the Ethiopian Rural Household Survey (ERHS) collected in 1994 and 1995 to construct several asset-based wealth indices. We find not all standard assets are relevant locally and signs and heights of factor loadings differ substantially between localities, supporting the case of specified (local) asset listings. The specified asset index performs best compared to other asset indices when considering the distribution of food security across wealth quintiles and is at least as good a predictor of food security as per capita consumption measure for the same households.

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1 Introduction[2]

In the past decade, several studies have advanced an asset-based index as an alternative measure of economic status. The indices used in these studies are based on a defined set of household assets including housing characteristics and durables. This measure of economic status is much easier to construct and far less demanding in terms of data collection compared to the conventional consumption or income based proxies used to compare outcomes across different economic groups. Asset-based wealth indices have, for example, been used to estimate the effect of wealth on educational attainment (Filmer and Pritchett, 1999) and nutrition status or to assess changes in poverty over time (Sahn and Stifel, 2000).

Although some studies have discussed the validity of an asset-based proxy for economic status versus an income or consumption based proxy (Sahn and Stifel, 2003, Filmer and Pritchett, 2001, and Lindelow, 2002) little attention has been given to the type of assets to be included in the index.[3] The wealth indices used in the literature so far are based on a more or less standard list of items including assets relating to housing conditions and ownership of consumption durables, sometimes extended to include productive capital (such as land) or human capital (level of education of the household head). The choice of assets is hardly ever discussed. The most commonly used assets for the index include durables such as television, fridge, car and access to electricity. Such assets may be relevant to construct a measure of economic status to make comparisons across countries or households at a national level, comprising both urban and rural households; they seem to be less relevant for a study conducted in poor rural communities. Even less so in more disaggregated studies, e.g. focussing on one village in specific, where ownership of particular assets, such as toilet facilities, may not vary within a village.

This leads to an important question that is central to this paper: What assets should be included in an asset-based wealth index that can be used as a control variable in research in rural Ethiopia? The availability of household data on both assets,

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[3] Moser (1998) addresses this question in a qualitative way while Filmer and Pritchett (2001) perform a robustness check on the type of assets included.

consumption and food security from the 1994/1995 round of the Ethiopian Rural Household Survey (ERHS) allows us to compare the relevance of five differently composed asset-based wealth indices and to explore geographical differences in terms of the importance of these assets. Looking at the factor loadings on assets, we find substantial differences across villages and argue for a location specific asset-based wealth index for studies at a disaggregated level. We also measure the effect of these five indices and per capita consumption on household food security, an important issue in Ethiopian livelihoods. In this paper, we use a self-reported food security measure, counting the number of weeks in a typical year that households have substantially less to eat than otherwise. The specified asset index performs best compared to the other indices when considering the distribution of food security across wealth quintiles and is at least as good a predictor of food security compared to per capita consumption measure for the same households.

The remaining part of this paper is organised as follows. Section two elaborates on the use and composition of asset-based indicators of wealth in the literature. Section three describes the data and methodology. In section four, we present five different wealth-indices while section five discusses geographical differences in terms of importance of assets. In section six, we use the asset-based wealth index to estimate the effect of economic status on food security. Section seven concludes.

2. Asset-based wealth indices

Economists have long relied on money-metric measures of income or consumption expenditures as indicators of poverty or living standards. These money metric measures are used as proxies for economic status. One of the most common criticisms of these measures is that they at best capture temporal dimensions of poverty as they measure consumption or income at only one point in time. For this reason, they may not reflect long-term economic status.[4] At the same time, collecting the information necessary to construct such a money metric measure is time consuming and especially in developing countries the data collection and metric construction is often constrained by measurement problems (Sahn and Stifel, 2003).

In the past decade, several studies have advanced an asset-based index as an alternative measure of economic status. See, for example, Sahn and Stifel (2000 and

[4] For a detailed discussion on the distinction between consumption expenditures and income as measures of household welfare, we refer to Deaton and Zaidi (2002) They argue consumption expenditures are a more precise measure of long term welfare compared to income, given the fluctuation in income streams, especially in rural areas where levels of income strongly depends on seasons and weather conditions while consumption is more smoothed over time.

2003), Filmer and Pritchett (1999 and 2001), Morris et al. (2000). The index used in these studies is a weighted sum of a defined set of household assets (including housing characteristics and durables) that is used to rank households and construct wealth quintiles. Compared to measures based on consumption, the data required to construct a wealth index are less demanding and the measure is simpler to calculate.[5] An asset-based wealth index may also capture dimensions of poverty not reflected in a one-time measurement of consumption or income, as is advanced by Sen (1985) in the capability approach or more recently in the livelihood-framework (see, for example, Ellis, 2000). More importantly, asset-based wealth indices have been shown to be at least as good predictors of outcome variables of interest such as nutrition or school enrolment, as are conventionally measured consumption expenditures (Filmer and Pritchett, 2001, Sahn and Stifel, 2003).

In most cases, the wealth index is used to compare outcomes across groups with different economic status, either at a national level or across countries, using nationally representative surveys. An index-based approach has, however, also been used at a more disaggregated level. See, for example, Janssens (2005) who uses a household asset index as a proxy for household wealth in measuring the externalities of a women's empowerment programme in the state of Bihar, India.

Filmer and Pritchett (2001) compare an asset-based wealth index with consumption expenditures and find a strong correlation between the index and per capita output and poverty. Yet, Sahn and Stifel (2003) argue it is not meaningful to consider the correlation between the asset index and consumption expenditures, as both are proxies for welfare and measure long-term wealth with error. Along these lines, they suggest it is more important to measure the impact on outcomes and evaluate the predictive power of asset-based wealth indices and consumption expenditures on child health and nutrition. Comparing indicators of relative measurement error[6], they show that the asset index they use measures long-term wealth with less error than expenditures. They suggest researchers may actually prefer to use the asset index as an explanatory variable in studies on economic welfare and capabilities such as health and nutrition.

Most of the asset-based wealth indices currently used in the literature consists of at least two sets of assets. The first is a set of household or housing characteristics, such as the availability and type of toilet facilities, type of water sources for drinking, type of building material used for walls, floors and roofs, access to electricity and the

[5] This is not to say that asset data are measured without error

[6] The indicator of relative measurement error is defined as the ratio of OLS to IV estimators of the two measures.

type of cooking fuel used. The second is a set of durable consumption goods whose ownership is expected to be indicative of wealth, such as a television, watch, refrigerator, bicycle, motorcycle, car, telephone, sewing machine and/or stove. Also, to varying degrees, other dimensions of wealth are included such as the education of the household head (Sahn and Stifel, 2000 and 2003), ownership of land (Filmer and Pritchett, 2001), the number of household members per room (Lindelow, 2002) and having a kitchen separate from bedrooms (Filmer and Pritchett, 2001).

The use of a standard list of assets is useful when comparing groups on a (cross-) country level, as it comprises information on what distinguishes the rich from the poor regardless of the place of residence (urban versus rural). In case one wants to use the wealth index as a control variable in an analysis at a lower level of aggregation, for example one village located in a poor rural setting, such a standard list including the ownership of durables such as a television or a car, may not be the most relevant. The challenge, then, is to define the assets relevant for the construction of a locally relevant wealth index.[7] In this paper, we explore this question for Ethiopia, where data from a large survey are available to allow comparison across localities and with a consumption measure.[8]

3. Data and Methodology

To construct and compare asset-based wealth indices and estimate the relation between long-term economic wealth and food security we use data from the Ethiopian Rural Household Survey (ERHS) collected in 1994 (two rounds) and 1995 (1 round) by the Department of Economics of Addis Ababa University in collaboration with the Centre for the Study of African Economies of Oxford University. The survey covers 20 sites and approximately 1450 households and captures many of the major socio-economic groups, agro-ecological zones and farming systems in Ethiopia. For more information on the dataset, we refer to Bigsten (2003) and Dercon (2004). The available data set covers a wide range of information, including asset ownership, food security and household consumption. We use information from different rounds to construct the asset-based wealth index and analyse a self-reported food security measure collected in 1995: the number of weeks in a typical year in which the

[7] Similar arguments are currently made in the literature on poverty lines based on Cost of Basic Needs (CBN) consumption measures where the use of a single consumption bundle to construct a national poverty line has shown to yield inconsistent poverty comparisons and the use of region-specific basic needs bundles is now advocated (Tarp et al. 2002).

[8] This data was used to select assets to construct an asset based wealth index for a study on intra-household risk coping, see Dekker (2008).

household has substantially less to eat than otherwise.[9] Data on asset ownership, housing and access to water were collected in the first round in 1994, while information on energy use and toilet facilities was asked in 1995. The aggregate household consumption measures used in this paper are constructed using the two 1994 rounds and have been provided by Bereket Kebede.

The construction of an asset-based wealth index is based on the assumption that wealth or economic status is a latent variable. We assume that economic status is the common factor behind the ownership of the assets, such that household economic status explains the maximum variance and covariance in the asset variables. Such factors can be extracted from a set of variables by creating a set of mutually uncorrelated components or factors of the data using principal component or factor analysis. The first linear component is that linear index of the underlying variables that captures most common variation among them. Each item, in our case asset, gets a different weight reflecting the contribution of this asset to the common factor. Principal component analysis only uses the variation in the variables that they have in common with other variables (communality), while factor analysis uses all the variability in a variable to extract the factors and also allows for a unique contribution of each of the assets (often referred to as uniqueness).[10]

In this paper, we will use both factor analysis and principal component analysis as outline below. Since we assume there is one common factor behind the ownership of the assets, household economic status, we use principal component analysis to derive the final weights for each asset (the factor loading) and to construct the index.[11] Ranking households on their score on the index then allows us to construct wealth quintiles where the first quintile represents the 20 percent of households with the lowest score on the wealth index the fifth quintile represents the 20 percent of households with the highest score on the wealth index.

[9] As respondents were asked to reflect on the situation of a "typical" year, rather than the situation they were experiencing at the time of the interview it is expected that this measure gives a more general impression of food security over time. It is however possible that the particular situation of a respondent in 1994 has affected the answer given to this question.

[10] Earlier studies have used both principal component analysis and factor analysis to derive the weights for the assets and construct the indices. Comparisons of the outcomes have shown no significant differences between the two methods (Sahn and Stifel, 2003, World Bank, undated).

[11] In practice, results obtained with factor analysis and principal component analysis are very similar.

Table 1: Variables used to construct wealth index in Young Lives Project Ethiopia[12]

Housing Quality	Consumer Durables	Services
Rooms/person *	Radio *	Electricity
Quality wall *	Fridge	Water *
Quality roof *	Bicycle	Sanitation *
Floor Durability	TV	Cooking Fuel *
	Motorbike/scooter	
	Motor car/truck	
	Mobile phone	
	Landline phone	
	Modern bed *	
	Table or Chair *	
	Sofa *	

Source: Alemu et al. (2003)
* Available in ERHS 1994/5

We will compare five asset-based wealth indices. First, the standard list of assets commonly used in the literature (see for example, Filmer and Pritchett, 2001). Second, the index used in the Young Lives project composed of the assets listed in Table 1. Third, an extended index including an extensive list of durables available in the ERHS. Based on the importance of particular assets in these three indices, we compose a fourth, specified index containing the most relevant assets in the rural Ethiopian context, using the uniqueness score calculated in factor analysis. Variables with low factor loadings and a high score on uniqueness contribute little to the common factor economic status and can therefore be excluded.[13] As a cut-off point, we use a uniqueness-score of 0.95: assets with a uniqueness-score higher than 0.95 will not be included in the index.[14] Finally, in the specified+ index we add information on the ownership of oxen, as this is an important productive asset in agriculture. As the sale of cattle may be an important consumption smoothing strategy, the results obtained with this index should, however, be interpreted with care.

The data set does not contain information on all assets that have been used elsewhere in the literature and not all asset variables are measured in the same way.

[12] Alemu et al (2003) used a slightly different approach compared to the studies mentioned above as the three components and different assets within the components received equal weights.
[13] This may be relevant for housing characteristics that are at least to some extent determined by the possibilities that are locally available; even wealthy households may not have a flush toilet or piped water sources when the technology (for instance, sewage or a tube system for water) is not locally available. This is especially relevant for toilet facilities, source of drinking water, electricity and to a lesser extent in relation to building material and cooking fuel.
[14] This cut-off point was empirically determined and is arbitrary. Future work should establish the sensitivity of the index to this cut-off point.

This may account for some of the differences we will find. It is also important to realize that the data used in this paper was collected more than 10 years ago and that over time, different or additional assets are indicative of long-term wealth or economic status, such as, for example, the mobile phone that is included in the asset-based wealth index used in the Young Lives project. Consequently, and also following from our subsequent analysis it will be important to have information on the situation in the particular site before deciding on the type of assets to be included in a survey instrument.

4. Assets and indices

Table 2 presents factor loadings and uniqueness-scores of the assets included in the five indices. These reflect the contribution of the variable to the common factor and the variation in the variable not in common with other assets respectively. The second column shows the scores on the assets that are commonly used in the literature on asset-based wealth indices, the standard index. We find high factor loadings on assets related to housing, with the clear exception of the availability of toilet facilities (latrine or flush), while the factor loadings on durables are relatively low. It should be noted, however, that the latter scores are comparable to the loadings on durables found by Filmer and Pritchett (2001); while the loadings on housing facilities found in the ERHS data are relatively high compared to other studies. Of the additional assets included in the so-called Young Lives Index (third column), only a bed seems to make a meaningful contribution to the wealth index. The factor loadings on sofa and table are low and the latter has a negative rather than an expected positive sign. The extended index presented in the fourth column includes a wide range of durables on which information is available. Most of these have a low factor loading and high uniqueness and therefore only marginally relate to our common factor economic status. Only a cart, a torch and a leather mat seem to be relevant. The latter is confirmed by qualitative information on asset-based wealth from Bevan and Pankhurst (1996).

Based on the uniqueness-score in these three indices, we constructed the fourth, specified index, by excluding toilet facilities and rooms per capita from the standard list of housing facilities and added cart, bed, torch and leather mat to the standard list of durables (fifth column). In the specified+ index in the sixth column, we also include oxen, an important asset in agricultural societies. The factor loading on oxen is considerable, reflecting a relevant contribution to the underlying factor. The eigenvalue-score reported that in the last row of Table 2 allows us to say something about the fit of the wealth index. It gives an indication on the proportion of the total variance in the asset variables that is captured by the factor extracted with principal component analysis. The first factor derived in the specified index has an eigenvalue of 2.94, while the specified+ index has an eigenvalue of 3.02. In these cases, the eigenvalue of the first components is slightly lower compared to those reported for other African countries in Filmer and Pritchett (1999).

5. Geographical differences

The asset weights and indices discussed so far in this paper have been constructed and determined using the whole sample, covering 19 survey sites.[15] Given the diverse nature of the socioeconomic groups, agro-ecological environments and farming systems covered by the survey sites, it is expected that the assets included in an index will not be equally important in all sites. To explore these issues further, we compare factor loadings on the assets across the villages included in the sample on the specified index composed in the previous section. We extend this index with three assets from the standard list that appeared not to be relevant in the analysis presented in the previous section (toilet facilities, cooking fuel and the number of persons living in one room) to explore potential reasons for low factor loadings on these assets in the rural Ethiopian context. The village specific factor loadings are listed in Table 3. Comparing the loadings on assets across villages provide us with at least three important insights.

First, in each village some assets are dropped from the list such as piped water, a well, a leather mat or a cart. This is the case when there is no variation in ownership of that asset in a village, either because all households own/use a particular asset or because no one owns or uses the asset. When conducting an analysis at a national level, this is not problematic as there is still variation in ownership across villages. At a village level however, the number of assets on which the index is based will reduce and one may want to think about adding assets that are locally relevant in distinguishing wealth differences.

Second, we see opposite signs on the factor loading for each asset across villages, meaning that ownership of an asset does not have the same type of effect in each of the villages. To some extent, this explains the low factor loadings on an asset at a national level; high positive loadings in some villages and high negative loadings in others single out into a low loading at a national level. One can, for example, compare the factor loadings on rooms per capita in village two and three. This means that an asset that is locally important in marking wealth differences between households does not get much weight in an asset-index used to capture wealth at a

[15] One site has been excluded from this analysis because of missing data on one or more of the variables included.

national level. Although this may not be problematic when interested in wealth effects at a national level, using the nationally representative weights at a disaggregated level will result in biased results. Moreover, excluding assets that do not contribute much to a factor at a national level may not be correctly reflecting the situation in a village.

Third, and related to this, even when most of the loadings on an asset have the same sign, the size of the loading can differ quite substantially across villages. This is for example the case for radio ownership that has a factor loading higher than 0.5 in village 10, 11, 12, 14 and 19, a particularly low factor loading in village 1, 2, 3, 5 and 8 and a low negative load in village 6 and 9. Similarly, there are considerable differences across villages in the variation explained by the first component and its eigenvalue.

These findings suggest one has to be careful in using a standard list of assets to construct an asset-based wealth index for the analysis of wealth differences at disaggregated levels. Assets that may be relevant to distinguish wealth differences at a national level may not provide a relevant distinction at a local level as ownership of that particular asset may not capture wealth differences in a specific locality.[16] It is, therefore, advisable to work with a list of assets that is more specified to the local situation. Additional information such as previously collected quantitative data or qualitative information on wealth dimensions will be essential in selecting the assets for a locally relevant index and possibly in constructing the data collection modules used in household surveys. [17]

6. Asset-based wealth indices and food security

In the previous sections of this paper, we have reviewed what assets could/should be included in an asset-based index for economic status in rural Ethiopia and discussed geographical differences in factor loadings on included assets across villages. We found the standard list of assets to proxy for economic wealth can be included in an analysis at a national level, but when the analysis is confined to a lower level of aggregation, especially when covering only one village, the standard list may not be sufficient. In such a case, the researcher should construct a locally relevant list of

[16] Another issue relevant to the level of aggregation is intra-household differences in wealth. Distinguishing wealth differences within the household will require even more detailed information about the local situation.

[17] Alternatively and when available, a comparison to consumption data can be made, and the asset-based wealth index may be used as a complement to consumption data. This paper however refers to a situation when no consumption data is available or when consumption data will not be collected.

assets, for example, by taking the relevant items from the standard list and extend it to include location specific assets.

To move away from the composition of the asset-based wealth index *per se*, and following Sahn and Stifel (2003) we turn to the use of an asset-based wealth index in estimating wealth differences in outcomes in this section and make a first comparison of outcomes and estimations based on asset indices with those based on per capita consumption. In this case, we focus on the relationship between wealth and self-reported food security, the number of weeks in a typical year that a household has substantially less to eat than otherwise. Of the 1404 households in the sample who answered this question, only 17 percent indicated they did not have any week in which they had substantially less to eat in a typical year. Of those who did report temporal food shortages, the average number of weeks was 13.3, with a minimum of 2 and a maximum of 52. The average number of weeks with substantially less to eat differs greatly across villages, ranging from 4.5 to 18 weeks.

A first glance on the relation between household economic status and food security is provided in Table 4. In this table, we list differences in the mean number of weeks in a typical year that a household has less to eat per wealth quintile, and expect to find a decreasing number of weeks with increasing wealth. We constructed six sets of quintiles, five sets based on the asset-based wealth indices discussed in section four and for comparison one set based on per capita consumption figures (the mean per capita consumption as measured in the two rounds in 1994). The distribution based on the standard asset list of quintiles shows the mean number of weeks a household has substantially less to eat decreases per quintile, although there is no difference between the second and the third quintile. The distributions based on the Young Lives, Extended Assets and Specified Asset-indices provide counter-intuitive results; the mean number of weeks for households in the third quintile is higher compared to those on the second quintile or even the first quintile (Young Lives). This is not the case for the specified assets-index including oxen, where the distribution of the number of weeks descends for the richer quintiles. For all asset-based indices, the mean scores for the three poorer quintiles are much closer together compared to the two richer quintiles.

In comparison, the mean number of weeks calculated for per capita consumption quintiles also shows the expected pattern; for each quintile the number of weeks in a typical year in which the household has substantially less to eat decreases when wealth, proxied by per capita consumption, goes up. The mean number of weeks in the fifth quintile, 9.2, is, however, substantially higher compared to the mean number of weeks based on the asset-based wealth indices.

To investigate the relationship between wealth and food security further, we perform a number of descriptive regression analyses. We regress the number of weeks in a typical year that a household has substantially less to eat on a number of explanatory variables, including wealth indices. We perform six regressions to compare the predictive power of the five asset-based indices and per capita consumption. Apart from the wealth indices, we also included the total acreage of land a household has access to, indicative of its potential to produce food, the size of the household and a set of village dummies that capture amongst others regional differences in food producing potential. We expect richer households as well as households with more land to report a lower number of weeks with substantially less food (a negative coefficient) while larger households are expected to have a higher number of weeks with less food, given the fact they have more mouths to feed. As we use count data, the number of weeks in a typical year, we use a Poisson regression model.

The results are presented in Table 5. The sign on total land owned cannot be interpreted as it is not estimated with sufficient precision. The coefficients on household size and wealth have the expected sign and are significant, with the exception of household size in the per capita consumption regression. This suggests indeed that households with higher economic status experience fewer weeks with substantially less food than otherwise, relative to households with a lower economic status. The differences between the regression results of the five different wealth indices and per capita consumption are small, with slightly higher coefficients (and more precision in estimation of the coefficient and the model fit) for the two specified indices. Given the explorative nature of these analyses, the results should be interpreted as preliminary only. These preliminary results do, however, confirm the findings of Sahn and Stifel (2003) that asset-based indices of wealth are at least as good a predictor of outcomes as are expenditures.

From the analysis presented above it is not exactly clear how to interpret the exact relationship between economic status and food security. There may be a direct link between assets and food security as assets can be used to smooth consumption over time, as a source of income or by selling them. However, the assets included in the index are not those typically sold or used to generate income in response to food shortages or other shocks.[18] Alternatively, and in line with the argument of this paper, the ownership of assets signals economic status. In that case, higher economic status, reflecting for example higher (non-farm) income, may result in more and better options to smooth consumption. The analysis needed to unravel the precise

[18] The literature on buffer stocks predominantly refers to cattle as an important asset to be sold in times of stress (see for example Rosenzweig and Wolpin, 1993, and Kinsey, Burger and Gunning, 1998). If productive assets, such as cattle, are sold to smooth consumption, future food security may be put at risk.

mechanism behind the relationship between wealth and food security is beyond the scope of this paper. Yet, if these results were to be confirmed in other studies, a case could be made for using asset-based indicators of wealth to target of public interventions, whether on food security or in other fields. In such case, community-based (or district-based) targeting is likely to be most suitable to take the geographical differences in the ownership of specific assets into account.

7. Conclusion

This paper explored some issues related to the use of an asset-based wealth index as a proxy for long-term household economic status and extended the use of asset-based wealth indices to food security. In particular, we addressed the potential composition of an asset-based wealth index and considered the influence of geographical differences in asset-ownership and the relevance of the standard list of assets used in the literature for the context of rural Ethiopia.

To this end, we used ERHS data on asset ownership to construct five different asset-based wealth indices and compared the factor loadings on the assets included, both at a national level covering 19 villages and on a village-by-village basis. The standard list of assets used in an index to compare economic status across different communities in one country or across countries may be useful. However, some dimensions of wealth, such as the type of drinking water facilities or the type of building material used, are to some extent determined by the community or environment in which one lives. For this reason, the standard list may not be the most relevant list to capture wealth differences between households or individuals living in one community. A list of assets that is more specified to the local situation is, therefore, advisable. Additional information, such as previously collected quantitative data or qualitative information on wealth dimensions is, therefore, essential in constructing such an index and the data collection modules underlying it.

We also looked at the predictive power of an asset-based wealth index in explaining differences in food security. We find that households with a higher economic status experience significantly fewer weeks of food insecurity compared to households with a lower economic status. Moreover, the results suggest the relation between household economic status and food security is measured at least as precisely when we use an asset-based index of wealth compared to a wealth proxy defined as per-capita consumption. In such case, a well-defined list of assets may provide policy makers with an opportunity to distinguish households capable of smoothing consumption from those who are not, making it easier to target food security interventions.

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Table 2: Factor loadings and uniqueness scores on assets for five different wealth indices

Assets included in the index:	Wealth index: standard assets		Wealth index: Young Lives Project		Wealth index: Extended ERHS asset list		Wealth index: specified asset list		Wealth index: specified +	
	Load	Uniq	Load	Uniq	Load	Uniq	Load	Uniq	Load	Uniq
Toilet	0.028	0.999	0.022	0.999	0.028	0.999				
Piped	0.566	0.680	0.540	0.708	0.575	0.670	0.569	0.676	0.551	0.697
Well	0.286	0.918	0.287	0.917	0.238	0.943	0.253	0.936	0.271	0.927
Open water	-0.594	0.647	-0.577	0.667	-0.574	0.671	-0.578	0.666	-0.562	0.685
Fuel	0.191	0.963	0.187	0.965	0.190	0.964				
Iron roof	0.653	0.574	0.642	0.588	0.637	0.594	0.654	0.572	0.652	0.575
Thatch roof	-0.577	0.667	-0.566	0.680	-0.571	0.674	-0.575	0.669	-0.563	0.683
Mud wall	0.731	0.465	0.747	0.441	0.728	0.471	0.724	0.476	0.725	0.474
Wood wall	-0.734	0.462	-0.750	0.437	-0.735	0.459	-0.722	0.479	-0.711	0.494
No. residents per room	-0.126	0.984	-0.117	0.986	-0.112	0.987				
Radio	0.258	0.933	0.262	0.932	0.265	0.930	0.272	0.926	0.294	0.914
Watch	0.221	0.951	0.225	0.949	0.205	0.958	0.221	0.950	0.242	0.942
Bed			0.251	0.937	0.209	0.956	0.220	0.950	0.265	0.930
Table			-0.1823	0.967	-0.181	0.967				
sofa			0.035	0.999	0.020	0.999				
Cart					0.215	0.954	0.227	0.949	0.248	0.938
Torch					0.249	0.938	0.278	0.939	0.248	0.939
Mill					0.025	0.999				
Cup-board					-0.042	0.998				
Pouch					0.036	0.999				
Weaving equipment					0.008	0.999				
Leather Mat					0.367	0.865	0.363	0.868	0.315	0.901
Oxen									0.345	0.881
Eigenvalue first factor	2.76		2.83		3.00		2.94		3.02	

Source: ERHS

Table 3. Factor loadings on asset index across different villages (numbered 1-20).

Asset	1	2	3	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Piped	0.781	-	0.052	-	-	0.107	0.187	-	-0.399	0.713	0.063	-0.214	-0.106	0.221	-	-	0.187	-	-0.017
Well	0.150	0.236	-	0.500	0.851	-0.112	-0.028	0.544	-	-	0.604	-	-0.047	-	-	-	-	-	-
Open water	-0.779	-0.408	-0.179	-0.530	-0.268	0.042	-0.102	-0.544	0.579	-0.633	-0.280	0.303	0.074	-0.437	-	0.583	-0.473	-0.492	0.659
Iron roof	-	0.034	-	0.727	0.842	0.830	0.817	-0.086	0.829	0.634	0.304	0.885	0.734	-0.566	-	-0.433	0.494	-0.514	0.428
Thatch roof	-	-0.691	0.702	-0.685	-0.704	-0.767	-0.818	0.585	-0.802	-0.634	-0.517	-0.807	-0.741	0.665	-	0.462	-0.369	0.125	-0.823
Mud wall	-0.316	0.391	0.869	0.755	0.847	-0.587	-0.361	-0.818	0.185	0.675	-	-0.040	0.701	0.430	-0.976	-0.486	0.707	0.740	0.515
Wood wall	0.250	-	-0.474	-0.755	-0.805	0.337	0.363	0.854	-0.166	-0.675	-	0.040	-0.701	-0.468	0.976	0.727	-0.351	-0.760	-
Radio	0.076	0.041	0.046	0.088	-0.045	0.495	0.021	-0.023	0.599	0.503	0.842	-	0.682	0.200	0.084	-0.210	0.473	0.634	-0.091
Watch	0.351	0.336	0.494	-0.424	0.373	0.191	0.420	-0.065	0.284	0.661	0.588	0.682	0.344	-0.166	0.054	-0.313	0.093	0.320	0.059
Bed	-0.128	-	-0.393	0.656	0.356	0.308	0.479	-0.150	0.528	0.492	0.808	0.190	0.395	0.351	0.017	-0.435	0.502	-0.405	-0.256
Leather mat	0.520	0.150	-	-	-	-0.191	-0.270	-	-	-	0.381	-	-	-	-	-	-	-	-
Torch	-0.053	0.728	-0.291	0.289	-0.108	0.539	0.314	-0.119	0.298	0.122	0.381	0.605	0.060	0.199	0.193	-0.195	-0.455	0.149	0.606
Cart	-	-	-	-	-	0.529	-	-	0.654	0.511	-	-	-	-	-	-	0.133	0.450	-
Toilet	-0.090	-	-0.091	-	-	0.364	0.237	0.169	0.560	0.726	0.358	0.336	0.167	0.065	-0.306	0.570	-	-	0.211
Fuel	0.198	-0.385	0.112	0.159	-0.146	0.196	0.251	0.129	0.187	0.675	0.186	-	0.216	0.207	-0.070	-0.595	0.272	0.174	-0.659
Rooms pc	-0.205	0.398	0.549	-0.333	0.075	0.122	-0.192	0.114	0.242	0.023	-0.166	0.068	-0.190	0.387	0.167	0.378	-0.116	-0.215	-0.211
Proportion	0.15	0.17	0.19	0.29	0.31	0.18	0.16	0.19	0.25	0.34	0.24	0.23	0.21	0.14	0.23	0.22	0.16	0.22	0.21
Eigenvalue	1.91	1.83	2.31	3.5	3.67	2.93	2.38	2.44	3.53	4.82	2.84	2.56	2.94	1.83	2.10	2.70	2.06	2.62	2.53

Source: ERHS

Notes: the numbers in the column represent the villages in the ERHS.

Table 4: Relation between asset-index and food security: mean number of weeks with substantially less to eat per wealth quintile based on the different type of indices

Type of index	First quintile	Second quintile	Third quintile	Fourth quintile	Fifth quintile
Standard	13.1	12.6	12.6	10.0	7.0
Young Lives	13.0	12.5	13.2	10.1	6.7
Extended Assets	13.0	12.6	13.0	9.6	7.2
Specified	13.6	12.2	12.7	9.5	7.3
Specified +	13.5	12.6	12.3	9.8	7.1
Percapita consumption (mean)	13.6	12.3	10.4	9.8	9.2

Source of data: ERHS

Table 5: Poisson regression of the number of weeks in a typical year that a household has substantially less to eat, random effects model

	Standard	Young Lives	Extended	Specified	Specified +	Pc cons[§§§§§§§]
Total land	-0.002 (-0.59)	-0.002 (-0.49)	-0.002 (-0.48)	-0.002 (-0.50)	-0.000 (-0.05)	-0.002 (-0.62)
Household size	**0.013 (4.40)**	**0.014 (4.40)**	**0.014 (4.35)**	**0.012 (3.95)**	**0.015 (4.71)**	0.005 (1.74)
Wealth	**-0.193 (-13.02)**	**-0.195 (-13.12)**	**-0.203 (-13.30)**	**-0.212 (-14.18)**	**-0.230 (-15.41)**	**-0.027 (-4.68)**
Pseudo R-squared	0.1915	0.1917	0.1920	0.1938	0.1964	0.1816
Observations	1399	1399	1399	1399	1399	1399

Source of data: ERHS

Notes: Village dummies included, coefficients not reported in the table.

t-values in brackets

Bald figures are significant at 0.05 level

[§§§§§§§] In 1000 birr