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Decomposing Sources of Productivity Change in Small-Scale Farming in Ethiopia

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Decomposing Sources of Productivity Change in Small-Scale Farming in Ethiopia

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Office of the Chief Economist

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Abstract

The average farm size in Ethiopia is shrinking and the option for expanding the land frontier is also very limited. As a result, increasing farm productivity is critical for achieving higher growth and national food security. Identifying the drivers of productivity and weighing their significance are therefore vital for effective policy making. This paper applied a stochastic input distance function to decompose and test the significance of economic efficiency improvement in boosting the productivity of small-scale farmers. The results show that small-scale farming exhibits scale, technical and scope economies and thus the opportunities for increasing productivity through improving efficiency alone is significant. However, most of the improvement in efficiency in the immediate term is expected to come from the increase in the technical, mix, and scope efficiencies. Farmers that cultivate diverse crops are technically more efficient and are also able to realize economies of scope and scale than farmers with specialized production. While farmer specific factors played some roles, most of the inefficiencies are traced to externally imposed policy and institutional constraints. Addressing market failures and enhancing competition in the goods and factor markets, particular those that led to further land consolidation, will have a significant impact on farm productivity.

***JEL classification*: Q1, Q12, D2.**

***Key words*: efficiency, productivity, distance function, small-scale, farming, Ethiopia.**

1. Introduction

Agriculture in Ethiopia is the key sector accounting for the bulk of the gross domestic product, employment, foreign exchange earnings, and tax revenue (Chavas and Di Falco, 2012). The pattern and pace of growth of the sector consequently have significant ramifications for the overall economic growth rate and the rate of poverty reduction that can be achieved. In recent years, the sector has registered growth, which was mainly driven by area expansion, with some contributions from improved terms of trade of farm commodities. Given the limited options for expanding the land frontier—particularly since such a strategy rests on unsustainable depletion of forest resources and erosion of soil fertility—improving productivity of the existing land is critical. Increasing productivity is also essential for maintaining the global competitiveness of the sector and mitigating the impacts of climate change. Effective public policy making in the sector therefore requires identifying the potential sources of productivity growth and testing their significance (O'Donnell, 2009).

In the agriculture sector, technical change and improvements in economic efficiency are the main drivers of productivity growth. Technical change, which shifts the production frontier, usually occurs in the long term, and economic efficiency improvement is the most important source of growth in the short to medium term (Bravo-Ureta and Pinheiro, 1997; Rasmussen, 2010). Improvements in economic efficiency also can be subdivided into improvements in technical, allocative, scale, and scope efficiencies. Improvement in technical efficiency occurs when resources are put to their best use and produce the maximum level of output possible. An increase in allocative efficiency comes from an improved ability to use resources in optimal proportions and produce a mix of outputs that are consistent with their market prices. If production technology is characterized by variable returns to scale, an improvement in farm productivity could also be achieved by changing the scale of operation and operating at the most productive scale size (Coelli et al. 2005). Similarly, if production is characterized by a multi-output and multi-input system, productivity improvement could also come by exploiting economies of scope that exist due to input jointness and the synergies and agronomic complementarities that exist within the production of different farm outputs (Chavas and Di Falco, 2014).

In the African context, there are accumulating evidences that the productivity gains that could come from improving technical efficiency, realizing economies of scale and scope alone are substantial, and even some claim that they may outweigh gains from technological progress (Rasmussen, 2010). Any public policy measures pursued to improve agricultural productivity must be therefore guided by an understanding of the sector's current achieved efficiency level, the potential sources of efficiency improvements and the policy instruments that would effectively bring about the desired efficiency improvements. Thus, testing for the presence and significance of the various sources of efficiency improvements would provide valuable information for policy making and strategy design.

Accordingly, considerable efforts have been made in testing for the presence of various sources of efficiency improvement, measuring their impact, and identifying the interventions that are still needed to further improve efficiency (O'Donnell, 2009). Although many studies have been conducted, few have been undertaken in the Ethiopian context. Most of the studies focus on technical efficiency, and the number of studies testing the significance of the other sources of efficiency improvement, particularly scope and scale, is limited (Irz and Thirtle, 2004; Ofori-Bah and Asafu-Adjaye, 2011; Chavas and Di Falco, 2014). The importance of realizing scope efficiency is particularly vital in situation where the land constraint is becoming more binding. Although some empirical findings show that economies of scope prevail in small-scale farming, their presence and importance in Ethiopia are under-investigated (Chavas and Di Falco, 2014).

The central goal of this paper is to measure and test the importance of the various sources of efficiency improvements in small-scale farming in Ethiopia (Paul and Nehring, 2005; Kim et al., 2012). Such analysis would not only shed light on the possible sources of productivity improvement and hence the policy measures required to realize them; but would also divulge the weaknesses of the existing policies (O'Donnell, 2008).

The main results of the analysis are that small-scale farming in Ethiopia is characterized by economies of scope and scale. Although farmers have achieved some level of efficiency improvement, the potential for further improvement is substantial. The total factor productivity in the study periods increased by 12%, with most of the improvement coming from improvements in scale efficiency (7.3%), mix efficiency (8.9%), and technical efficiency (8.3%). During the same period, however, technological regression occurred by 12%, which was likely caused by weather shocks as well as a decline in average fertilizer use. Farmers that cultivated a diversified crop portfolio were found to be technically more efficient and likely to realize economies of scope. Most of the improvement in efficiency in the short to medium term is expected to come from improving technical efficiency and by exploiting economies of scope and scale.

The remaining sections of the paper are organized as follows. Section 2 discusses the data and is followed by the methodology in section 3. The empirical model specification and estimation are discussed in Section 4, and section 5 covers the empirical results. The final section concludes with a summary and discussion of the policy implications.

2. The data

The data used in the analysis come from the Living Standard Measurement Survey of the World Bank. For the analysis, we used 2011–2012 and 2012–2013 survey data of 773 farm households. The samples included in the study were drawn from all regions that cultivate maize and other crops. The efficiency analysis considers the crop subsector only, and the crops included are maize and other crops. The share of each crop from the total value of crop production is used to aggregate the quantity of the crops included in the "other crops category" and subsequently deflated by the consumer price index. The production inputs considered are land, labor, and fertilizer. The cultivated land is measured in hectares and includes both owned and rented land. The labor input includes family, hired, and group labor and is measured in man-days. The fertilizer input, which is measured in kilograms, includes both organic and chemical fertilizers. The degree of crop diversification of the sample is measured by constructing a Herfindahl index. The education variable represents the educational attainment of the household head and is measured on a Likert scale, 0 for preschool, 1 for primary school, 2 for high school, and 3 for postsecondary. The summary statistics of the variables included in the empirical model are presented in Table 1.

(Insert Table 1 here)

As the summary statistics suggest, the levels of both inputs and outputs showed perceptible changes from one study period to the next. Between 2011 and 2013, the productions of all crops have increased. The levels of inputs used by the sample also showed some changes. While the labor and fertilizer inputs declined, the average amount of land cultivated increased. Similarly, crop diversity also showed a significant change. In 2013, the sample farm households produced a greater variety of crops on average compared to 2011. Although its impact on productivity has yet to be established, diversification may have enabled farmers to exploit scope economies and could be on contributor for the observed increase in productivity. Although it will be determined below, the descriptive statistics suggests that despite a decline in some of the inputs, the observed output increases must be explained by an increase in productivity. The number of households that participated in the extension program also increased significantly. This participation is expected to improve the farmers' managerial and technical skill and their technical efficiency.

Relatively high standard deviation of the variables compared to their mean, such as the size of land holding, suggests high heterogeneity of the sample both regarding access to inputs and volume of crops produced. As the efficiency analysis, in general, assumes that farmers are operating under identical resources, technology, and environmental conditions, such heterogeneity is expected to create biased parameter and efficiency estimates. To specify the efficiency frontiers while addressing such bias, the panel data model suggested by Greene (2005) will be used. Unlike the conventional frontier models, by allowing each cross-sectional unit to have a unit-specific intercept, this model disentangles time varying inefficiency from unobserved heterogeneity and, therefore, generates unbiased parameter estimates (Ibid, Belotti, et al., 2012). Given short duration of the data (two years), as the fixed effects model does not generate consistent parameter estimates, we employ the true random effects model (Greene, 2005).

3. Methodology

To decompose the components of productivity growth and test their significance, we postulate a parametric distance function. Besides its suitability for modeling multi-input and multi-output production technologies, the advantage of the distance function is that it does not require cost minimization or profit maximization assumptions that may not always be valid in the context of small-scale agriculture in Africa. In addition, and probably most importantly, the distance function does not require information on market prices of outputs and inputs, such as the value of family labor and the price of land, which are rarely available or are difficult to obtain in a ‘‘truly” exogenous form. Moreover, because input and output prices do not vary much within the cross-sectional unit, the use of the distance function is more appropriate than a cost function (Brummer et al., 2002). Besides, results from this function still hold whether markets are competitive or not.

The distance function can also be postulated as an input or output orientation. The choice depends on whether the input or the output comprises more of the “choice variables” or is considered less fixed (Coeli et al., 1998; Paul and Nehring, 2005). For the sample in this study, no obvious choice exists because both the extent of output and inputs can be interpreted as choice variables. However, assuming that farmers have more control over inputs than outputs, we specify an input distance function.

The input distance function measures the proportion by which the input vector could be contracted and placed on the technically efficient input isoquant, while still producing the same output vector. The efficiency of the units is, therefore, measured by the scale/proportion by which the inputs can be feasibly contracted and still produce a given output level. The input distance function introduced by Shephard (1970) is defined as

$$D_I^t(x_t, y_t, t) = max\left\{\emptyset \geq 1 \colon \left(\frac{x_t}{\emptyset}, y_t, t, r\right) \in L(y_t, t)\right\}, \qquad (1)$$

where $\emptyset$ is a scalar, and $L(y_t, t)$ is the set of all input vectors, $x_t = (x_{1t}, \cdots, x_{nt}) \in \mathcal{R}_+^N$, which in year *t* can produce the output vector $y = (y_{1t}, \cdots, y_{nt}) \in \mathcal{R}_+^M$.

The input distance function is nondecreasing, linearly homogeneous, and concave in *x*, but nonincreasing and quasi-concave in *y*. If $x \in L(y_t, t)$, then $D_I^t(x_t, y_t, t) > 1$; however, if x belongs to the frontier input set, then $D_I^t(x_t, y_t, t) = 1$. Since our interest is to measure and test the significance of the various sources of productivity growth by using the distance function, we apply the Malmquist productivity index, which was first suggested by Fare et al. (1994). Under the assumption of constant returns to scale, the Malmquist productivity index that is decomposed into technical efficiency and technical change over the adjacent periods can be written as

$$M_c = \frac{D_I^{t+1}(x^{t+1}, y^{t+1}, t+1)}{D_I^t(x^t, y^t, t)} \times \left[\frac{D_I^t(x^{t+1}, y^{t+1}, t+1)}{D_I^{t+1}(x^{t+1}, y^{t+1}, t+1)} \frac{D_I^t(x^t, y^t, t)}{D_I^{t+1}(x^t, y^t, t)}\right]^{1/2} \qquad (2)$$

The first term denotes the ratio of the distance of two different points from different technologies and measures the change in technical efficiency. The second term, which is the ratio of the distance of the same data points from two different technologies, measures the degree of technical change. However, in order to avoid the arbitrary choice of benchmark, the geometric mean of the two Malmquist indexes will be taken

(Fare, et al, 1994). To accommodate the other sources of productivity change, particularly scale efficiency, Orea (2002) later generalized the Malmquist productivity index and defined it as the difference between the average growth rates of outputs and inputs. After some rearrangement, the productivity index can be written as

$$lnM_c = -[lnD_I^{t+1}(x^{t+1}, y^{t+1}, t+1) - lnD_I^t(x^t, y^t, t)] - \frac{1}{2} \times \left[\frac{\partial lnD_I^t(x^{t+1}, y^{t+1}, t+1)}{\partial t} + \frac{\partial lnD_I^t(x^t, y^t, t)}{\partial t}\right] \quad (3)$$

The second term, which denotes the technical change, includes both neutral and nonneutral components of the technical change. To allow for nonconstant returns to scale and to accommodate the possible effect of scale change on productivity, and assuming an input-oriented distance function, the derivative of the distance function with respect to the outputs over the two adjacent periods can be included as an additional component[2] (Orea, 2002). Accordingly, the productivity index can be rewritten as

$$lnM_P = lnM_c + \frac{1}{2}\sum_{m=1}^{M}\left[\left(\left(\frac{\partial lnD_I^t(x^{t+1}, y^{t+1}, t+1)}{\partial y_m}\right)^{-1} - 1\right) \cdot e_{m(t+1)} + \left(\left(\frac{\partial lnD_I^t(x^t, y^t, t)}{\partial y_m}\right)^{-1} - 1\right) e_{m(t)}\right] \cdot ln\left(\frac{{y_m}^{t+1}}{{y_m}^{t}}\right) \quad (4)$$

Where $e_{m(t)} = \frac{\partial D_I^t(x, y, t)/\partial y_m}{\sum_{k=1}^{M}\partial D_I^t(x, y, t)/\partial y_k}$

If the underlying production technology is characterized by constant returns to scale (CRS), since the sum of the first derivative of the distance function with respect to the outputs is equal to one, all farmers are automatically efficient in terms of scale, and therefore the scale terms will disappear.

4. Parametric model specification and estimation

To empirically estimate the components of productivity change, choosing a particular functional form that the distance function will take is necessary. Ideally, the chosen functional form should impose minimum restrictions on the associations between inputs, outputs, and inputs–outputs. Due to its desirable properties[3], we use a translog functional form (Kumbhaka, 1989). Accordingly, introducing a time dummy to represent the technical change and considering *M* outputs and *K* inputs case, a second-order Taylor series approximation to the true distance function at a given data point can be approximated as follows[4]:

[2] The scale effect represents the productivity improvement that could come by changing the scale of operation to be the most productive. This source of productivity change, however, is present only if the production technology is characterized by variable returns to scale (VRS).

[3] Flexibility is a major desirable property first because it allows the data to determine the correct functional form rather than requiring assumptions about elasticities of production and substitutions among inputs and complementarity between outputs. Second, homogeneity and symmetry restrictions can easily be imposed; thus, the number of parameters to be estimated is reduced, saving degrees of freedom (Brummer et al., 2002).

[4] Although many factors could influence the relationship between inputs and outputs, hence the magnitude of the distance function, they are not considered here to enable remaining within the scope of our immediate objective.

$$lnD_{it}^{I}(x,y,t) = \alpha_o + \sum_{m=1}^{M}\beta_m lny_{mit} + \sum_{k=1}^{K}\gamma_k lnx_{kit} + 0.5\sum_{j=1}^{M}\sum_{k=1}^{M}\beta_{jk}\, lny_{jit}lny_{kit} + 0.5\sum_{j=1}^{K}\sum_{k=1}^{K}\gamma_{jk}\, lnx_{jit}lnx_{kit} + \sum_{j=1}^{M}\sum_{k=1}^{K}\delta_{jk}\, lny_{jit}lnx_{kit} + \alpha_T \mathrm{t} + \rho \mathrm{lnR}_t + \sum_{j=1}^{M}\sigma_j ty_{jit} + \sum_{k=1}^{K}\psi_k tx_{kt} \quad (5)$$

where all the other variables are as defined above, and *i* represents the farm household, *t* represents period dummy (2013 = 1), *R* represents the log of rainfall level during the wettest quarter in millimeters, and $\mathrm{tx_{jt}}$ and $\mathrm{ty_{jt}}$ are the interactions of time trend with the vectors for inputs and outputs, respectively.

The interaction terms are included to capture the neutral and nonneutral technical change component of the total factor productivity change[5] (Nishimizu and Page, 1982; Coeli[6] et al., 1998). To be consistent with theory, the distance function must be nondecreasing, concave, and homogeneous of degree one in inputs, and nonincreasing and quasi-concave in outputs (O'Donnell and Coelli, 2005). Symmetry requires $\gamma_{jk} = \gamma_{kj}$ and $\beta_{jk} = \beta_{kj}$. The restrictions required for homogeneity of degree one in inputs are $\sum\gamma_k = 1$, $\sum\gamma_{jk} = 0$, $\sum\psi_k = 0$ and $\sum\delta_{jk} = 0$.

To meet the homogeneity requirement of the distance function with respect to the inputs, we can normalize the function by one of the inputs: $D_I^t\left(\frac{\mathrm{x}_n}{x_i}, \mathrm{y}.t\right) = D_I^t(\mathrm{x},\mathrm{y}.t)/x_i$. In this case, the land variable will be used to normalize the inputs. Applying the natural log to both sides, the equality becomes $lnD_I^t(\mathrm{x},\mathrm{y}.t) - \ln x_i = lnD_I^t\left(\frac{\mathrm{x}_n}{x_i}, \mathrm{y}.t\right)$. Substituting the left-hand side and normalizing the inputs on the right side of equation (5) by x_i, while the homogeneity restrictions can be met, it also provides an observable variable on the left-hand side so that the model can be empirically estimated.
To empirically estimate the model, however, we need to make an assumption about the nature and distribution of the deviation from the frontier, that is, $\ln D_I^t(\mathrm{x},\mathrm{y}.t)$. The distance is generally assumed to be a composite of two error terms, μ_{it} and v_{it}. While the former denotes the systematic deviation from the input isoquant that arises due to technical inefficiency, the latter represents a deviation due to random factors that are beyond the control of the farmers as well as errors of econometric approximation of the distance function. Taking these error terms to the right side, the input distance function can be converted into a typical econometric model of the following form:

$$-lnx_{kit} = \alpha_o + \sum_{m=1}^{M}\beta_m lny_{mit} + \sum_{k=1}^{K-1}\gamma_k lnx_{kit}{}^{*} + 0.5\sum_{j=1}^{M}\sum_{k=1}^{M}\beta_{jk}\, lny_{jit}lny_{kit} + 0.5\sum_{j=1}^{K-1}\sum_{k=1}^{K-1}\gamma_{jk}\, lnx_{jit}^{*}lnx_{kit}^{*} + \sum_{j=1}^{M}\sum_{k=1}^{K-1}\delta_{jk}\, lny_{jit}lnx_{kit}^{*} + \alpha_T \mathrm{t} + \rho_R \mathrm{lnR}_t + \sum_{j=1}^{M}\sigma_j t * lny_{jt} + \sum_{k=1}^{K-1}\psi_k t * lnx_{kit} + v_{it} - \mu_{it} \quad (6)$$

The two error terms, μ_{it} and v_{it}, are assumed to be independently distributed. The random error term, v_i, is assumed to be independently and identically distributed as $N(0,\ \sigma_v^2)$. The systematic error term, μ_{it}, on the other hand is assumed to be nonnegative, independently distributed, and truncated at zero, but with a mean equal to θZ_{it}, where θ represents a vector of parameters to be estimated and Z_{it} is a *p×1*

[5] When technological change merely increases average output, including the time trend is sufficient. However, when we assume that technological progress changes the marginal rates of technical substitution among the inputs, including additional interaction terms is necessary.
[6] If the time and inputs interaction term has a positive effect, such as for labor, the result suggests that the technical change is labor augmenting; if negative, it is labor displacing.

vector of farm-, farmer-, household-, and community-specific characteristics that could influence the technical inefficiency of the sample (Battese and Coelli, 1995). The measures of output diversification, farming experience (age of the household head), family size, distance to road, extension service, and the educational attainment of the household head, which proxies the managerial ability of the head, are chosen as the explanatory variables of the inefficiency model. The degree of output diversification is measured in terms of the Hirschman index (Ofori-Bah and Asafu-Adjaye, 2011). The calculated index ranges between one and infinity, where values farther from one correspond to more diversified portfolios, and values closer to one correspond to more specialization.

The main inputs considered here are land, labor, and fertilizer. Land is defined as the total hectares of land cultivated by the household, and labor input is the sum of family, hired, and traditional labor sharing contributed labor time measured in man-days. The fertilizer input includes both organic and inorganic fertilizers measured in kilograms. Since the farmers produce numerous crop types, aggregating some of the crops is necessary. For our purpose, the crops were categorized into two groups: maize and other crops. Maize was chosen because it is widely cultivated by many farmers and in all regions. The outputs of the remaining crops were aggregated based on their share of the real value of the total crops produced by the household. The consumer price index is used to deflate the nominal values of the crops.

4.1. Decomposing the components of TFP changes

As already argued, when the production process exhibits variable returns to scale, total factor productivity defined in terms of the input distance function can be decomposed into four major independent sources of productivity change, namely, technical efficiency change (TEC), technical change (TC), scale efficiency change (SEC), and an input mix effect[7] (IME). The indicators of these sources of productivity growth can be generated from the parameter estimates of the above distance function. Accordingly, while the technical inefficiency of the sample is generated by taking the anti-log of the inefficiency estimates of each households, that is, $exp(\mu_i)$, its change is calculated as the differences in the technical efficiency estimates between period t and period $t + 1$[8].

The technical change estimate is generated by taking the first derivative of the distance function with respect to the time variable and inserting the mean values of the variables that appear in the first derivative. A negative value for this elasticity indicates technological regression, while a positive value indicates technological progress (Irz and Thirtle, 2004). However, as the technical change normally involves the contraction/expansion of inputs and outputs, the estimated technical change is

[7] From the parameter estimates, the Morishima's elasticity of substitution and complementarity between inputs can be calculated. These are particularly useful for determining how farmers respond to the policy/infrastructure-induced price changes. The shadow prices of the inputs and outputs can also be estimated. However, in order to remain within the immediate objective of the paper, we will not derive and discuss such measures.

[8] Alternatively, the time trend can be introduced in the inefficiency model that is jointly estimated with the distance function, and the antilog of the coefficient, $exp\left(\frac{\partial\mu_i}{\partial t}\right)$, provides the proxy for household specific technical efficiency change.

sensitive to which period data are used[9] (Balker, 2001). To purge the bias that arises because of the change in input and output quantities between period *t* and *t* + 1, following Patzios et al. (2011), the technical change estimate is generated as follows:

$$\frac{\partial lnD_I^t(x,y,t,r)}{\partial t} = exp\left[\alpha_T + \sum_{j=1}^{M} \sigma_j lny_{jt} + \sum_{k=1}^{K-1} \psi_k lnx_{kt}\right] \cdot exp\left[\sum_{j=1}^{M} \sigma_j\left(lny_{jt+1} - lny_{jt}\right)\right] \cdot exp\left[\sum_{k=1}^{K-1} \psi_k\left(x_{kt+1} - x_{kt}\right)\right] \quad (7)$$

The technical change estimate will be derived as the product of the above expressions. The first expression is the pure technical change, which is measured as the relative distance between the two periods' frontiers using the period *t* data. The two other components measure the bias that arises because of the change in output and input quantities. If inputs and outputs quantities do not change, the product of the bias terms will be 1.

The improvement in scale efficiency, which is the other source of productivity change, can also be derived from the distance function. To do that, we follow the approach suggested by Orea (2002), which is the second element of equation (4). However, Orea's (2002) suggested measure does not disentangle the effect of the change in input mix on the change in scale efficiency. To control that, we also estimate the scale change following the approach suggested by Bark (2001). Accordingly, given a certain input mix, the change in the scale efficiency of a given farm can be calculated as follows:

$$\mathrm{SEC}(x_t, y_t, t) = \exp\left\{\frac{1}{2\beta}\left[\left(\frac{1}{\varepsilon_{t(x_t,y_{t+1})}} - 1\right)^2 - \left(\frac{1}{\varepsilon_{s(x_t,y_t)}} - 1\right)^2\right]\right\} \quad (8)$$

Where $\beta = \sum_{j=1}^{M}\sum_{k=1}^{M}\beta_{jk}$ and $\varepsilon_{it}(x_t, y_t) = -\left[\sum_{m=1}^{M}\frac{\partial lnD(x_t,y_t,t)}{\partial lny_{mt}}\right]$

The mix effect on the other hand is be measured as

$$\mathrm{ME}(x_{t+1}, x_t, y_{t+1}) = exp\left\{\frac{1}{2\beta}\left[\left(\frac{1}{\varepsilon_{t(x_{t+1},y_{t+1})}} - 1\right)^2 - \left(\frac{1}{\varepsilon_{s(x_t,y_{t+1})}} - 1\right)^2\right]\right\} \quad (9)$$

The scale efficiency change is computed as the product of equations (8) and (9). For testing the significance of the presence of economies of scale, the delta method is used to generate the standard error estimate of the economies of scale.

[9] The second derivation of the distance function with respect to the inputs and outputs could show whether technical change is neutral or nonneutral. A positive (negative) value of the coefficient indicates that technical change is biased in favor of (against) the respective outputs and inputs. The LR model specification test showed that for our sample, the technical change is nonneutral.

4.2. Testing the presence of scope economies

In addition to decomposing sources of productivity change, we are also interested to test the presence and importance of scope economies[10]. Scope economies, which are conventionally derived from the cost function, are said to be present when joint production of different crops costs less than each crops being independently produced, which is

$$C(w_i, y) < \sum C(w_i, y_j) \tag{14}$$

Where C represents cost, w_i is a vector of input prices, and y is output.

Scope economy arises as a result of effective use of inputs as well as the presence of synergies and agronomic complementarities that exist between the productions of different crops[11]. If crop production is characterized by synergies between outputs and inputs, increasing one of the outputs, say y_j, reduces the marginal cost of production of the other crop, say y_k, so that

$$\frac{\partial C(w_i^*, y)}{\partial y_j \partial y_k} < 0 \tag{15}$$

Since the input price data are not readily available and the cost-minimization assumption is invalid, postulating the cost function will not be possible. It will also be inappropriate. To circumvent these constraints and test the presence of economies of scope, we follow the approach suggested by Hajargasht et al. (2006). Provided that the distance function is twice differentiable, they suggested that scope economies can be derived by exploiting the duality between the cost and the input distance function. Based on Euler's theorem and assuming that farmers are shadow cost minimizers, that is, $D^I(x, y, t)C(w_i^*, y) = w_i^* x_i$, where w_i^* is the shadow price of input *i*, Hajargasht et al. (2008) developed a derivative-based measure of economies of scope. Accordingly, the presence of economies of scope, say between outputs y_m and y_k, can be checked by the following result[12]:

$$EOS = \frac{1}{C(y,w)} \frac{\partial^2 C(y,w)}{\partial y_m \partial y_k} = C\{D_y D_y' - D_{yy} + D_{yx}[D_{xx} + D_x D_x']^{-1} D_{xy}\} < 0 \tag{16}$$

Weak economies of scope are said to exist if the estimated value is nonpositive. However, the above result only indicates the presence of the economies of scope, but

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[10] Since scale efficiency is a measure of the potential productivity gains that come through exploiting the economies of scale, mix efficiency measures the productivity gains that come through exploiting economies of scope (O'Donnell, 2010).

[11] For instance, intercropping increases yield by controling soil erosion, improving the soil quality, reducing weeds, and acting as a natural control for pests and diseases[11]. The possibility of more efficient use of resources like sunlight, nutrients, and water is also higher in multiple cropping systems. Diversity of the root systems and differences in the phenologies of intercrops will also reduce the potential of erosion (Willey, 1979). By producing toxins and preventing the growth of competitive weeds, intercropping also reduces weeds, increases yield, and saves labor time devoted to weeding, an advantage that has not received adequate attention[11] (Glass and Thurston, 1978; Yih, 1982; Altieri et al., 1983). By enhancing nutrient availability and alleviating soil erosion, intercropping will also reduce fertilizer use**[11]** (Horwith, 1985). Similarly, by deterring and reducing the effects of pests and diseases, intercropping will also reduce pesticide and fungicide inputs. Thus, intercropping not only increases yield at a lower cost, but also reduces health risks and environmental pollution by reducing the application of fertilizer, pesticides, and herbicides (Horwith, 1985).

[12] $$\frac{\partial D^I}{\partial y_m}\frac{\partial D^I}{\partial y_k} - \frac{\partial^2 D^I}{\partial y_m \partial y_k} + \left(\frac{\partial^2 D^I}{\partial y_m \partial x_1} \cdots \frac{\partial^2 D^I}{\partial y_m \partial x_n}\right) \begin{bmatrix} \frac{\partial^2 D^I}{\partial {x_1}^2} + \frac{\partial D^I}{\partial x_1}\frac{\partial D^I}{\partial x_1} & \cdots & \frac{\partial^2 D^I}{\partial x_1 \partial x_n} + \frac{\partial D^I}{\partial x_1}\frac{\partial D^I}{\partial x_n} \\ \vdots & \ddots & \vdots \\ \frac{\partial^2 D^I}{\partial x_n \partial x_1} + \frac{\partial D^I}{\partial x_n}\frac{\partial D^I}{\partial x_1} & \cdots & \frac{\partial^2 D^I}{\partial {x_n}^2} + \frac{\partial D^I}{\partial x_n}\frac{\partial D^I}{\partial x_1} \end{bmatrix}^{-1} \begin{bmatrix} \frac{\partial^2 D^I}{\partial x_1 \partial y_k} \\ \vdots \\ \frac{\partial^2 D^I}{\partial x_n \partial y_k} \end{bmatrix}$$

not its significance. To test the significance of the presence of economies of scope, we use the delta method to generate standard error estimates of the economies of scope.

4.3. Monotonicity, homogeneity, and curvature conditions

Consistency with the production theory requires that the input distance function is monotonically increasing and concave in inputs but nonincreasing and quasi-concave in output. The monotonicity condition requires that the marginal product of the inputs must always be positive. Increasing inputs for a given output vector increases the distance from the isoquant, hence the inefficiency. As a result, the distance function must be increasing in inputs. The input distance is nonincreasing in output because increasing output for a fixed input level reduces the distance from the input isoquant, or the technical inefficiency (Henningsen and Henning, 2009). The monotonicity conditions of the distance function are satisfied if the value of the first derivative of the distance with respect to each input is positive and that to each output is negative. The homogeneity condition, which requires an increase in the input vector to lead to a proportionate increase in output, will be imposed during estimation.

Following O'Donnell and Coelli (2005), the curvature conditions of the input distance function can be imposed when a model is estimated in a Bayesian framework[13]. However, when access to inputs is restricted and input prices are not competitively determined, even a non–quasi-concave point of the distance function can reflect profit-maximizing behavior (O'Donnell and Coelli, 2005). As a result, it is generally suggested that imposing quasi-concavity be avoided while estimating the distance functions (Rungsuriyawiboon and O'Donnell, 2004). We follow this approach and check only the fulfillment of these conditions after the model estimation. Accordingly, we check concavity by the sign of the second derivative of the output and input variables[14].

[13] Quasi-concavity guarantees that the marginal rates of technical substitution are decreasing (i.e. their isoquants are convex) and, hence, an interior solution to the profit-maximizing problem exists.

[14] The curvature conditions of the input distance function can also be tested by examining the principal minors of the bordered Hessian matrix. This requires that the Hessian matrix of the first- and second-order partial derivatives with respect to inputs is negatively definite at the point of approximation. The condition of quasi-concavity in output is fulfilled when the principal minors of the Hessian matrix are strictly positive. Hessian matrix is given by the second-order derivatives of the distance function (Antonelli matrix) (March et al., 2003).

5. Empirical Results

We estimated two alternative input distance models; that is, we assumed neutral and non-neutral (both in inputs and outputs) technical change. We conducted the specification test to determine which model specification is appropriate to the data. The LR test, with a chi-square value of 39.5, rejected the null hypothesis of neutrality and confirmed that non-neutral specification is more appropriate. The subsequent discussion of results will therefore be based on the result of the non-neutral form of specification. The model is also estimated assuming that distribution of the inefficiency term is half normal. The parameter estimates of the model is presented in Table 3.
(Insert Table 3 here)

At the point of approximation, the sign of the parameter estimates of the output and the input variables are consistent with theory; that is, the input distance function is increasing in inputs and nonincreasing in outputs. The quasi-concavity of the distance function with respect to the output can also be verified by looking at the second derivative of the function with respect to both outputs.

We also tested a hypothesis related to the significance of the various sources of productivity changes. As shown in Table 2, the null hypothesis of no technical inefficiency, constant returns to scale, no technical change, and economies of scope are rejected at less than 1%.

In what follows, we discuss the parameter estimates of technical efficiency, technological change, returns to scale, and their contributions to the observed change in productivity. The significance of the ${\sigma_\mu}^2$ suggests that technical inefficiency is a significant contributor to the observed output variations of the sample farmers. The coefficient of theta, which is the share of inefficiency from the composite error of the model, is also highly significant and suggests that technical inefficiency contributed 26% of the output variation between the samples. The average measured efficiency of the sample in 2013 was 61%, which showed a 7% improvement compared to 54% in 2011. The result generally suggests that while improved technical efficiency did contribute to the observed increase in output, improving technical efficiency has the potential to increase output by as much as 39% with the existing technology and resources. Our estimates are also comparable with technical efficiency reported by previous studies. Although Croppenstedt and Demeke (1997) used a different form of specification, they reported an average technical efficiency of 41%, with 54% of the farms being between 30% and 60%. Abrar and Morrissey (2006) also reported a technical efficiency of 57%.

The technical efficiency level of the sample is also strongly associated with individual, household, and location characteristics. Educational attainment by the head of household, family size, and farming experience (age) are important household-specific factors that positively influence technical efficiency. Among factors that are amenable to policy interventions, the degree of crop diversification pursued by farm household and access to extension services and infrastructure (although the latter is weakly significant) are important determinants of technical efficiency. The diversification index variable, which increases with the extent of specialization, is also positive and highly significant. This suggests that farmers who cultivate diverse crops are technically more efficient than those who specialize in one or a few types of crops.[15] Among other variables that could have contributed to such a high level of inefficiency are weather shocks, disease, and pests as well as postharvest losses.

As the model specification test and the significance of the trend variable suggest, significant technical change occurred. However, the negative sign and the significance of the trend variable imply that the input frontier shifted outward, suggesting that there was a technological regress in the periods considered. The estimated pure technical change index was 0.84, but when the input and output biases are accounted for (1% and 4% change, respectively), the overall estimated technical change index was 0.88, suggesting that there was a technical regress of 12%. However, as aptly noted by Irz and Thirtle (2004), literally interpreting the result as "technological regression" may not be appropriate, mainly because the weather-related factors that could shift the input isoquant have not been fully accounted for. As such, the declines in fertilizer application and rainfall level, which enhance the productivity of other inputs, might be the main causes of the apparent regress rather than a deterioration in technology (Rasmussen 2010).

The rejection of the null hypotheses of constant returns to scale at less than 1% confirmed that small farming is characterized by scale economies, and scale efficiency improvement was one contributor to the change in productivity. The estimated economies of scale of the sample for 2011 and 2013 were 0.82 and 0.97, respectively. Actual values of RTS also range from increasing to mildly decreasing returns to scale, with more than 92% of the observations falling into the region of increasing returns to scale. To test the significance of economies of scale, we used the delta method to generate the standard error estimate of the economies of scale estimates. The estimated standard error for the sample was 0.1, which suggests that the presence of scale economies is highly significant.

Although the sample farmers were still operating over the quadrant of increasing returns to scale, they registered a 17% improvement in scale efficiency, of which 7% was due to pure scale efficiency improvement and the remaining proportion was the effect of changes in the quantity of inputs and the input mix. The result is almost similar (16.6%), when the scale efficiency improvement is measured by using the approach suggested by Orea (2002). The result suggests that although the sample farmers exhibited an improvement in scale efficiency (i.e., operating close to the most productive scale), they were still operating within the increasing quadrant of the production function. As rational decision makers, operating within the increasing returns to scale region of the production function is inconsistent with economic theory. Absence of a competitive land market might be a primary factor that prevented farmers from fully exploiting economies of scale. For instance, the land size at the most efficient scale size is estimated to be 2.5 ha. However, the average land size in the sample is 0.5 ha[16]. As Figure 1 illustrates, although the relationship between land size and scale efficiency exhibits some degree of nonlinearity, there is a strong correlation between the two. This implies that further land consolidation could be one potential sources of future productivity growth.
(Insert Figure 1 here)

[15] Although it is not reported here, we estimated a similar model using a Ugandan sample, and the results were the same irrespective of the model specification, as was found in the current study.
[16] The average land size of farmers that exhibited an economic scale estimate between 1 and 1.02.

The presence of scope economies was also tested. The negative trend and the significance of the second derivative of the distance function with respect to the outputs, which is represented by the interaction terms of maize and other crops, suggests cost complementarities in crop production. The coefficient estimate implies that when farmers cultivated maize and other crops, their marginal costs of maize production declined by as much as 11%. The dual measure based on equation (16), which is a sufficient condition for the presence of economies of scope, also conveys a similar message. The estimates generated by the derivative method are negative in both years and meet the sufficient conditions for the existence of scale economies. The average estimates for the sample for both years was −0.085, which was −0.067 for 2011 and −0.10 for 2013, respectively. The estimate implies that a 10% increase in the production of other crops led to a 0.85% reduction in the marginal cost of maize production. In other words, farmers that had a diversified crop portfolio incurred lower production costs on average compared to farmers that grew only maize. Using the delta method, the standard error estimate of the economic scope was 0.003, suggesting that the presence of economies of scope is highly significant. Our result is also similar to the findings reported by other studies (e.g., Fernandez-Cornejo et al., 1992; Chavas and Aliber, 1993; Paul and Nehring, 2005). For instance, Chavas and Kim (2007), using data from a sample of farm households from Ethiopia, reported the existence of a significant economies of scope. According to their result, the benefit due to diversification outweighs the incentive to specialize and generates up to a 17% additional benefit.

We also calculated the optimal number of crops for maximizing the scope economies. For this purpose, based on random effect model, we regressed the economies of scope estimate on the number of crops cultivated, the squared number of crops, as well as the time trend. The result shows that the economies of scope reaches its maximum with eight crops. Although the actual number of crops produced within the sample ranges from 1 to 13 in 2011 and from 1 to 18 in 2013, the average number of crops produced in each year was 2 and 6, respectively, suggesting that while there was improvement in scope efficiency in 2013, there was still room for improvement in scope economies[17]. In general, although our result suggests significant economies of scope, to clearly establish the significance and draw clear policy conclusions, estimating the economies of scale on the basis of disaggregated output data might be necessary.

Finally, by assembling the conventional components of TFP changes, the calculated growth in TFP change between 2011 and 2013 was 11.8%. The bulk of the change is accounted for by a change in technical efficiency (8.3%), input mix effect (9%), and a change in scale efficiency (7.2%). The positive effects of these sources of efficiency change on productivity was counteracted by the effect of technical regress (−12%), which, as argued above, is more likely to represent weather shocks than technological regress.

To check the sensitivity of the result to estimation techniques and specification, we also estimated the productivity change and its components using a nonparametric

[17] The change in cropping pattern in response to better market prices, which arises due to population growth and urbanization, could be the other factor for the observed increase economies of scope.

approach developed by O’Donnell (2008)[18]. The estimation results are reported in Table 4. Based on the results, the change in TFP over the study periods was 17.3%, which is higher than the estimate of the parametric model. When the change is decomposed into its principal sources, improvement in technical efficiency (13.7%), scale efficiency (7%), mix efficiency (2.5%), and technical regress (−6.1%) are the main contributors. However, the estimated magnitude of each component differs slightly and is sensitive to the aggregator functions and also to whether input/output orientation is considered.

According to this method, the overall total efficiency, which is measured by the ratio of the observed to the maximum potential growth achievable given the existing technology, was estimated to be 50%. Although productivity could be increased through improving technical efficiency and scale efficiency, which were 82% and 85%, respectively, the bulk of the increase in productivity in the short term is expected to come from a change in input and output mixes or scope economies.

Both the input mixes used and output mixes produced were not efficient. The residual mix efficiency (RME), which is the efficiency improvement that can be gained by relaxing the constraints in input use and output mix produced, is expected to be the main source of future productivity growth. Although it showed a 27% improvement in recent years, the current mix is 67% of the optimal. Identifying and addressing the constraints that give rise to such mix inefficiency is expected to generate valuable information for policy making. As rational decision makers, farmers will optimally adjust their scale and input/output mix (and, therefore, levels of scale-mix efficiency) in response to changes in production incentives; however, this may not occur when there are market failures and imperfections, and a government policy response may thus be required.

6. Conclusion

The paper examined the significance of farm efficiency improvement in raising the total factor productivity of small-scale farmers in Ethiopia. The results show that small-scale farming is characterized by increasing returns to scale and economies of scope. The analysis shows that huge potential exists for increasing farm output by improving the economic efficiency alone. Even though farmers exhibited some level of efficiency improvement in the most recent years, significant technical, scale, scope, and mix inefficiencies persist.

In the short to medium term, a substantial increase in productivity is expected to occur through improving technical efficiency and exploiting economies of scope. In this regard, policy measures on encouraging more farmers to participate in extension services and improve their schooling will have significant impact on the technical efficiency of the farmers. Improving the competitiveness of the markets for goods and other factors as well as reducing transaction costs, which influence farm gate relative prices, promote a more optimal cropping and input use pattern and enable farmers to

[18] The framework computes *productivity* index numbers and decomposes into its various components using the data envelopment analysis (DEA) linear programming (LPs). The approach decomposes *changes* in productivity into technical change (measuring movements in the production frontier); technical efficiency change (movements towards or away from the frontier); scale efficiency change (movements around the frontier surface to capture economies of scale); and mix efficiency change (movements around the frontier surface to capture economies of scope) (O'Donnell, 2008).

realize economies of scope. Identifying the factors that give rise to suboptimal application of fertilizer in particular and taking the necessary measures to address them will have significant and immediate impacts on farm productivity. Since farmers currently operate at a level of scale that is below the most productive scale, promoting a competitive land market and further land consolidation would have a significant impact on farm productivity. Combined improvements in mix and scale efficiencies would have a cumulative impact on productivity.

Finally, although attempts were made to control the effect of location-specific factors, significant regional variations in the level of farm efficiency calls for targeted analyses for creating location-specific policy conclusions. Similarly, further research is necessary to identify the household-specific characteristics that contributed to the observed differences in the level of efficiency achieved by farm households located in the same region.

Table 1: Summary Statistics of the Variables

		2011				2013				
Variable	Measure	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Min	Max	%Change
Outputs										
Other crops	Quintal	4.92	1.47	0.29	9.44	5.96	1.16	0.57	10.13	21.03
Maize	Quintal	4.58	1.40	-0.92	7.60	4.95	1.50	0.00	8.63	8.03
Inputs										
Land	Hectare	0.51	1.17	-5.26	2.30	0.60	1.11	-4.89	2.30	17.82
Labor	Man Days	3.72	1.43	-0.21	9.56	3.50	0.96	-0.23	8.93	-5.99
Fertilizer	Kg.	3.31	1.49	-1.69	11.50	3.17	1.13	-1.46	7.52	-4.19
Household Characteristics										
Education	Likert Scale	0.36	0.58	0.00	3.00	0.43	0.60	0.00	3.00	17.44
Crop Diversification*	Index	0.75	0.26	0.18	1.00	0.47	0.24	0.11	1.00	-37.89
Extension	Dummy	0.28	0.45	0.00	1.00	0.65	0.48	0.00	1.00	133.49
Distance from Road	Km.	2.09	1.43	-2.30	5.48	2.11	1.39	-2.30	5.48	0.76
Credit	Dummy	0.26	0.44	0.00	1.00	0.23	0.42	0.00	1.00	-13.07
Age of HH Head	Years	3.74	0.34	2.89	4.57	3.78	0.32	2.08	4.60	1.16
Family Size	Number	1.56	0.47	0.00	2.64	1.58	0.48	0.00	2.64	0.82

*Herfindahl Index; Km= kilometer; Kg.=kilogram; HH=Household

Except theeducation and dummy variables, all variables are in natural log.

Table 2

Model specification test

Hypothesis	LR-test	$P > \chi^2$
Technical efficiency ($\sigma_\mu{}^2 = 0$)	65.97	0.00
No technical change ($\alpha_T = 0\,, \sigma = 0$)	25.77	0.00
Non-neutral technical change ($\sigma = 0$)	56.69	0.00
CRS($\sum_{m=1}^{M} \beta_m = 1, \sum \beta_{jk} = 0\,, \sum \delta_{jk} = 0$)	206.60	0.00
Economies of scope ($\beta_{jk} = 0$) (weaker form)	12.32	0.00

Table 3: Parameter estimates of the translog input distance function

Variables	Coeff	z	*P*
β_O	-0.44	-3.44	0.00
β_M	-0.14	-1.17	0.24
γ_L	0.35	3.24	0.00
γ_F	0.65	5.90	0.00
γ_{LF}	-0.11	-3.08	0.00
γ_{L^2}	-0.18	-5.94	0.00
γ_{F^2}	-0.06	-3.47	0.00
δ_{ML}	-0.01	-0.36	0.72
δ_{FL}	-0.03	-2.46	0.01
β_{M^2}	0.11	6.11	0.00
β_{MO}	-0.11	-4.23	0.00
β_{O^2}	0.11	5.20	0.00
δ_{OF}	-0.03	-1.96	0.05
δ_{OL}	0.06	3.62	0.00
α_T	-0.08	-1.04	0.30
ψ_{LT}	-0.23	-5.29	0.00
ψ_{FT}	-0.05	-1.47	0.14
σ_{MT}	0.08	2.71	0.01
ρ_R	0.10	2.44	0.02
σ_{OT}	0.07	2.69	0.01
α_o	1.19	2.30	0.02
Inefficiency Model (σ_μ^2)			
Education	-0.30	-2.14	0.03
Diversification index	4.46	7.89	0.00
Extension	-0.42	-2.33	0.02
lndistanceroad	0.09	1.56	0.12
Credit	-0.07	-0.46	0.65
lnage	-1.00	-3.85	0.00
lnhhsize	-0.91	-5.18	0.00
ω_o(_cons)	2.15	2.04	0.04
σ_v^2	-2.85	-9.36	0.00
Theta			
_cons	-0.22	-6.21	0.00
E(sigma_u)	0.52	0.54	
Sigma_v	0.24	6.57	0.00
Wald $\chi^2(15)$	695,650		
Log-likelihood	−534.228		

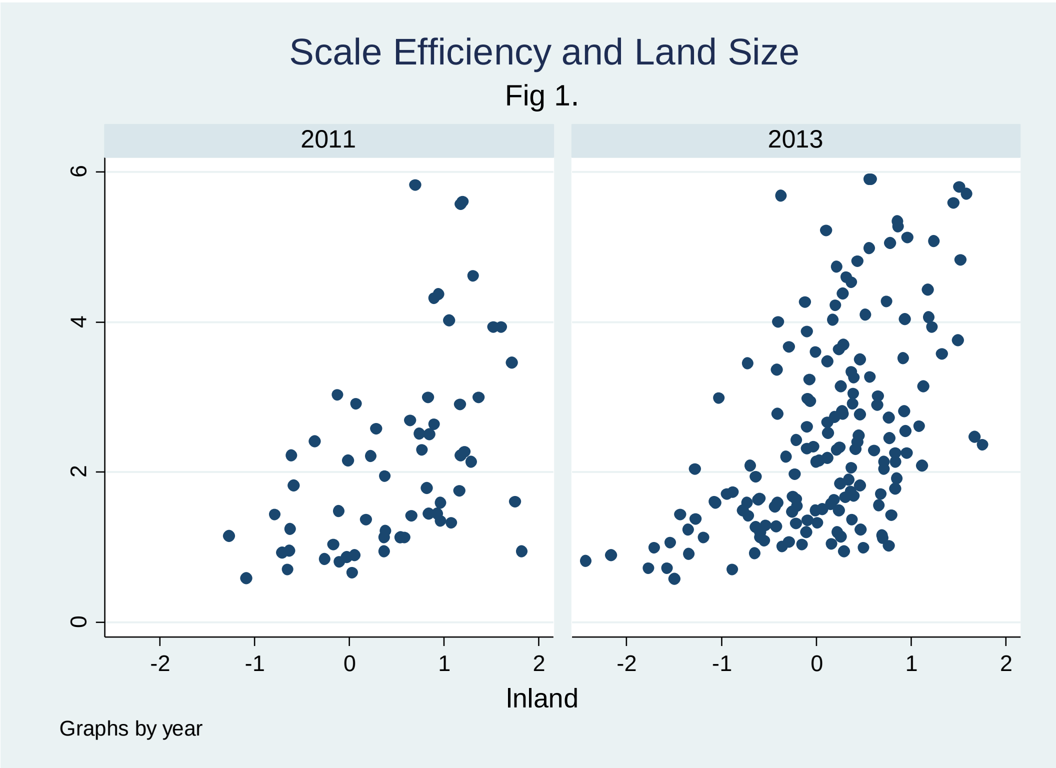
O, other crops; M, maize; L, labor; F, fertilizer.

Table 4
Decomposition of input- and output-oriented productivity index*

Parameters	Index	Parameters	Efficiency change
TFP	0.74	ΔTFP	1.18
TFPE	0.50	ΔTech	0.94
OTE	0.86	ΔOTE	1.14
OSE	0.87	ΔOSE	1.02
OME	0.97	ΔOME	0.91
ROSE	0.53	ΔROSE	1.16
OSME	0.58	ΔOSME	1.22
ITE	0.82	ΔITE	1.08
ISE	0.91	ΔISE	1.07
IME	1.02	ΔIME	1.03
RISE	0.66	ΔRISE	1.31
ISME	0.64	ΔISME	1.31
RME	0.69	ΔRME	1.27

* Using nonparametric method and Malmquist Index.
TFP, total factor productivity; TFPE, TFP efficiency; O, output; I, input; R, residual; ME, mix efficiency; TE, technical efficiency; SE, scale efficiency; Δ, change; ΔTech, technical change.

Fig. 1. Scale efficiency and land size



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