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Does the inverse farm size productivity hypothesis hold for perennial monocrop systems in developing countries? Evidence from Kenya

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Abstract

The inverse farm size and productivity relationship (IR) is a recurring theme in the literature. However, most previous studies were undertaken within a setting of mixed cropping systems. In this article, we investigate the effect of farm size on productivity within the context of a perennial mono-cropping system, acute competition for farmland, frequent subdivision of farms and declining yields. We apply household survey data of smallholder tea farms in western Kenya and consider both technical efficiency (TE) and the yield per hectare as indicators of productivity. The findings show that the effect of farm size on productivity is nonlinear, with TE initially declining and then rising with farm size. The findings also demonstrate that the farm size and productivity relationship is important for perennial monocrops and that the use of robust measures of productivity is important for the IR. The findings have important implications for agricultural policy in developing countries.

Key words: farm size; perennial monocrops; productivity; technical efficiency; fractional regression model (FRM)

1. Background

The association between farm size and productivity has dominated discussions amongst development economists since the pioneering study by Chayanov (1926). Chayanov, along with a number of other subsequent works, shows a persistent finding that large farms are less productive than smaller farms (Sen 1962; Bardhan, 1973; Heltberg 1998; Barrett *et al*. 2010; Carletto *et al*. 2013; Larson *et al*. 2014; Desiere & Jolliffe 2018). Following the recurrent finding that there is an inverse relationship (IR) between farm size and productivity, agricultural and development economists have for decades generally held that a smallholder-led growth strategy presents a promising pathway for economic transformation in developing countries (e.g. Lipton 2006; Hazell *et al*. 2010). The main premise is that the redistribution of farms can enhance agricultural productivity and therefore support smallholder livelihoods, if small plots are at all fundamentally more efficient than large farms (Chand *et al*. 2011). This belief remains a central basis for many agricultural interventions in developing countries (Gollin 2019).

There are several explanations in the literature for the IR. Theoretically, productivity differences based on variability in farm size are not expected if input and output markets are complete (Sheng *et al*. 2019). This is because, in the absence of market failures, farmers will instinctively reallocate resources to more efficient farms (by subdividing their farms and thus eliminating the IR). Consequently, most studies tend to suggest that the IR is an outcome of market imperfections, which manifest mainly in variability in labour use across farms of different sizes. The variability is often associated with the large differences in the opportunity costs for family and hired labour. This is because the hiring of agricultural labour attracts additional transaction costs associated with search, screenings and monitoring due to the information asymmetries that characterise rural labour markets (Kiani 2008).

While the existence of the IR has dominated debates on agricultural development for decades, a new strand of literature appears to cast reservations on the feasibility of a smallholder-led poverty reduction strategy in developing countries (Collier & Dercon 2014; Dercon & Gollin 2014; Gollin 2019). Underlying these doubts are two main arguments. The first strand comprises studies showing that, in some circumstances, small farms in developing countries could be less efficient than their larger counterparts (Otsuka *et al*. 2016; Foster & Rosenzweig 2017; Otsuka & Muraoka 2017). Consequent to this are observations that the changes emanating from mega-trends such as shifts in markets, climate variability, urbanisation, globalisation and advances in technology could significantly affect the viability of smallholder systems (Gollin 2014; Gollin *et al*. 2014). The second strand argues that errors of measurement, as well as the statistical failure to control for unobserved variables (e.g. variations in soil quality), could cause empirical contamination of the association between farm size and productivity, leading to the observed IR (e.g. Barrett *et al*. 2010; Carletto *et al*. 2013; Bevis & Barrett 2018). The need for new empirical evidence to address these contestations explains the renewed research attention on the IR in the recent past (Barrett *et al*. 2010; Carletto *et al*. 2015; Otsuka *et al*. 2016; Foster & Rosenzweig 2017; Desiere & Jolliffe 2018; Muyanga & Jayne 2019; Sheng *et al*. 2019).

In this article, we assess the association between farm size and productivity among smallholder tea producers in western Kenya. Our contribution to the literature is threefold. Firstly, it is the first effort, to the best of our knowledge, to test the IR in the context of a perennial monocropping system in Kenya. The study considers the case of smallholder tea production under a situation of acute competition for farmland, small tea plots (less than an acre), frequent subdivision of plots and declining yields (Republic of Kenya 2014; Ateka *et al*. 2018). The farm size-productivity relationship has important significance in the Kenyan tea sector, given that some of the policy options being considered, such as legislations on minimum farm size, appear inconsistent with the IR literature.

Secondly, we applied a dataset whose features help in overcoming a number of measurement limitations in testing the IR in a smallholder setting. Most previous studies on the IR are based on data drawn from mixed farming systems, where cultivated plots simultaneously support multiple crop and livestock enterprises (Lowder *et al*. 2016). This makes the measuring of farm size and the estimation of crop yields to be neither simple nor straightforward, and therefore prone to many errors (Gollin 2019). While such complex mixed systems dominate production in developing countries, tea is produced as a monocrop, a feature that allowed us to skirt many of the aforementioned problems. In addition, the study took advantage of the existence of a tea industry database[1] on crop area and tea yields, which allowed us to validate the self-reported survey information. Our strategy allowed us to disentangle the productivity dispersion that arises from self-reported measurement errors.

[1] The tea industry in Kenya conducts a periodic census of tea bushes in which information is collected on every tea farm in the country. Plot measurements are obtained using global position system (GPS) technology.

Thirdly, we tested the IR hypothesis using technical efficiency (TE), which is a more robust indicator of productivity than other, alternative measures such as yield or gross output per unit area. Furthermore, in terms of methodology we applied fractional regression modelling (FRM) and argue that efficiency models that ignore the fractional nature of efficiency scores are possibly mis-specified and therefore lead to misleading conclusions. A number of previous studies on the IR applied ordinary least squares (OLS), which suggests that the effect of farm size on productivity is expected to be constant across the entire distribution of plot sizes. By expanding the analysis to consider the distribution of plot sizes, we show that there is an upper limit of farm size beyond which productivity increases with farm size. We therefore conclude that, in order to avoid misleading generalisations, empirical analysis of the IR should take into account the range and distribution of farm size (over which results apply).

The rest of the paper proceeds as follows. We provide context to the study in section 2 and present the overview of the literature in section 3. We turn to the description of the data and estimation strategy in section 4, while the discussion of the results is presented in section 5. The article concludes with policy implications in section 6.

2. The context of the study

Tea production in Kenya is characterised by a dual structure comprising large-scale estates and the smallholder subsector (Ateka *et al*. 2018; Tea Directorate of Kenya 2019). Tea growing by smallholder farmers commenced in the 1960s after the country's independence. Before then (attaining self-rule), the country's colonial agricultural policy did not encourage the growing of the crop by smallholder producers due to misgivings that African peasants lacked sufficient skills to engage in a technically demanding enterprise (Leonard 1991). This policy was also consistent with the need to create a class of landless peasants to provide labour for the white settlers (Swynnerton 1957). In Kenya, tea growing is practised in the country's highlands, on the eastern and western sides of the Rift Valley, between altitudes of 1 500 to 2 700 metres above sea level. These are areas with good soils and well-distributed rainfall, and therefore are generally considered to have good potential for agricultural production (Tea Directorate 2019).

Since its inception, Kenya's smallholder subsector has experienced substantial growth in terms of planted area, production and number of tea growers. The subsector supports over 600 000 smallholder farm families, produces about 60% of Kenya's tea crop and is reported to be one the biggest and most successful smallholder schemes in the world (Ateka *et al*. 2018; Tea Directorate 2019). Globally, Kenya is among the top four leading tea producers (alongside China, India and Sri Lanka), who together account for 75% of the global production (Republic of Kenya 2014; Tea Directorate 2019). According to the Kenya tea industry statistics, the planted area under the crop (by the smallholders) expanded from about 3 000 hectares in the early 1960s to more than 110 000 hectares in the 2000s, while output increased from roughly one (1) million kilograms to more than one (1) billion kilograms over the same period (Republic of Kenya 2014; Tea Directorate 2019). The notable growth, especially in the earlier years, is attributed to various factors, including the land distribution policy in the early years of independence, attractive world market prices and breakthroughs in research, leading to the release of high-yielding clones (Republic of Kenya 2017; Ateka *et al*. 2019).

Notwithstanding the impressive growth in tea cultivation and its contribution to the economy, productivity among the smallholder farmers is low. Tea productivity in the subsector varies widely, characterised by wide differentials between the actual and potential yields (about 1 800 kilograms of processed tea per hectare compared to a potential of more than 3 500 kilograms). The analysis of industry trends reveals that yields rose impressively in the earlier years after independence, but thereafter started to experience setbacks (Figure A.1 in the Appendix). These unimpressive trends point to the existence of inefficiencies and therefore a potential to increase productivity (Mbeche & Dorward 2014; Ateka *et al*. 2018).

One of the key features characterising tea production in Kenya is that farm holdings are generally small due to the rapid subdivision of farms, which can be explained by population growth, the country's land tenure practices and its pattern of land inheritance (Muyanga & Jayne 2014). In addition to the subdivisions, farms in the subsector are also under the threat of conceding a share of their land to other, competing enterprises. Against the backdrop of a constrained land resource base in Kenya's tea sector, questions on the role played by plot size in the relative performance of the industry are increasingly becoming important. This is in the light of increased stakeholder concerns that the subdivision of farms is one of the main causes of declining tea yields (based on qualitative interviews with stakeholders and focus group discussions). Associating the stagnation in productivity with the subdivision of farms, however, is theoretically inconsistent with the many empirical studies supporting the IR in many developing countries. Indeed, if the IR exists in the tea sector, then the success of farm-size reforms being considered in the sector would be doubtful.

The reforms envisaged by the industry to address the diminishing farm units include the consolidation of farms, legislation on minimum farm size and livelihood diversification to encourage producers with small plots to exit the tea enterprise (Republic of Kenya 2014). The majority of the stakeholders in the industry believe that the diminishing farm units have a negative influence on productivity (based on key informant interviews with various agricultural officers and the Kenya Tea Development Agency (KTDA) management). However, there is insufficient empirical evidence to support farm size policy restrictions, considering that these policies are very controversial and difficult to implement. In Eastern Europe, for instance, efforts towards land consolidation have led to mixed outcomes, including insecurity of tenure and institutional inefficiencies (Deininger *et al*. 2012). In addition, an empirical farm-size threshold based on economic efficiency that would guide the implementation of the reforms has not been established.

3. Overview of the literature

Issues relating to land are complex and varied, and can be viewed from many different perspectives (political, social, legal, economic, and sustainability and productivity). Agricultural land reforms have been a recurring theme in the agricultural economics literature (De Janvry 1981; Narh *et al*. 2016). The focus is justified, given the challenges related to how land is accessed and utilised, such as land degradation, fragmentation, skewed access, land-use conflicts, a high share of smallholders without formal titles and other pervasive market failures in rental markets (Migot-Adholla *et al*. 1991; Place 2009; Guirkinger & Platteau 2014; Narh *et al*. 2016).

In sub-Saharan Africa (SSA), land has commonly been considered an abundant resource (Deininger *et al*. 2012). However, recent trends indicate that scarcity of farmland is increasingly becoming important, especially in densely populated rural areas (Jayne *et al*. 2014). Various nationally representative farm surveys in the region consistently indicate that most of the farms are small (the median size of a crop farm is less than one hectare), with limited or no potential area for expansion (Jayne *et al*. 2014; Von Braun & Mirzabaev 2015; Lowder *et al*. 2016). While various changes could explain the trend (e.g. sharp increase in demand for alternative land uses, especially in areas near urban centres, expansion of crop and livestock frontiers into marginal areas, environmental degradation and institutional structures that are not well tailored to handle the emerging land pressures), the rising population growth, along with the concomitant rapid sub-division of farm holdings, is perhaps the most prominent (Jayne *et al*. 2014; Muyanga & Jayne 2014). Concerns that the sub-division of farms into uneconomical units could be a factor explaining the decline in agricultural productivity have led to attempts by some countries to legislate on minimum farm holding (Syagga & Kimuyu 2016). This view is consistent with a wider strand of recent literature that appears to cast doubts on the viability of a smallholder-led strategy pathway for poverty reduction (e.g. Adamopoulos & Restuccia, 2014; Collier & Dercon 2014; Dercon & Gollin 2014).

The association between productivity and farm size is a widely acclaimed subject in the literature, with a preponderance of previous studies focusing on the IR (Gollin 2019). While the IR has been observed widely in Asia (Bardhan 1973; Sen 1975; Heltberg 1998; Lipton 2006), similar evidence is also reported in SSA, although the evidence base is much smaller (Barrett *et al*. 2010; Carletto *et al*. 2013; Larson *et al*. 2014; Desiere & Jolliffe 2018). Understanding this empirical regularity under different contexts has important policy implications. The most apparent of these is the notion that the restructuring of farms can result in productivity gains, if large farms are primarily less productive than smaller farms. In contrast, polices in support of redistribution are less effective if the IR is a spurious statistical result arising from estimation or measurement blunders.

Several explanations for the empirical regularity of the IR have been put forward and tested. A number of the early studies on the subject focused on the incompleteness of factor markets (Eswaran & Kotwal 1985; Barrett 1996). The market failure hypothesis is inconsistent with the predicted equalisation of factor prices under the microeconomic theory of market equilibrium (Sheng *et al*. 2019). An important explanation of the IR based on market imperfections relates to the relatively less use of labour on larger farms. This phenomenon is associated with the belief that large farms often face higher opportunity costs of labour than smaller farms (Barrett *et al*. 2010). The reason is that larger farms often have to rely on hired labour, which is presumed to be less motivated and difficult to hire due to market indivisibilities (for instance, while a family member can take a small fraction of an hour each morning to feed livestock, setting up a similar arrangement is problematic for hired labour). Furthermore, hired labour attracts additional transaction costs of search, screenings and supervision due to moral hazard and information asymmetries (Kiani 2008). In contrast, family labour (which is often applied in small family-operated farms) is associated with various advantages, including being less prone to shirking, and the fact that the supply of family labour is relatively more flexible. The flexibility allows labour to be mobilised virtually right around the clock, even during peak periods (Gollin 2014). While there is literature showing the influence of the other factor markets (apart from labour), including credit and insurance, on productivity, the ability of family labour to solve many incentive issues facing agricultural labour markets is the most dominant explanation for the IR in the literature.

Drawing from the market failure hypothesis, later studies on the IR, such as that by Barrett *et al*. (2010), posit that some of the factor market explanations could be coupled with intra-household issues to generate the IR. The studies therefore include some household-specific variables, such as the size of the household and its composition, the heterogeneity of farmers' skills, the level of penury and dependency, and household gender dimensions, in testing the IR (Juliano & Braido 2007). In addition, concerns related to risks and uncertainties may influence investment decisions in agriculture and therefore in generating the IR (Barrett 1996; Savastano & Scandizzo 2009). The mixed nature of the findings from the studies helps to show how various context-specific variables interact to influence the relationship between farm size and productivity. The implication is that empirical investigations of the linkage between productivity and farm size should take into account the complex and context-specific heterogeneities that typify agricultural production in developing countries, including the differences in geolocation and cropping patterns.

A second key explanation for the IR is based on omitted variables. Proponents of this hypothesis attribute the IR to unobserved variables, including soil quality and agroclimatic conditions – especially if these factors vary disproportionately across farms of different sizes (Bhalla & Roy 1988). For instance, the IR can arise if soil characteristics or features that are negatively correlated with farm size (but positively linked with yields) are omitted. As observed by Gollin and Udry (2018), these features are unobservable to the econometrician, but are well recognised by farmers and often include inherent physical and chemical properties of the soil or the slope and topography. In addition, the unobservable land quality heterogeneities may involve complex interactions between location characteristics and plot characteristics. Similar to this is the possibility that production practices or techniques might be correlated with farm size, leading to heterogeneities in yields or productivity. While a number of studies show a drop in the magnitude of the IR after controlling for the omitted variables (soil quality or agroclimatic variables), empirical evidence is mixed.

The third explanation for the IR relates to the methodological issues around measurement errors in land and agriculture output. The need to incorporate such dimensions into the investigations of IR stems from the difficulties of estimating productivity at the farm level – especially if based on self-reported land area and output estimates by the farmers. The estimation of agricultural productivity is particularly problematic for mixed farming systems in which the land under cultivation simultaneously supports multiple agricultural activities. This feature makes the measurement of plot area and crop yields difficult and prone to many errors (Bevis & Barrett 2018; Gollin 2019). Recent studies that have focused on measurement errors have shown evidence that the IR may arise from inaccuracies in self-reported survey data (Deininger *et al*. 2012; Carletto *et al*. 2013, 2015; Kilic *et al*. 2017; Desiere & Jolliffe 2018). Although the increased availability of sophisticated remote-sensing and georeferencing technologies is able to partially address some of these challenges, obtaining reliable estimates for crop yields in the context of complexities of mixed agricultural systems remains a key weakness in the IR literature. In this article, we apply a cross-sectional dataset, complemented by secondary census information of a perennial mono-cropping system, a feature that allowed us to skirt many of the above-mentioned problems.

4. Materials and methods

4.1 Data

The data applied in this study was obtained through a cross-sectional survey of tea-producing households that was implemented through a multistage random sampling procedure between 2016 and 2017. The survey covered two leading tea-producing counties in Kenya – Bomet and Nyamira in western Kenya – which were selected to provide good representation of farm size variability in the country. The two regions represent counties with a fair distribution of small and large farms. Equally, the counties have close similarities in agro-ecological potential, which enabled us to control for the effects of land quality heterogeneities. The survey collected information on crop yield, land use, household composition, education, labour and capital assets, the allocation of time to household production and market labour, self-reported indicators of soil quality (including topo-sequence, erosion and tree cover), and other household and institutional variables relevant to the farm size–productivity analysis. The sampling approach yielded 331 respondents in Nyamira and 194 in Bomet. The farmers' self-reported survey information was compared with secondary information from a database of tea yields and acreage maintained by the Kenya Tea Directorate (industry regulator). The comparison revealed that the self-reported data was very similar to the secondary data, suggesting that the farmers' recall was generally accurate. This enhanced the validity of our findings. The use of existing secondary datasets to validate self-reported data is important to address the measurement errors that are widely reported in productivity literature (Gollin & Udry 2018).

The quantitative data from the survey was complemented with qualitative information from key informant interviews (KIIs) and focus group discussions (FGDs). The qualitative data helped in developing an understanding of the factors likely to explain differences in productivity across farms of varying sizes.

4.2 Estimation strategy

This study considers a population of tea-producing households indexed by h. The production of tea depends on purchased and farmer-controlled inputs, including fertiliser, land and labour. Based on agricultural production theory, the production process can be described using a production function, specified as:

$$Q_h = F\left(\mathrm{X}_h^{\mathrm{t^i}}, \mathrm{Z}_h^{\mathrm{t^i}} \middle| \sum_i Z_h^{\mathrm{t^i}} \leq K_h \right), \tag{1}$$

where Q_h represents tea outputs, $\mathrm{X}_h^{\mathrm{t^i}}$ and $\mathrm{X}_h^{\mathrm{t^i}}$ are purchased and farmer-owned inputs respectively, while the superscript $\mathrm{t^i}$ shows the sequence of crop production cycles imposed by agro-ecological conditions. The recursive structure of crop production suggests, for example, that the labour (nature and type) used in weeding and fertiliser application is separable from the labour needed for harvesting and postharvest activities. The vector K_h shows the maximum stock of farmer-controlled resources available at each stage of the production cycle (Debertin 2012).

The current study applied technical efficiency (TE) to test the existence of the IR in tea production, given that it is a superior representation of productivity compared to other, alternative measures such as output per unit area, which are often biased in favour of small farms. As argued by Helfand and Levine (2004), the magnitude of the IR would decline or even be reversed if more robust measures of productivity are used. In this study, TE is achieved using the data envelopment analysis (DEA) model based on variable returns to scale. Apart from plot area, the other inputs considered in the DEA analysis include fertiliser and labour applied to the various tea-production activities, including weeding, pruning, fertiliser application and harvesting.

On the basis of the TE scores, the influence of plot size on productivity was explored using the fractional regression model (FRM) following Papke and Wooldridge (1996, 2008). The model (Equation 2) imposes the condition that the predicted values of TE remain within the interval [0, 1]. Using OLS would be inconsistent with the nature of the TE scores. OLS also suggests that the farm size has a constant influence on productivity across all distributions of land area (Ramalho *et al*. 2010).

$$\mathrm{T}E = h(z)[\mathrm{A_i}\beta; Z_i\alpha_j] + \varepsilon_i \qquad \textit{for } \mathrm{i} = 1,2,\ldots,\mathrm{N} \text{ and } \mathrm{j} = 1,2,\ldots,\mathrm{M}, \tag{2}$$

where $h(.)$ is a nonlinear function that meets the condition that $0 \leq h(Z) \leq 1$ for all $Z \in R\, z \in R$. In the model, A_i is the logarithm of plot area at the holding level, Z_i is a vector of farm and household variables that include household composition, marketing and institutional arrangements and subjective land quality indicators; β and α_j are parameters to be estimated, and α_i is a random error term. The model (Equation 2) was first estimated using a parsimonious model that omits Z_i, before incrementally adding controls for possible market imperfections and soil quality heterogeneities at the farm and household level. We further checked the robustness of our results by estimating the semi-log yield equation specified in Equation 3, following previous literature (Barrett *et al*. 2010; Muyanga & Jayne 2019).

$$LnY_{\mathrm{i}} = f(\mathrm{A_i}\beta; Z_i\alpha_j) + \varepsilon_i \qquad \textit{for } \mathrm{i} = 1,2,\ldots,\mathrm{N} \text{ and } \mathrm{j} = 1,2,\ldots,\mathrm{M}, \tag{3}$$

where Y_i is the logarithm of tea output per hectare for the i^{th} household, while the other variables are as defined earlier (for Equation 2). The procedure of initially beginning with a parsimonious estimation and then incrementally adding control variables was also applied in estimating the semi-log model.

5. Results and discussion

5.1 Descriptive summaries

The summary statistics are presented in Table 1. From the results we observed that farms are generally small, with a mean of 1.3 acres. The mean annual tea yields (output of tea per acre) was below the potential of about 5 000 kg per acre based on the predominant tea cultivars. The application of fertiliser was about 4.6 bags compared to the recommended annual rate of five (5) 50 kilogram bags per acre (Tea Research Foundation of Kenya [TRFK] 2002). The distribution of the TE suggests that smallholder tea farmers in Kenya are less efficient (as shown in Figure A.2 in the Appendix), implying that there is a potential to improve their well-being through the adoption the practices and production techniques of the best-practice producers.

Table 1 further shows that male-headed households are more prevalent (84%), and most farmers have relatively low levels of education, with 45% of respondents having attained primary education. In addition, most of the farmers were aged 49.2 years and had a sizable share (58%) of family labour that was used in tea production. The distinction between family and hired labour is particularly relevant in the light of the literature suggesting that labour market imperfections in developing countries contribute significantly to the empirical regularity of the IR. It is also notable that most of the respondents (60%) had planted improved tea varieties. This might be explained by the proximity of the study sites to the Tea Research Institute (TRI), which has been implementing programmes targeting the release of improved tea varieties to tea farmers in Kenya. The average age of the tea plants was 27 years. The age of a tea farm has significance, given that the maximum yields are obtained between 25 and 40 years after establishment. Thereafter, yields decline gradually to levels at which the tea quality may decline (Kamau 2008).

Table 1: Descriptive summary statistics

Variable	Description	Mean	SD
Input-output variables			
Yield	Tea output per acre (kg/acre)	2 746.0	2 068.0
TE (score)	Level of technical efficiency	0.46	0.24
Farm size	Plot area (acres)	1.30	1.10
Fertilizer	Quantity of fertiliser (50 kg bags/annum)	4.60	3.80
Labour	Quantity of labour (man-days/annum)	163.90	138.50
Household socio-economic characteristics			
Gender	Household head being male or female (1 = male)	0.84	0.37
Age of farmer	Age of the household head (years)	49.20	14. 50
Education	Highest level attained (primary)	0.45	0.50
	Highest level attained (secondary)	0.40	0.49
	Highest level attained (tertiary)	0.10	0.29
	Highest level attained (university)	0.05	0.22
Labour structure	The share of family labour used (%)	58.20	45.50
Technology and soil quality			
Variety	Type of planted variety (1 = improved tea)	0.60	0.49
Slope	Topography of tea plot (1 = gentle, 0 otherwise)	0.092	0.29
Soil quality	Perception of suitability of soil for tea production (1 = good, 0 otherwise)	0.49	0.05
Age of farm	Age since establishment (years)	27.00	14.90
Institutional and market access variables			
Extension (FFS)	Participation in FFS (1 = yes)	0.82	0.39
Market channel	Participation in farmgate channels (1 = yes)	0.36	0.48
Distance	nearest distance to market (km)	2.90	2.73

The results also reveal that the formal marketing systems (led by KTDA) dominate, accounting for 63.6% of the tea sales among the farmers. The rest of the tea sales (36%) are organised through alternative channels (ATMCs), which are largely dominated by middlemen who buy the tea harvests at farm gate or roadside spot markets (Ateka *et al*. 2018, 2021). A county dummy is included in the analysis to account for spatial heterogeneity not captured in the regressors.

Before estimating the econometric models, we checked for the presence of labour market imperfections, being the most acclaimed explanation for the IR in most studies. To achieve this, farms in the sample were divided into terciles (3) of plot sizes, which allowed for a comparison of input use intensities across the categories. We present the results in Table 2 and then highlight the two key relationships that emerge from the analysis.

Table 2: Intensity of input use and productivity across farms size terciles

	Acres < 0.75		**0.75 < Acres ≤ 1.5**		**Acres > 1.5**		**Kruskal-Wallis H test**
Sample size (n)	**198**		**177**		**150**		
Variable	Mean	SD	Mean	SD	Mean	SD	P value
Measure of productivity							
Tea output per acre	3 135.7	2 326.2	2 845.5	2 041.2	2 114.0	1 530.5	0.000
Technical efficiency (TE)	0.56	0.20	0.41	0.21	0.39	0.27	0.000
Input intensity							
Labour (man-days per acre)	333.8	306.3	145.5	128.3	78.1	64.5	0.000
Fertilizer (bags per acre)	6.3	5.6	4.1	2.8	2.8	1.7	0.000
Labour structure							
% of family labour used (%)	7.3.1	40.9	56.2	45.5	40.8	34.8	0.000

The results (Table 2) show that the two unconditional measures of productivity (output per acre and technical efficiency) are consistently highest among farms smaller than 0.75 acres. The results also show that large farms have higher land-to-labour ratios than smaller farms (334 labour days per acre compared with 78 labour days for large farms; P = 0.000). Tea farming is highly intensive in labour, with a continuous calendar of highly recurrent husbandry activities, suggesting its significance in the empirical investigations of the IR (Ateka *et al*. 2018).

5.2 Econometric results

In this section we present the results from the FRM and semi-log productivity models (Equations 2 and 3). The results of the FRM regressions are presented in Table 3, in columns 1 to 4. Regression one (1) estimates the association between farm size and TE and includes a quadratic term of farm size (square of farm size) to allow for the consideration of a wide distribution of plot of sizes and influence of non-linearities in the relationship. In the subsequent regressions (columns 2 to 4), we introduce additional covariates to control for labour, institutional and market variables, household characteristics, tea variety and soil quality. The rationale is that, if market failures are important for the IR, as suggested in literature, the coefficient β would be significant in the parsimonious specification but miss significance with the addition of more control variables.

The results show that coefficient for plot size is negative in all four regressions, suggesting that our data is consistent with the broad body of literature on the topic. As shown in Table 3, the coefficient of the quadratic term (the square of farm size) was positive, suggesting that a negative influence of plot size on productivity is non-linear, with TE initially declining (as farm size increases) and then increasing with the increase in farm size. The results imply that, at lower levels of farm holding, productivity declines with an increase in farm size, but there is a unique threshold (turning point) of farm size beyond which an increase in farm size would lead to increases in productivity. We therefore conclude that, in order to avoid over generalisations, any empirical analysis seeking to test the association between productivity and farm size should take into account the distribution or range of farm sizes over which the results apply. Interestingly, the results show that the coefficients of farm size and the square of farm size both maintain the same sign across the four regressions, suggesting that the estimated relationship is robust and would still persist, even after controlling for market imperfections and other land quality variables. It is also notable that controlling for land quality variables does not change the farm size coefficients, except for minor changes in their magnitude.

Table 3: Results of FRM on farm size and productivity (TE)

Variable	**One (1)**		**Two (2)**		**Three (3)**		**Four (4)**	
TE score	Coefficient	P value	Coefficient	P value	Coefficient	P value	Coefficient	P value
Farm size	-0.168***	0.000	-0.157***	0.000	-0.180***	0.000	-0.178***	0.000
Farm size squared	0.023***	0.000	0.022***	0.000	0.023***	0.000	0.023***	0.000
Labour structure			0.070***	0.003	0.043*	0.070	0.044*	0.071
FFS extension			0.053***	0.009	0.052***	0.008	0.054***	0.006
Distance (market)			-0.003	0.554	-0.002	0.604	-0.003	0.526
Market channel			0.089***	0.000	-0.073***	0.000	-0.073***	0.000
Gender of head					-0.016	0.576	-0.017	0.557
Education (primary)					0.063*	0.084	0.066*	0.072
Education (secondary)					0.064*	0.068	0.065*	0.067
Education (university)					0.072*	0.083	0.074*	0.075
County dummy					0.165***	0.000	0.165***	0.000
Tea variety							0.016	0.420
Soil quality							-0.003	0.908
Slope							-0.024	0.448

Note: The asterisks denote significance, as follows: *** is significant at 1%, ** at 5% and * at 10%

Using the results of the fourth regression (column 4), which includes indicators of tea varieties, topo-sequence and self-reported measures of soil quality, the empirical threshold representing the scale at which further increases in farm size would lead to improvement in productivity was determined. This was achieved by applying differential calculus based on the first order conditions with respect to farm size. The analysis revealed that the critical level of farm size was about four (4) acres, which represents the scale at which the economies of scale of large farms would outweigh the corresponding diseconomies of size. Our finding is consistent with that of Muyanga and Jayne (2019), who show that the inverse farm size productivity hypothesis could hold on farms ranging between zero and three (3) hectares. Overall, the results imply that the envisaged farm consolidation and enterprise diversification programmes contemplated in the Kenyan agricultural policy are potentially feasible, if the targeted minimum holding exceeds the estimated threshold. In Kenya, Article 68 of the Constitution empowers the country's parliament to prescribe minimum and maximum land holding acreages (Republic of Kenya 2010). In pursuance of this provision, the Land Laws (Amendments) Bill was published in 2015, but was not enacted due to a lack of consensus among stakeholders. There were also concerns that the proposals in the Bill did not account for socio-economic and environmental factors driving land use, suitability and productivity (Syagga & Kimuyu 2016). As shown in Table 4, the other factors – apart from farm size – having an influence on TE include access to extension, the age of the tea plants, education and the share of family labour applied in tea production. The results reinforce the need to strengthen extension and input distribution, and improve the functioning of markets to efficiently serve geographically dispersed smallholders (Ateka *et al*. 2019; Mbeche *et al*. 2021).

Due to space limitations, the results of the semi-log regressions (Equation 3) estimated to check the robustness of our results are reported in Table A.1 in the Appendix. Consistent with the FRM results, the coefficient of farm size was negative across all the estimations (columns 1 to 4), pointing to the existence of a robust IR within the smallholder tea production system in Kenya. Interestingly, the results show that the magnitude of the coefficient becomes stronger with the addition of more controls, which affirms the observations that the inverse relationship would persist even after controlling for other productivity covariates. In addition, it is notable that the coefficient of the quadratic term (the square of farm size) is consistently insignificant across all the regressions (columns 1 to 4), suggesting that the effect of farm size on productivity is expected to be constant across the entire distribution of tea plot sizes. The difference between the FRM results and the semi-log results affirm the view that the selection of robust indicators of productivity is important for IR assessments (Helfand & Levine 2004).

6. Conclusions and policy implications

Farm size is an important subject in contemporary policy debates. This paper focuses on smallholder tea production against the backdrop of rising stakeholder concerns about the subdivision of farms. While a large body of literature has tested for yield differences across farms of different sizes, most of the previous studies have been undertaken within a setting of mixed cropping systems. In this article, we apply household survey and secondary census data of smallholder tea farms in Kenya to show the influence of farm size on productivity in the case of an industrial perennial monocrop system. Secondly, by applying alternative measures of productivity, we demonstrate that using robust indicators of productivity is important for IR investigations. In addition, our findings reveal that farm size has a nonlinear effect on productivity in perennial production systems, with productivity initially dropping and then increasing with farm size. This relationship appears to hold even after controlling for labour and land quality differences. Finally, our findings show that there exists a threshold (an equilibrium turning point) of farm size beyond which an increase in farm size results in an increase in productivity. Our findings indicate that the policies targeting farm consolidation potentially are feasible in the context of smallholder perennial crop producers in SSA. The findings also point to the policies that could enhance productivity and agricultural growth in smallholder tea production.

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Appendix

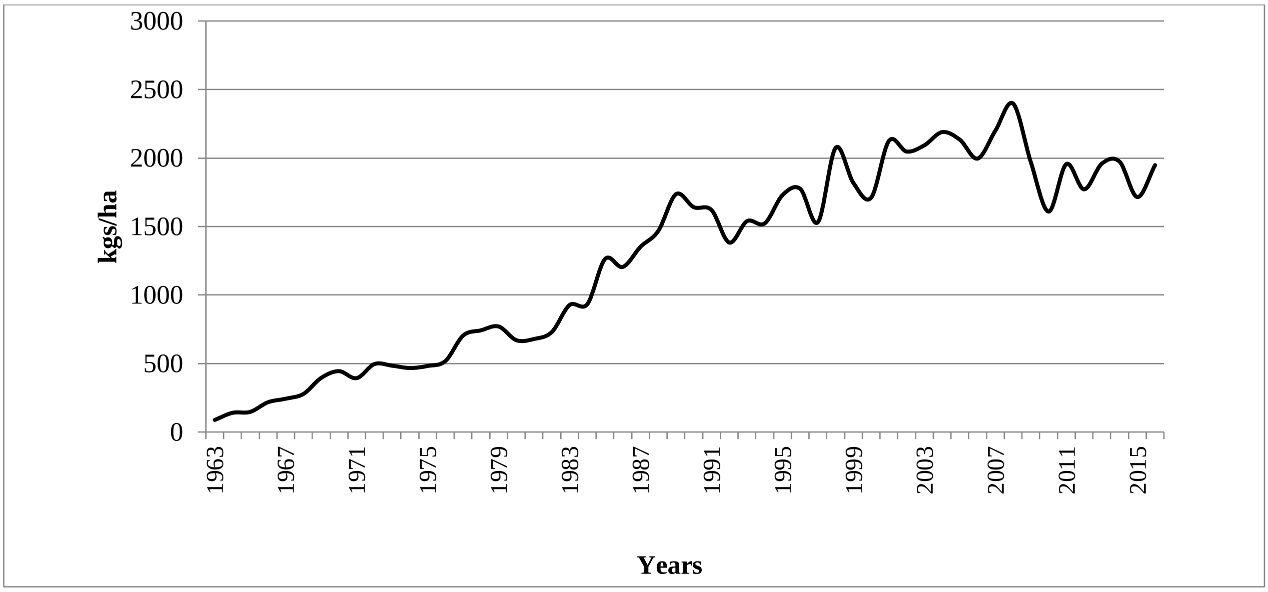

Figure A.1: Kenya's smallholder tea productivity (1963 to 2017)
Source: KTDA statistics (various issues, 1964 to 2018)

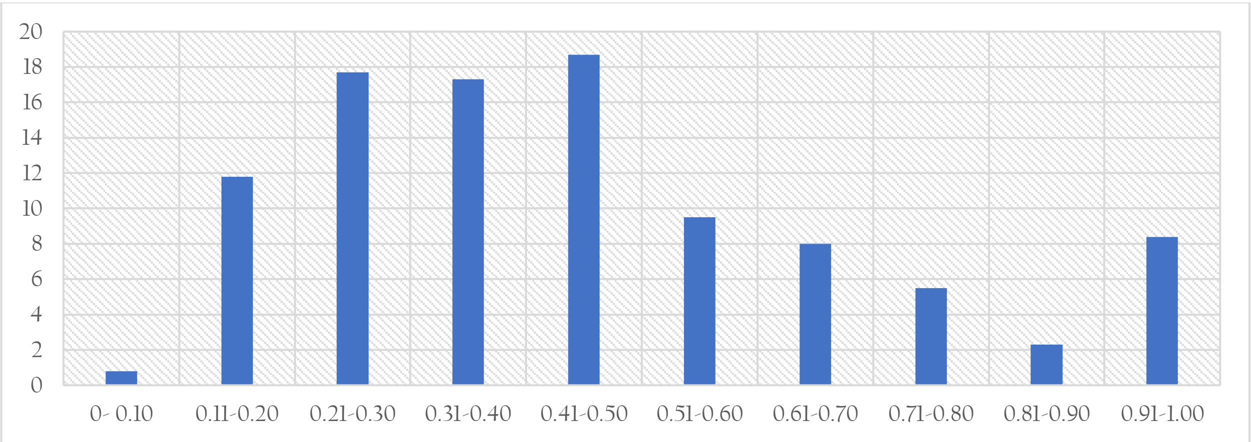

Figure A.2: Distribution of TE scores

Table A.1: Results of semi-log model on farm size and productivity (output per Ha)

Ln(yield)	**One (1)**		**Two (2)**		**Three (3)**		**Four (4)**	
	Coefficient	P value	Coefficient	P value	Coefficient	P value	Coefficient	P value
Farm size	-0.230***	0.005	-0.239***	0.004	-0.33***	0.000	-0.353***	0.000
Square of farm size	0.013	0.398	0.012	0.438	0.02	0.235	0.019	0.155
Labour structure			-0.028	0.729	-0.12*	0.093	-0.119	0.103
Extension (FFS)			0.245***	0.000	0.21***	0.000	0.213***	0.000
Distance to market			-0.018	0.140	-0.01	0.268	-0.013	0.224
Market channel			-0.334***	0.000	-0.26***	0.000	-0.249***	0.000
Gender of head					0.23***	0.006	0.219***	0.008
Education (primary)					-0.10	0.498	-0.097	0.506
Education (secondary)					-0.14	0.333	-0.147	0.309
Education (university)					-0.11	0.495	-0.100	0.542
County dummy					0.79***	0.000	0.744***	0.000
Tea variety							-0.007	0.907
Soil quality							0.104	0.119
Slope							0.126	0.227

Note: The asterisks denote significance, as follows: *** is significant at 1%, ** at 5% and * at 10%