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Effects of Tractor Ownership on Agricultural Returns-to-scale in Household Maize Production

Evidence from Ghana

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ABSTRACT

The rise in returns-to-scale (RTS) has often been an integral part of the agricultural transformation process around the world. Although tractor ownership is often associated with greater RTS in agriculture, whether tractor ownership actually causes such increase in RTS has not been formally tested in the literature. We provide evidence that partly bridges this knowledge gap, using unique survey data of tractor-owning farm households in Ghana. We find that owning tractors significantly increases RTS in maize production from the households' largest monocropped plot. Specifically, owning tractors raises RTS for farmers because they can till greater areas, even though returns from tilling more land remain relatively unaffected. The increase in RTS holds regardless of the values of tractors owned. These sets of evidence are obtained by addressing jointly the multiple sources of endogeneity of tractor ownership, tractor values, tillage intensity, and other inputs used, through combinations of inverse-probability weighing method, generalized method of moments method, and the mediation effects model with multiple mediators. The adoptions of mechanical technologies (tractors) and their ownerships are causing, rather than simply responding to, the rise in RTS in Ghanaian maize production.

These findings are consistent with the hypotheses regarding how tractor ownership may affect farm production practices. Improved timeliness of land preparation realized through ownership may mitigate declines in marginal returns to tillage because more areas can be prepared at optimal timing. Fixed costs may be incurred for simply getting the tractors ready for operations, independent of the scale of operations. Such costs may be incurred in the form of labor, cash, or land set aside. Then as the production scale expands, greater shares of these inputs may be used for productive activities on the farm, raising their marginal productivities and thus realizing increasing RTS. The findings also lead to important hypotheses about the role of tractor ownership on agricultural transformation. Where tractor investments are led by the private sector, as in parts of Ghana, the rise in RTS in the agricultural sector may be driven by the factors raising the demand for tractors, potentially including rising population density, market access, urbanization, and rising wages. The rise in RTS enabled by tractor ownership may shift comparative advantage to medium to larger farmers, from smallholders. While these hypotheses must be formally tested in future studies, our findings on RTS suggest that these hypotheses are likely to be relevant.

Keywords: returns-to-scale, tractor ownership, inverse probability weighted generalized method of moments estimators, mediation effects, maize, Ghana

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1. INTRODUCTION

The changes in returns-to-scale (RTS) in agriculture have broad implications for production intensification patterns, demands for different types of modern agricultural inputs, farm size distributions and productivity, labor movement into/out of agriculture, and the impacts of various agricultural policies (Deininger and Byerlee 2012; Foster and Rosenzweig 2011). The rise of RTS has been one of the important phenomena of agricultural transformation throughout history (Hayami and Ruttan 1985; Takeshima 2017). Despite the importance of the role of RTS, the causes of such increase in RTS have not been widely investigated in the literature.

Agricultural mechanization has often been considered a primary factor associated with the rise of agricultural RTS (Christiaensen 2013; Foster and Rosenzweig 2011; Diao et al. 2014; Otsuka, Liu, and Yamauchi 2016). Intuitively, increased uses of bulky capital items like tractors can raise RTS in agriculture. Recently, Takeshima (2017) showed that renting in tractors through custom hiring services raises RTS among smallholders in Nepal. However, few studies have formally tested whether the ownership of machines like tractors causes an increase in RTS among more medium to large farms, for whom the effects of the increase in RTS has greater implications.[1]

Investigating the factors that increase RTS is important because there are other potential factors that either are thought to cause or are associated with the increase in RTS, including specialization, land consolidation (Wan and Cheng 2001), and a change of crop mix (Cramb 2011). Some biological innovations (particularly use of varieties that are resistant to various pests) are also associated with growing farm size in some regions of the world (Deininger and Byerlee 2012).2 Mechanization and mechanical invention have often been relatively more endogenous responses when compared to other factors like biological innovations (at least conventional breeding), which have been more exogenously

[1]While this study does not directly investigate implications of the rise in RTS, medium to large farms are likely to be affected more than small farms from greater RTS. For example, the rise in RTS can shift the comparative advantage in production in favor of larger farms over smaller farms.

[2]This is partly why many virus- and pest-resistant varieties have been developed in land-abundant countries like the United States, where the labor costs required for pest control would otherwise be prohibitive.

led by the public sector (Hayami and Ruttan 1985). It is therefore possible that tractor ownership is simply a response to, rather than a cause of, the rise of RTS caused by these other factors. If RTS is raised before tractor adoptions or ownership, tractor ownership simply may be substituting other inputs without affecting the production function. If RTS is raised by tractor adoptions or ownership, it is also transforming the production function. Whether tractor ownership actually causes the rise in RTS is therefore an important research question.

Using the unique dataset of a fairly large number of tractor-owner farm households in Ghana, we provide key evidence about how tractor ownership affects RTS in agriculture. Aside from its availability of data, Ghana offers an ideal condition to test our hypotheses because it is one of the countries where tractor ownership has started rising (albeit rather gradually), unlike in more advanced countries where mechanization occurred a long time ago and where relatively more medium-sized farms are found compared to some other developing regions like Asia, where mechanization has been growing but smallholders still dominate. Similarly, maize is a good example because maize production is generally less labor intensive than production of other major crops like rice, with regard to operations that are conducted after land preparation (Ngeleza et al. 2011), so that land-extensive cultivation is relatively more common where own tractors may be particularly attractive relative to hired-in tractors. In addition, maize requires less water, and land-extensive rainfed maize production is widely practiced around the world.

Specifically, we assess (1) whether tractor ownership increases RTS in maize production compared to nonownership and (2) what may be some of the mechanisms through which RTS is increased. For (2), we assess (2a) whether the degree of increase in RTS is associated with tractor size (measured as the average values of tractors owned by the households) and (2b) whether RTS is exhibited in tillage intensity[3] or in the returns to tillage on maize production.

[3] We use the term "tillage intensity" to indicate the frequency of tillage multiplied by the areas tilled. Tillage intensity is one of the important intermediate outputs that affect the final maize outputs.

By doing so, we address complex endogeneity structures involved with these types of empirical exercises. Typically, the estimations involve multiple sources of endogeneity, such as the decisions to invest in tractors or the sizes of tractors acquired and the uses of various agricultural inputs on outputs, or tillage intensity. We employ combinations of the inverse-probability-weighting (IPW) method, generalized methods of moments (GMM), and mediation effects model.

Our paper contributes to various strands of literature. Our work provides empirical evidence about the productivity role of tractors, supplementing the earlier analyses that focused on the economics of tractor ownership in Ghana (Houssou, Diao, and Kolavalli 2014). It also significantly complements the growing body of literature analyzing the custom hiring service in Ghana (Diao et al. 2014; Benin 2015; Houssou et al. 2017) and elsewhere (Takeshima et al. 2015; Takeshima 2017). Although our paper does not cover custom hiring services, the impact of tractor ownership on own farm indirectly affects the opportunity costs of service provisions. Our analyses also supplement the general agricultural mechanization literature (Binswanger 1986; Pingali 2007) by providing more detailed pictures of the farm technological implications on tractor ownership.

Our paper also contributes to the agricultural productivity literature, as few papers investigate changes in RTS over time (Hayami and Ruttan 1985; Hayami and Kawagoe 1989) or factors directly causing the change in RTS (Takeshima 2017). Our study also provides some evidence on RTS in tillage intensity as well as returns to tillage in maize production, which are rarely separated in the literature.

Our paper also contributes to the growing literature on the relationship between productivity and farm size (Hazell et al. 2010; Masters et al. 2013; Otsuka, Liu, and Yamauchi 2016; Rigg, Salamanca, and Thompson 2016) and the growths of medium to large farms in Africa (Diao et al. 2014; Jayne et al. 2016). Specifically, our findings offer insights into how tractor ownership affects the relationship between productivity and farm size and its possible role in farm size growth.

Last, our paper contributes to the literature on impact evaluations. The paper ties together the literature on inverse probability weighting (Wooldridge 2007) with regression adjustments (Cavatassi et al. 2011) and its GMM extension (Takeshima 2017), continuous treatment effects (Hirano and Imbens

2004), and mediation effects (Huber 2014a) and show that combining their uses can provide insights into various dimensions of interlinkages between technologies adoption and agricultural production characteristics.

This paper is structured as follows: section 2 presents the conceptual framework; section 3 describes the empirical methods; section 4 summarizes the data, variables, and descriptive statistics; section 5 discusses the empirical results; and section 6 concludes.

2. CONCEPTUAL FRAMEWORK

We follow the same conceptual framework, slightly modified from Takeshima (2017), which estimated similar effects of rented-in tractors on RTS in Nepal.

RTS typically refers to the elasticity of output increases with respect to the increases in all inputs at a fixed proportion, often measured as the sum of the output elasticities of all inputs in a production function (Kislev and Peterson 1996). We investigate the effect of tractor ownership on RTS in the following framework. A farm household belongs to one of two regimes R, each with different production function: (1) with own tractors (denoted as regime $R = 1$), and (2) without own tractors ($R = 0$). For each farm household, output Y is realized by

$$Y = \begin{Bmatrix} f_1(K_1; A) \text{ if } R = 1 \\ f_0(K_0; A) \text{ if } R = 0 \end{Bmatrix}, \tag{1}$$

in which f_Rs are regime-specific production functions in which Y depends on inputs/services vector K_R, given the agroecological and socioeconomic conditions, A. Important to note, f_1 and f_0 can be the same if owning tractors does not affect the production function. We are specifically interested in whether owning tractors actually changes the underlying production function.

The farm household maximizes utility U that depends on the maize production profit π by selecting R and K_R;

$$\max_{R,K_R} U(\pi) \tag{2}$$

$$\pi = R \cdot [f_1 \cdot (K_1; A) - c_1(w, K_1)] + (1 - R) \cdot [f_0 \cdot (K_0; A) - c_0(w, K_0)], \tag{3}$$

where $c_R(w, K_R)$ is the cost of using K_R given factors (w) affecting inputs costs (including opportunity costs of family labor) standardized by setting output price at 1. Decisions (2) and (3) are made subject to constraints (liquidity constraints, and so forth) which are expressed in general forms as

$$g_R(K_R, A, w, \eta) \geq 0, \forall R, \tag{4}$$

where η are factors affecting the liquidity of the households. Each of f_R, c_R, and g_R varies across R.

The optimization problems (2) through (4) are associated with a Lagrangian function $\mathcal{L}_R$,

$$\mathcal{L}_R = U[f_R(K_R; A) - c_R(w, K_R)] + \lambda_R \cdot g_R(K_R, A, w, \eta), \forall R \qquad (5)$$

with Lagrange multiplier λ_R. The optimal solutions for K_R, K_R^* (asterisks indicate the solution values hereafter) meet the following Kuhn-Tucker conditions, for each R; (i) $\frac{\partial \mathcal{L}_R^*}{\partial K_R} \leq 0$, (ii) $K_R^* \frac{\partial \mathcal{L}_R^*}{\partial K_R} = 0$, (iii) $K_R^* \geq 0$, (iv) $\frac{\partial \mathcal{L}_R^*}{\partial \lambda_R} \geq 0$, (v) $\lambda_R^* \frac{\partial \mathcal{L}_R^*}{\partial \lambda_R} = 0$, and (vi) $\lambda_R^* \geq 0$, where the negative sign in (i) holds if $K_R^* = 0$. The farmer chooses $R^* = 1$ if $U|_{R^*=1} \geq U|_{R^*=0}$ given K_R^* and vice versa.

These Kuhn-Tucker conditions depend on f_R, c_R, g_R, A, w, and η, and parameters defining f_R, c_R, and g_R are also functions of exogenous variables A, w, η. The general expressions of our empirical models are therefore the following reduced-form equations r and k:

$$R^* = r(f_R, c_R, g_R, A, w, \eta) = r(A, w, \eta). \qquad (6)$$

$$K_R^* = k(f_R, c_R, g_R, A, w, \eta, R^*) = k(A, w, \eta, R^*). \qquad (7)$$

Y_R^* is related to K_R^* through structural equation f_R, so that

$$Y_R^* = f_R(K_R^*; A, R^*), \qquad (8)$$

from which regime-specific RTS (ρ_R) are obtained and allow one to test their difference.

Tractor Ownership and Potential Increase in RTS

Although the idea that tractor ownership may raise RTS is generally intuitive, it is worth elaborating briefly the potential mechanisms (while these are not directly tested). Some mechanisms are also likely to be more relevant than the other, given the specific contexts of our paper, maize production in Ghana.

Compared to the increase in average productivity, the increase in RTS largely occurs due to the increased productivity (or reduced loss of productivity) at the intensive margins of various inputs or services. Generally, farm mechanization mitigates the decline of marginal productivity at intensive margins as, unlike manual labor, the continuous work may not lower the productivity through fatigue. Switching from rented tractors to owned tractors may further raise RTS. For example, the supply of rented tractors can be sometimes price inelastic due to accessibility constraints (Takeshima 2015) so that its intensive uses can face rising marginal costs (so that marginal productivity of expenditures on renting tractors decline). This is less so for owned tractors, whose opportunity costs may not rise quickly at the intensive margins. This is because, despite the active participation of tractor owners in custom-hiring services, the limited mobility of tractors and seasonality of demand still limit the spatial and temporal scope of tractor uses outside their farms (Takeshima et al. 2015). Consequently, as the farm expands beyond the medium scale, tractors become exclusively used on farms owned by the tractor owners, reducing their uses for hiring out (Houssou et al. 2015).

In rainfed farming, the timing of land preparation and planting often substantially affects productivity (Haggblade 2005). When accessibility to custom hiring services is still constraining, owning tractors may allow timely land preparation of large plots, which can again raise RTS in addition to average productivity (Houssou et al. 2015). The increase in RTS may be realized either through the efficiency of tilling greater areas or the returns to each unit of tilled area. Of course, the timeliness issue may be resolved if the renters have access to multiple tractors at the same time. However, tractor owners can also hire additional tractors from others.

Timely land preparation may also encourage the planting of homogeneous varieties that grow, flower, and mature at the same time, inducing the sourcing of larger quantities of homogeneous seeds from the market, rather than relying on diverse varieties that are more suitable for varying land preparation dates. Such patterns of increased backward and forward linkages may also raise RTS (Takeshima 2017).

3. EMPIRICAL METHODS

We investigate the effects of tractor ownership on RTS in maize production and its potential mechanisms. All models are estimated by a class of IPW regressions that are suitable for each outcome as described below.

Effects of Tractor Ownership on RTS

The effects of tractor ownership on RTS are estimated through the following steps. First, we use the probit model to estimate the probability that a household owns a tractor: We first estimate (6) with a Probit model:

$$\text{Probability}(R^* = 1|Z) = \hat{p} = \Phi(Z\gamma) = \int_{-\infty}^{Z\gamma} \phi(v)dv, \tag{9}$$

where Z is the vector of A, w, and η. Predicted propensity of owning tractor is $\hat{p}$, whereas γ is a set of estimated parameters. Φ and ϕ are the standard normal distribution function and density function, respectively, and v is its element.

We then estimate f_R in (8) separately for tractor owners and nonowners:

$$\ln Y = \beta_0 + \sum_i \beta_i \ln K_i + \frac{1}{2} \sum_i \sum_j \beta_{ij} \ln K_i \ln K_j + \beta_A A + \varepsilon, \tag{10}$$

in which βs are parameters with corresponding subscripts, ε is the idiosyncratic error term, and i, j = labor (family labor and hired labor combined), land area cultivated, agricultural capital, and all the other monetary expenses (fertilizer, seeds, agrochemicals, and other services including the expenses of tractor rental). The estimated RTS is $\widehat{\rho_R} = \sum_i \frac{\partial \ln Y}{\partial \ln K_i} = \sum_i \hat{\beta}_i + \sum_i \left[\left(\hat{\beta}_{ii} + \sum_{j \neq i} \hat{\beta}_{ij}\right) \ln K_i\right]$ (Kim 1992).

If we assume $\beta_{ij} = 0$, (10) reduces to Cobb-Douglas specification. It is well-known that while Cobb-Douglas specification is more feasible and approximates the production function relatively well, it is more restrictive. The Translog specification is less restrictive, but the estimation is less feasible, particularly if multiple K_j are endogenous, and less inefficient if multicollinearity is severe. Following Takeshima (2017), we estimate both specifications (Translog forms are estimated treating all K_j as exogenous), focusing on the IPW sample medians of $\widehat{\rho_R}$ in the Translog case. In the Results section, we show that the evidence is robust to the choice of specification. Equation (10) is estimated by IPW-GMM, which is simply one type of weighted GMM, where the inverse of $\hat{p}$ is used as the weight (Takeshima 2017). IPW-GMM is "doubly-robust" (Robins and Rotnitzky 1995) in the sense that consistency of the overall model requires the consistency of only one of (9) or (10).

Potential Mechanisms of the Increase in RTS

We then assess a few potential mechanisms RTS may increase through tractor ownership. First, we assess whether the values of tractors owned affect the extent of change in RTS. Second, we decompose the change in RTS to the RTS in tillage intensity and the RTS to tillage on maize production.

Effects of Tractor Value on RTS

The effects of the value of tractors on RTS are estimated through

$$\ln Y = \beta_0 + \sum_i \beta_i \ln K_i + \beta_{V0} V_T + V_T \cdot \sum_i \beta_{V,i} (\ln K_i) + \beta_A A + \varepsilon, \tag{11}$$

in which V_T is the value of tractors. The effects of the marginal increase in tractor values on RTS are estimated as $\sum_i \beta_{V,i}$.

We estimate (11) through generalized propensity score (GPS)–IPW-GMM, which is an extension to IPW-GMM with binary treatment (9) and (10), to a continuous treatment case, in which the treatment is the value of tractors owned. The idea of GPS-IPW has long been proposed (Imbens 2000; Bodnar et al. 2004; Flores and Mitnik 2013) and has been used increasingly in the literature (Takeshima et al. 2017).

Specifically, GPS-IPW-GMM is estimated in the following way: first, we estimate stabilized weights w_i for the case of GPS, $w_{GPS,V} = \sqrt{r(T)/r(T,X)}$, in which $r(T,X)$ is the GPS that the household with characteristics X chooses tractor values T, while $r(T)$ is the marginal probability of T based on the normal distribution function that $\ln(T)$ is assumed to follow. We then estimate (11) by using the inverse of $w_{GPS,V}$ as a weight.

The GPS-IPW-GMM model addresses the endogeneity of input variables K_i and V_T. Model (11) also can be estimated with standard GMM if appropriate instrumental variables are available for both K_i and V_T. However, while commonly used instrumental variables, such as their market prices, are relatively available for K_i, prices of tractors can vary considerably depending on their designs and are often unavailable because the tractor market is still underdeveloped in Ghana. In such circumstances, GPS-IPW offers alternative means to address the endogeneity of V_T, under the uncomfoundedness assumptions (Hirano and Imbens 2004).

Tillage Intensity

The effects of tractor ownership on RTS in tillage intensity are estimated through the application of IPW-GMM for the tillage intensity function in which (10) is replaced by

$$\ln T = \beta_0 + \sum_i \beta_{T,i} \ln K_{T,i} + \beta_A A + \varepsilon, \tag{12}$$

in which T is an indicator of tillage intensity, calculated as the tillage frequency times the plot area. Tillage frequency is counted as the sum of the maximum number of plowing (two, one, or no plowing) and harrowing (one or no harrowing), taking one of the integer values between 0 and 3. We denote the inputs in tillage intensity as $K_{T,i}$, which is a subset of K_i and constitutes labor used specifically for tillage, expenditure on tractor rentals. Land and capital are the same as in (10). RTS in tillage intensity is estimated as $\sum_i \beta_{T,i}$ and compared across tractor owners and nonowners.

RTS to tillage on maize production is assessed through the multiple-mediation effects model,

$$\ln Y = \beta_0 + \beta_T \ln T + \beta_A A + \beta_Z Z + \varepsilon, \tag{13}$$

with weights w_T

$$w_T = \frac{1}{\hat{p}} \cdot w_{GPS,T}, \tag{14}$$

in which $\hat{p}$ is defined after (9) above and $w_{GPS,T}$ is the weights based on GPS applied to T, in a similar way as $w_{GPS,V}$ above. Operationally, this model also belongs to a class of nested propensity score methods proposed by Huber (2014b).[4]

Note that (13) is in reduced form because the exact shape of a production function with tillage as an input has not been studied widely in the literature. While the estimated coefficient β_T cannot be used to measure the exact RTS to tillage on maize production, its comparison across tractor owners and nonowners still informs whether tractor ownership affects the returns to tillage on maize production.

Distinguishing the rise in RTS in tillage intensity and the rise in RTS to tillage in maize production is important as they have different implications. The rise in RTS in tillage intensity would mean that farmers benefit from economies of scale in tilling more areas in aggregate. In contrast, the rise in RTS to tillage in maize production would suggest that farmers benefit from concentrating intensive tillage on specific plots, rather than equally tilling all plots, and thus lead to greater variations in tillage intensity across plots or farms.

[4]Whereas Huber (2014b) focuses on the binary treatment case, he also states that the model is applicable to the case with multiple treatment levels (Huber 2014b, 872).

4. DATA

Data used for these analyses consist of farm household data and other spatial agroclimatic data.

Farm Household Data

The farm household data for this study were collected jointly by the International Food Policy Research Institute (IFPRI) and the Savannah Agricultural Research Institute (SARI) of the Council for Scientific and Industrial Research and Ministry of Food and Agriculture, Ghana, between August 2013 and February 2014 (IFPRI/SARI survey hereafter). More details are provided in Chapoto et al. (2014). The survey specifically targets medium to large farmers and is intended to capture information that helps one understand their various characteristics, farm productivity and technical efficiency, spillover effects, aspirations, machinery ownership, uses, supply and demand for tractor hiring services, motivations, and linkages with farm size growth.

The IFPRI/SARI survey data were collected based on a two-stage, stratified cluster sampling design. In the first step, the target population was stratified by eight purposively selected districts in Ghana and three farm size categories (24 strata in total). The three farm size categories are defined based on the cultivated area in the 2012 rainy season: large (>50 acres), medium (12~50 acres), and small (<12 acres). In the second stage, 20 villages in each stratum were randomly sampled (so that village is the primary sampling unit). For each village, a prior listing exercise had identified all medium to large farmers. Out of them, 10 medium to large farmers were randomly selected from each village. In contrast, small farmers were randomly selected through multistage random sampling, using the sampling frame derived from the Ghana Agricultural Production Survey enumeration areas and the list of small farmers in each enumeration area.

In addition, tractor owners were sampled separately from above, using United States Agency for International Development tractor census data as the sampling frame in districts where the census data were available and through a listing exercise otherwise. In total, 408 tractor owners were interviewed, which is one of the largest samples of tractor owners in Africa south of the Sahara and many developing countries.

In total, 1,843 farmers were interviewed. Among them, 802 farmers are found to be renting in tractor services.

Other Agroclimatic Data

In addition, various geographic information system data on agroecological variables are obtained from other sources. These variables are extracted for each household using the locations of villages/towns reported. Monthly rainfall in 2013 was extracted from National Oceanic and Atmospheric Administration (2016), from which two months' rainfall during land preparation and four months' rainfall during maize production seasons were calculated. Soil-related data, including bulk density and sand and clay composition (percentages) are taken from International Soil Reference and Information Centre (2013). Terrain ruggedness is calculated using the elevation data from GTOP30 data (U.S. Geological Survey 1996) and a formula by Riley, DeGloria, and Elliot (1999). Distance to the nearest town with a population greater than 20,000 is obtained from Harvest Choice (2016). Last, population density is obtained from Harvest Choice (2015).

Exogenous Variables

Variables are selected based on related literature on agricultural mechanization in Ghana, including Benin (2015) and Houssou et al. (2017). All monetary values are deflated by the local maize prices calculated as the village median values from the data and expressed in terms of how many kilograms of maize they are worth (*MKG*).

Variables *A* include rainfall during the four months of the production season (*RAIN4M* in millimeters), farming experiences measured as the number of years engaged in farming (*FEXP* in years), age, and age squared (*AGE*, *AGE2* in years). *RAIN4M* and *FEXP* clearly capture the intercept of the production function, which often measures the total factor productivity. Aside from these, *AGE* and *AGE2* control for the potential effects of important agricultural mechanization histories in Ghana; support for mechanization (among other agricultural programs) had once been greater in the 1970s and early 1980s (Wiemers 2015), and older farmers who had experienced such exposures may exhibit better management abilities, particularly in systems using tractors. Variables *A* also include a district dummy variable, which can capture any other regional variations in agroclimatic conditions and district-level variations in other relevant government policies that potentially affect productivity.

Variables *w* include factors affecting the prices or opportunity costs of inputs. For labor, *w* includes the number of household members in terms of adult male (*HHSIZEM*), adult female (*HHSIZEF*) 20 years old or older, and children (*HHSIZEC*); average years of formal education completed among working-age household members (*EDUAVE* in years); and village average wages for hiring labor for land clearing and manual tillage per hectare and its square (*WG*, *WG2*, in *MKG*). For seeds, *w* includes the village sample shares of households adopting hybrid varieties (*VARIETY_V* in proportion), whether having received government assistance for seed (*ASSTGSEED*, yes = 1, no = 0). For chemical fertilizer, *w* includes the average prices per kilogram of fertilizer from all private (nongovernment) sources reported by the households and its squared terms (*PFERT*, *PFERT*2 in *MKG*). For tractor rental, *w* includes the hiring cost per hectare and its squared term (*PTRH*, *PTRH2* in *MKG*). The population density of the area (*POPDEN* in person per square kilometers) and the size of farmland owned (*LN_LANDOWN* in *ln*[hectare]) proxies the opportunity cost of land for cultivation. The general costs of accessing information are proxied by membership in any cooperative/association, farmer-based organization, women's group, youth group, church-based or faith-based group, or block farm scheme (*MEMBER*, yes = 1, no = 0). Distance to the nearest town with a population of at least 20,000 (*D20K* in hours taken to travel) is included to further control for other factors affecting the overall prices of inputs and outputs.

The cost of providing tillage, particularly with own tractors, is also proxied by the types of soils in the area, measured by its bulk density (*SOILBULK* in tones per cubic meter), its sand and clay compositions (*SOILSAND*, *SOILCLAY* in proportion). Generally, the tillage costs are lower for sandy soils with lower bulk density. Soil types are found to often affect the types of tractors invested in by the owners in West Africa (Takeshima et al. 2015). Similarly, two months' rainfall prior to the production season (*RAIN2M* in millimeters) is included to control for the soil moisture level specific to the study year (2013), which might have affected the tillage costs. Terrain ruggedness (*RUG*) proxies other various costs. More rugged terrain generally raises the costs of moving tractors. On the other hand, however, tractors may be sometimes more suitable than other vehicles on rugged terrain, raising the opportunity costs of using tractors for maize production.

While some variables included in *A* and *w* also capture η, other variables are specifically included to proxy η only. Factors potentially affecting the costs of obtaining tractors are proxied by the following: typical costs at the village of bringing tractors from the sellers, estimated using the sample median values among tractor owners (district median is used for village with no tractor owners in the sample) (*TRNSCOST* in *MKG*); district sample shares of tractors obtained with subsidies (*SUBSIDY* in proportion); similar sample shares but only for tractors obtained in 2010 or later, for which subsidy programs might have been different from previous periods (*SUBSIDYNEW* in proportion);[5] sample average years of tractors obtained in the district/major cities (*TRYEAR*). A dummy variable indicating whether any household members work for the government is included as well, as it may reduce the cost of obtaining information about tractor subsidies (*WKGOV*, yes = 1, no = 0). In addition, variables on certain past events that might have affected decisions to invest in tractors are included. Namely, they are dummy variables indicating whether having inherited land or not (*INH_LAND_Y*, yes = 1, no = 0), whether having inherited a machine or not (*INH_MAC_Y*, yes = 1, no = 0), whether having inherited cattle or not (*INH_CAT_Y*, yes = 1, no = 0), total real value of subsidized mechanization services received between 2008 and 2012 (*ASST_MECH0812* in *MKG*), and the total real values of government assistance received between 2008 and 2012 other than subsidized mechanization services (*ASST_0812* in *MKG*). Last, the value of all assets owned (excluding farmland and tractors) (*LN_ASSET* in ln[*MKG*]) proxies overall wealth of the household, affecting the ability to make required upfront payments for tractors, which are often substantial because many tractor owners in West Africa are found to use their own savings as the primary source of finance (Takeshima et al. 2015).

[5] Samples in Gushegu Town, Dromankuma, and Yendi are further separated from the rest of the respective districts because their sample shares of subsidized tractors are relatively different from the rest of the respective districts. The same applies to the sample shares of subsidized tractors obtained in or after 2010.

Production and Input Variables

There are two output variables of our interest. The total value of maize produced from the household's largest monocropping plot is the dependent variable in the production function. The other is tillage intensity, defined earlier in the article.

Inputs K_i include the size of the largest monocropped plot (*LN_LAND* in *ln*[hectare]), total labor used with family and hired labor combined (*LN_LAB* in *ln*[person-hour]), agricultural capital (*LN_CAP*, *ln*[*MKG*]), dummy variable indicating the use of hybrid maize varieties or not (*HYBRID*, yes = 1, no = 0), and other material expenditures (seeds, fertilizer, agrochemicals, rental of draft animals, rental of machines including tractors and attachments, expenditures on machines (fuels, operator wages, maintenance) (*LN_EXP* in *ln*[MKG]). Expenditures on machine maintenance and hiring of attachments are for the entire farming operations and may exceed the expenditures for operations on the largest maize plot. This is due to the lack of additional information about how these expenditures can be allocated to the large monocropping maize plot. We, however, tried adjusting these expenditures in various ways and found that the results are robust.

Inputs $K_{T,i}$ for tillage intensity include *LN_LAND*, total labor (both family and hired labor combined) used exclusively for tillage, harrowing, or both (*LN_LAB_T* in *ln*[person-hours]), expenditures that are subset of *LN_EXP*, that are related to tillage intensity (*LN_EXP_T*, in *ln*[*MKG*]).

Among these, all input variables except the agricultural capital are assumed endogenously determined. Variables *w* are used as instrumental variables for these inputs. As shown, the orthogonality conditions, overidentification conditions, and underidentification conditions are satisfied so that the models are consistent. The value of all agricultural capital is assumed exogenous, even though the values of tractors are treated as endogenous in one of the specifications: (11). This is because values of tractors alone may fluctuate more, while the aggregate values of all agricultural capital (including tractors) may be relatively more fixed in the short term. This is particularly so if the purchase of the tractor is partly financed by liquidating other agricultural capital.

Descriptive Statistics

Table 4.1 summarizes the means of exogenous variables and the statistical significance of their differences between tractor owners and nonowners, for both the raw sample and the IPW sample. Although the estimation of IPW is conducted in the next section, we include the IPW-adjusted statistics here to show how IPW successfully generates comparable samples of tractor owners and nonowners. The means of numerous variables differ significantly in the raw sample, indicating that the household characteristics differ considerably. In the IPW sample, however, only one variable exhibits a statistically significant difference at 10 percent level, suggesting that household characteristics in IPW samples are comparable. Any significant differences in the household production behaviors and estimated RTS can therefore be attributed to the differences in tractor ownership.[6] Similar arguments are made in the literature (Cavatassi et al. 2011; Takeshima 2017).

Table 4.1 Descriptive statistics of raw sample and inverse-probability-weighting sample[a]

	Raw sample		Inverse-probability-weighting sample	
Variable	**Tractor owners**	**Nonowners**	**Tractor owners**	**Nonowners**
Population density of the area (*POPDEN*, person per square kilometers)	101.126	97.226	95.463	113.248
Whether any household members work for the government (*WKGOV,* yes = 1, no = 0)	0.249**	0.193	0.174	0.187
Typical costs at the village of bringing tractors from the seller: (*TRNSCOST*)	526.242**	634.424	590.661	582.579
Value of all assets owned (excluding farmland and tractors) (*LN_ASSET,* natural log)	9.615***	8.246	8.747	8.914
District sample shares of tractors obtained with subsidies (*SUBSIDY,* proportion with 1 = all, 0 = none)	0.072	0.076	0.067	0.081
Sample shares but only for tractors obtained in 2010 or later (*SUBSIDYNEW,* proportion with 1 = all, 0 = none)	0.114**	0.128	0.101	0.123
Sample average years of tractors obtained in the district/major cities (*TRYEAR,* year)	2008.490	2008.384	2007.704*	2008.316
Whether having inherited land or not (*INH_LAND_Y,* yes = 1, no = 0)	0.173***	0.287	0.175	0.222
Whether having inherited machine or not (*INH_MAC_Y,* yes = 1, no = 0)	0.015	0.006	0.007	0.011
Whether having inherited cattle or not (*INH_CAT_Y,* yes = 1, no = 0)	0.058**	0.098	0.109	0.079
Total real value of subsidized mechanization services received between 2008 and 2012 (*ASST_MECH0812*)	0.423	1.199	0.212	0.781

[6]Note that reduced statistical differences in IPW samples may be partly due to the increased sample variances as a result of IPW. However, this should also increase the variances of estimated RTS so that we are more likely to accept the hypotheses that RTS are the same between tractor owners and nonowners. Nevertheless, as is shown, we find that their RTS are still statistically significantly different.

Table 4.1 Continued

	Raw sample		Inverse-probability-weighting sample	
Variable	**Tractor owners**	**Nonowners**	**Tractor owners**	**Nonowners**
Total real values of government assistance received between 2008 and 2012 other than subsidized mechanization services (*ASST_0812*)	119.776	28.328	65.432	38.652
Rainfall during the four months of the production season (*RAIN4M* in millimeters)	220.451	208.487	200.523	222.706
Village sample shares of households adopting hybrid varieties (*VARIETY_V* in proportion with 1 = all and 0 = none)	0.048	0.058	0.050	0.053
Whether having received government assistance for seed (*ASSTGSEED,* yes = 1, no = 0)	0.044	0.067	0.032	0.050
Average years of formal education completed among working-age household members (*EDUAVE* in years)	3.708**	2.931	4.007	3.786
Two months' rainfall prior to the production season (*RAIN2M* in millimeter)	179.315	168.496	175.454	172.315
Terrain ruggedness (*RUG,* index)	0.179	0.208	0.288	0.181
Soil bulk density (*SOILBULK* in tones per cubic meter)	1.457***	1.471	1.486	1.455
Soil sand compositions (*SOILSAND,* proportion with 1 = all and 0 = none)	0.589***	0.575	0.565	0.580
Soil clay compositions (*SOILCLAY,* proportion with 1 = all and 0 = none)	0.185***	0.180	0.172	0.181
Number of adult male household members (*HHSIZEM,* number)	3.184***	2.490	3.069	3.312
Number of adult female household members (*HHSIZEF,* number)	2.904***	2.423	2.825	2.789
Number of nonadult household members (*HHSIZEF,* number)	6.029***	5.012	5.779	5.466
Distance to the nearest town with the population of at least 20,000 (*D20K* in hours taken to travel)	1.698***	1.858	1.718	1.735
Village average wages for hiring labor for land clearing and manual tillage per hectare (*WG*)	63.093	56.253	56.531	56.081
Squared values of *WG* (*WG2*)	9748.176	6519.858	6347.395	6827.081
Size of farmland owned (*LN_LANDOWN* in *ln*[hectare])	3.169***	2.529	2.741	2.808
Average prices per kilogram of fertilizer from all private (nongovernment) sources (*PFERT*)	0.931***	0.956	0.967	0.947
Squared values of *PFERT* (*PFERT2*)	0.877***	0.928	0.950	0.908
Hiring cost per hectare and its squared term (*PTRH*)	89.628***	94.300	97.820	91.473
Squared values of *PTRH* (*PTRH*2)	8307.603***	9342.249	10062.160	8766.072
Whether a member of any of cooperative/association, farmer-based organization, women's group, youth group, church-based or faith-based group, or block farm scheme (*MEMBER,* yes = 1, no = 0)	0.547	0.564	0.612	0.544
Age of respondent (*AGE,* year)	46.927***	44.259	46.873	46.453
Squared term of *AGE* (*AGE2,* year)	2358.073**	2141.548	2350.119	2327.786
Number of years engaged in farming (*FEXP* in years)	20.801***	18.682	20.837	20.337

Source: Authors' analyses.

Note: [a]Unless otherwise specified, units of variables are in values equivalent to kilograms of maize.

Asterisks indicate the statistical significance: *10 percent. **5 percent. ***1 percent.

5. RESULTS

Effects of Tractor Ownership on RTS in Maize Production

Results are summarized in Tables 5.1 through 5.4 (Appendix Table A.1 summarizes the estimated factors associated with propensity scores for owning tractors). Table 5.1 presents the coefficients in production functions among tractor owners and nonowners, respectively. Our main interest here is the differences in the coefficients, particularly RTS, between two groups of farmers rather than the estimated production functions themselves. As was described above, these production functions are estimated using IPW so that their differences are attributable to the ownership of tractors.

Table 5.1 Estimated returns-to-scale from maize production on the largest monocropped plot (inverse-probability-weighting–generalized methods of moments)

Dependent variable = *ln*(value of maize production)	Tractor owners			Nonowners		
Variable	Coefficient	Standard error	*p* value	Coefficient	Standard error	*p* value
LN_LAND	0.553***	(.196)	.005	0.438**	(.191)	.022
LN_LAB	0.557***	(.211)	.008	0.381*	(.199)	.055
LN_EXP	0.199	(.145)	.171	0.084	(.177)	.635
LN_CAP	–1.199***	(.367)	.001	–0.777**	(.322)	.016
HYBRID	–.005	(.064)	.932	0.030	(.029)	.302
RAIN4M	0.000	(.000)	.779	0.000	(.000)	.578
AGE	0.062**	(.025)	.012	0.027*	(.016)	.100
AGE2	–0.001***	(.000)	.001	0.000**	(.000)	.026
FEXP	0.001	(.007)	.926	0.001	(.005)	.848
District dummy	Included			Included		
Intercept	Included			Included		
Returns-to-scale	1.303***	(.136)	.000	0.933***	(.125)	.000
Difference from nonowners	0.370**	(.185)	.045			
Difference from 1	0.303**	(.136)	.026	–0.067	(.125)	.590
Sample size	299			485		
p value						
H_0: model is not overidentified	.732			.367		
H_0: model is underidentified	.000			.000		

Source: Authors.

Note: Standard errors are estimated through 200 paired-bootstrap to account for the fact that probability weights are estimated. Similarly, the coefficients are bias-corrected estimates (Efron and Tibshirani 1993) obtained from the original and the bootstrapped estimates.

Asterisks indicate the statistical significance: *10 percent. **5 percent. ***1 percent.

Table 5.2 Robustness of estimated differences in returns-to-scale by other specifications

Specification	Estimated difference in returns-to-scale	Standard error	p value (H_0: no difference)
Using Translog production function (inverse-probability-weighting–Translog)[a]	.186*	(.114)	.099
Excluding tractor nonusers (inverse-probability-weighting–nested propensity score)	.349**	(.188)	.063

Source: Authors.

Note: [a]Because of high multicollinearity, the interaction terms with "expenditure" variable are dropped from the variable. Asterisks indicate the statistical significance: *10 percent. **5 percent.

Table 5.3 Estimated effects of tractor values on returns-to-scale

	Estimate	Standard error	p value
Effects of 100 percent increase in tractor values on returns-to-scale	–.012	(.064)	.857

Source: Authors.

Table 5.4 Returns-to-scale in tillage intensity

Dependent variable = *ln*(tillage intensity times tilled areas)	Tractor owners			Nonowners		
Variable	Coefficient	Standard error	p value	Coefficient	Standard error	p value
LN_LAB_T	–0.001	(.109)	.994	0.002	(.068)	.977
LN_EXP_T	0.029	(.024)	.227	0.023	(.023)	.311
LN_LAND	1.076***	(.082)	.000	0.979***	(.043)	.000
LN_CAP	0.068**	(.032)	.033	0.001	(.009)	.912
RAIN4M	0.000	(.000)	.336	0.000*	(.000)	.064
AGE	0.006	(.008)	.468	0.001	(.005)	.806
AGE2	0.000	(.000)	.374	0.000	(.000)	.643
FEXP	0.000	(.002)	.956	0.002	(.002)	.162
RAIN2M	0.000	(.000)	.507	0.000	(.000)	.228
SOILBULK	–0.110	(.433)	.799	–0.349	(.270)	.196
SOILSAND	0.005	(.010)	.630	–0.003	(.006)	.556
SOILCLAY	–0.014	(.012)	.234	–0.013*	(.007)	.084
RUG	0.040	(.080)	.621	–0.024	(.050)	.623
District dummy	Included			Included		
Intercept	Included			Included		
Returns-to-scale	1.172	(.078)	.000	1.006	(.040)	.000
Difference from nonowners	0.166*	(.088)	.058			
Difference from 1	0.172**	(.078)	.028	0.006	(.078)	.943
Sample size	278			370		
p value						
H_0: model is not overidentified	.278			.279		
H_0: model is underidentified	.000			.000		

Source: Authors.

Note: Because of high multicollinearity, the interaction terms with "expenditure" variable are dropped from the variable. Asterisks indicate the statistical significance: *10 percent. **5 percent. ***1 percent.

Most important, Table 5.1 suggests that tractor ownership increases RTS by 0.37, which is statistically significantly at the 10 percent level. This increase can be generally decomposed into the increases in RTS for land and labor (from 0.438 to 0.553 and from 0.381 to 0.557, respectively).

In addition, RTS rises from 0.93 (which is statistically insignificantly different from 1) to 1.30 (which is statistically significantly greater than 1), increasing RTS. While the IPW production function is not necessarily representative of all tractor owners in Ghana, the finding of increasing RTS is consistent with the conditions in many developed countries today (Hayami and Ruttan 1985; Hayami and Kawagoe 1989).

The signs of other factors are also intuitive. The use of hybrid rice significantly raises overall productivity. The impact may be greater, particularly among tractor owners, possibly because many hybrid maize varieties might have been imported from the United States, where maize hybrid development has focused on the varieties that are suited well to large farms (such as pest-resistant varieties). Similarly, conditional on the same farming experience, older farmers are generally more productive, possibly because of their exposure to intensive mechanization programs in the 1970s and early 1980s.

Robustness Check

Table 5.1 is based on the more restrictive Cobb-Douglas form. We test the robustness of the findings in Table 5.1 by estimating the IPW-Translog specification. We, however, do so by treating all input variables as exogenous because treating them as endogenous is infeasible.[7] Translog specification allows RTS to vary across observations. Following Takeshima (2017), we calculate the median values of RTS and compare them between tractor owners and nonowners. Results are shown in Table 5.2 (coefficient estimates for the Translog production function are shown in Appendix Table A.2). Ownership of tractors raises the median RTS by 0.186, which is statistically significant at 10 percent. While the evidence of increasing RTS among tractor owners is weaker, the evidence of the rise in RTS is consistent with that in Table 5.1.

Another potential concern is that nonowners in Table 5.1 include not only those hiring in tractors but also those who are not using tractors. They are included as long as their observed characteristics are comparable to tractor owners' characteristics. The estimated effects on the rise of RTS may therefore be

[7]For example, the number of endogenous variables can become 17.

somewhat affected by the potential heterogeneity among nonowner samples. We therefore ran another model excluding nonuser households and comparing RTS among tractor users only. To account for the households' self-selection into tractor uses, we estimated this model using Huber's (2014a) aforementioned nested propensity score method (Appendix Table A.3 summarizes the factors associated with the propensity to use tractors, which differs from Table A.1, which is for the propensity to own tractors). The result in Table 5.2 suggests that RTS rises by 0.349 even when compared to tractor renters only, with statistical significance. While future studies must examine more formally how RTS changes between tractor renters and tractor owners, the result in Table 5.2 indicates the robustness of our finding that tractor ownership generally raises RTS compared to nonowners (full results of the nested propensity score production function are shown in Appendix Table A.4).

The values of owned tractors vary considerably across households. We tested whether the results in Table 5.1 are driven by such variations, estimating model (11). The result is presented in Table 5.3 (full results are presented in Appendix Table A.5). The result suggests that increasing the values of tractors owned by 100 percent would reduce RTS by 0.012, which is marginal and statistically insignificant. The significant effect of tractor ownership on RTS in Table 5.1 is therefore robust against the variations in the values of tractors owned.

RTS in Tillage Intensity

Table 5.4 presents the results for tillage intensity function (12), estimated with IPW-GMM. Most important, Table 5.4 suggests that tractor ownership raises RTS in tillage intensity by about 0.17, which is statistically significant at 10 percent. This rise can be decomposed into the returns to land and agricultural capital (including tractors) (from 0.979 to 1.076 and from 0.001 to 0.068, respectively). Similar to Table 5.4, estimated RTS indicates that tractor ownership changes tillage intensity from constant RTS (1.006) to increasing RTS (1.172, which is statistically and significantly greater than 1).

We then estimate (13) and (14) to assess whether the returns to tillage in maize production differ between tractor owners and nonowners. Table 5.5 shows the results (full results are presented in

Appendix Table A.6). The results suggest that after adjusting by w_T and conditional on other exogenous factors, increasing tillage by 1 percent increases maize production by 0.720 percent among tractor owners and 0.812 percent among nonowners. Their difference is not statistically significant. Therefore, there is no clear evidence that returns to tillage are higher for tractor owners.

Table 5.5 Tractor ownership and returns to tillage in maize production

Dependent variable = *ln*(maize production)	Tractor owners			Nonowners		
	Coefficient	Standard error	*p* value	Coefficient	Standard error	*p* value
LN_T	.720***	(.065)	.000	.812***	(.045)	.000
Difference from nonowners	–.092	(.079)	.245			
Other household characteristics	Included			Included		
District dummy	Included			Included		
Intercept	Included			Included		
Sample size[a]	280			367		

Source: Authors.
Note: [a]Sample sizes are smaller since a fraction of samples with very low propensity are dropped to retain the efficiency of the results. In addition, as was described in the section 3, farm households with no tillage are excluded.
Asterisks indicate the statistical significance: ***1 percent.

The results in Table 5.4 and Table 5.5 suggest that tractor ownership raises RTS primarily through raising RTS in tillage intensity rather than changing the returns to tillage in maize production. In other words, owning tractors enables providing tillage in greater areas, although it may not affect how tillage increases the maize output. Although the fuller implications of these findings must be more formally investigated in future studies, these results suggest that the growth in number of tractor owners in Ghana may be associated with increased overall tillage intensity (particularly in areas tilled) rather than increased variations in tillage intensity across farms.

6. CONCLUDING REMARKS

RTS are important economic and technological characteristics of production structures. RTS have important implications on the distributional effects of agricultural policies and the transformational patterns of the agricultural sector. Specifically, agricultural development around the world has often been associated with the rise in RTS. Few studies in the past, however, investigated what causes such rises in RTS. Consequently, the literature has offered relatively limited insights into how the developing countries are expected to experience such processes.

In this study, using the unique data on tractor owners and detailed maize production inputs data in Ghana, we empirically tested whether tractor ownership causes the rise in RTS. We did so by addressing the multiple types of endogeneity that are associated with the estimation, including the tractor investment decision, tractor values, tillage intensity, and inputs uses decisions.

We find that owning tractors significantly raises RTS in maize production from the households' largest monocropped plot, after controlling for the variations in household and farm characteristics. We also found weak evidence that owning tractors brings the farm household from declining/constant RTS to increasing RTS. This is partly achieved through the increase in RTS in tillage intensity rather than the change in RTS to tillage on maize production. In other words, owning tractors enables providing tillage in greater areas, although it may not affect how tillage increases maize output. The increase in RTS is positively (though insignificantly) related to the value of tractors owned. Overall, the adoptions of mechanical technologies (tractors) and their ownerships are causing, rather than simply responding to, the rise in RTS in Ghanaian maize production.

The findings also have important policy implications. The main finding of our study is that tractor ownership alone may raise RTS in farming. While our study does not assess whether RTS is affected by other socioeconomic factors, including other production technologies, public infrastructure, or institutions, our findings show that the effects of tractor ownership on RTS hold even after these other factors are controlled for. Thus, overall RTS in the agricultural sector is more likely to be affected by underlying factors affecting the demand for tractors and the nature of imperfections in the tractor market. In Ghana, the private sector has been leading investment in tractors, particularly in the secondhand tractor market, even though the government's provision of subsidized tractors has contributed to overall tractor ownership (Diao et al. 2014). This implies that there may be a force toward rising RTS in the agricultural sector in Ghana, which may be driven not so much by direct public-sector interventions but by the growing private demand for tractors as a result of various factors including rising population density and increased demand for more intensive land preparation as well as rising rural wages and urbanization (Cossar 2016). Investments in tractors have often been a response to farmers' desires not only to raise incomes through custom hiring but also to grow large (Houssou and Chapoto 2014), which may partly explain why medium to large farms are growing in Ghana, as described in Jayne et al. (2016).

At the same time, the findings imply that interventions in the tractor market, as have often been exercised in Ghana, uniquely affect smallholders. Increased tractor ownership may eventually induce in the long run the exit from farming by smallholders who are not in the position to own tractors but in the position to rely on hiring services. This is because the rise in RTS realized by tractor ownership shifts the comparative advantage in farming to medium to larger farmers so that it is more profitable for smallholders to rent out or sell their farms to medium to larger farmers who now have a higher willingness to pay for their farms. Policies aimed at enhancing mechanization of smallholders may in fact facilitate their exit from farming if such policies involve promoting tractor ownership among medium to larger farmers with the hope that they provide hiring services to smallholders. Therefore, while custom hiring services by medium to large farmers owning tractors may initially benefit smallholders through reduced costs of land preparation, their benefits may be relatively small compared to the gains enjoyed by medium to large farmers from tractor ownership. Therefore, promoting tractor ownership among medium to large farmers may be more effective if the government's goal is to assist more smallholders in exiting farming.

However, it must also be noted that such promotion of tractor ownership among medium to larger farmers may be less effective in supporting smallholders through increased agricultural incomes, which must be complemented by policies directly aimed at raising agricultural productivity. This is particularly so because in reality there are other factors that induce smallholders to remain in the farming sector even when tractor ownership by larger farms may shift comparative advantages from smallholders to larger farmers.

APPENDIX: ADDITIONAL RESULTS

Table A.1 Marginal effects of covariates on the propensity to own tractors (first-stage probit)

Variable	Coefficient	Standard error	*p* value
RAIN4M	.000	.000	.509
RAIN2M	.000	.000	.878
RUG	.007	.014	.610
SOILBULK	–.145	.145	.316
SOILSAND	–.003	.002	.225
SOILCLAY	–.002	.003	.573
AGE	.002	.003	.509
AGE2	.000	.000	.673
FEXP	–.001	.001	.128
EDUAVE	–.003*	.002	.062
HHSIZEM	–.010	.013	.469
HHSIZEF	.000	.012	.995
HHSIZEC	.001	.004	.828
WG	.000**	.000	.046
WG2	.000	.000	.112
LN_LANDOWN	.073***	.008	.000
POPDEN	.000***	.000	.006
PFERT	–.442	.694	.524
PFERT2	.220	.370	.553
PTRH	.565***	.107	.000
*PTRH*2	–.003***	.001	.000
VARIETY_V	–.037	.074	.616
ASSTGSEED	.018	.028	.529
MEMBER	.016	.013	.228
D20K	.022**	.011	.042
TRNSCOST	.000	.000	.155
LN_ASSET	.049***	.004	.000
SUBSIDY	.009	.008	.287
SUBSIDYNEW	.027***	.009	.001
TRYEAR	.030	.049	.542
INH_LAND_Y	–.064***	.016	.000
INH_MAC_Y	.173***	.068	.010
INH_CAT_Y	.000	.026	.992
ASST_Mech_0812	.000	.001	.757
ASST_0812	.000**	.000	.050
WKGOV	–.031*	.016	.051
District dummies	Included		
Intercept	Included		
Number of observations	1,841		
p value (H_0: model is jointly insignificant)	.000		

Source: Authors.

Note: Asterisks indicate the statistical significance: *10 percent. **5 percent. ***1 percent.

Table A.2 Translog production function coefficients

Variable	Tractor owners			Nonowners		
	Coefficient	**Standard error**	***p* value**	**Coefficient**	**Standard error**	***p* value**
LN_LAND	0.829	(.828)	.317	0.330	(.512)	.519
LN_LAB	–0.022	(.901)	.981	0.449	(.541)	.407
LN_EXP	0.165*	(.095)	.081	0.076*	(.041)	.062
LN_CAP	0.122	(.246)	.619	0.055	(.264)	.834
LN_LAND × *LN_LAND*	0.086	(.214)	.688	0.110	(.127)	.387
LN_LAND × *LN_LAB*	–0.020	(.152)	.895	0.075	(.091)	.409
LN_LAB × *LN_LAB*	0.121	(.193)	.529	–0.035	(.100)	.724
LN_LAB × *LN_CAP*	0.033	(.074)	.657	0.022	(.028)	.445
LN_CAP × *LN_CAP*	0.122	(.104)	.243	–0.016	(.018)	.377
HYBRID	0.656***	(.000)	.000	0.250***	(.087)	.004
RAIN4M	0.274*	(.156)	.079	0.000	(.000)	.381
AGE	0.037	(.025)	.140	0.019	(.016)	.228
AGE2	0.000**	(.000)	.047	0.000**	(.000)	.043
FEXP	0.011*	(.006)	.070	0.004	(.005)	.465
District dummy	Included			Included		
Intercept	Included			Included		
RTS	1.095	(.100)	.000	0.910	(.051)	.000
	0.186	(.114)				
Sample size	303			488		
R-squared	.800			.825		
p value						
H_0: Significant difference in RTS	.100					

Source: Authors.

Note: Standard errors are estimated through 200 paired-bootstrap to account for the fact that probability weights are estimated. Similarly, the coefficients are bias-corrected estimates (Efron and Tibshirani 1993), obtained from the original and the bootstrapped estimates. RTS = returns-to-scale.

Asterisks indicate the statistical significance: *10 percent. **5 percent. ***1 percent.

Table A.3 Marginal effects of covariates on the propensity to use tractors (first-stage probit in nested propensity score model)

Variable	Coefficient	Standard error	*p* value
RAIN4M	.000	.000	.427
RAIN2M	.000	.000	.306
RUG	–.005	.006	.442
SOILBULK	–.864***	.261	.001
SOILSAND	–.002	.003	.537
SOILCLAY	–.013**	.006	.025
AGE	.000	.004	.936
AGE2	.000	.000	.744
FEXP	.001	.001	.567
EDUAVE	.005**	.002	.013
HHSIZEM	.010	.021	.645
HHSIZEF	–.006	.024	.809
HHSIZEC	.007	.008	.351
WG	.000	.001	.368
WG2	.000	.000	.606
LN_LANDOWN	.042***	.012	.001
POPDEN	.000	.000	.132
PFERT	–.265	.858	.758
PFERT2	.124	.421	.768
PTRH	–.007	.008	.376
PTRH2	.000	.000	.421
VARIETY_V	.197*	.118	.093
ASSTGSEED	.042	.045	.352
MEMBER	.047**	.019	.011
D20K	.012	.018	.488
TRNSCOST	.000	.000	.875
LN_ASSET	.013***	.004	.004
SUBSIDY	–.186	.578	.748
SUBSIDYNEW	.026	.915	.978
TRYEAR	–.023	.042	.580
INH_LAND_Y	–.016	.022	.468
INH_MAC_Y	.047	.100	.641
INH_CAT_Y	–.014	.033	.675
ASST_Mech_0812	.001	.001	.596
ASST_0812	.000	.000	.550
WKGOV	–.026	.022	.239
District dummies	Included		
Intercept	Included		
Number of observations	952		
p value (H_0: model is jointly insignificant)	.000		

Source: Authors.

Note: Asterisks indicate the statistical significance: *10 percent. **5 percent. ***1 percent.

Table A.4 Nested propensity score production function (tractor owners and nonowners)

	Tractor owners			Nonowners		
Variable	**Coefficient**	**Standard error**	***p* value**	**Coefficient**	**Standard error**	***p* value**
LN_LAND	0.508***	(.173)	.003	1.059***	(.267)	.000
LN_LAB	0.594***	(.197)	.002	–0.301	(.253)	.234
LN_EXP	0.173	(.139)	.214	0.003	(.275)	.991
LN_CAP	–0.093	(.065)	.154	0.072*	(.037)	.052
HYBRID	1.213***	(.402)	.003	0.046	(.458)	.919
RAIN4M	0.000	(.000)	.324	0.000	(.000)	.870
AGE	0.070**	(.029)	.015	0.013	(.022)	.541
AGE2	–0.001***	(.000)	.004	0.000	(.000)	.154
FEXP	0.001	(.007)	.898	0.010	(.009)	.233
District dummy	Included			Included		
Intercept	Included			Included		
RTS	1.183	(.124)	.000	0.834	(.141)	.000
	0.349	(.188)				
Sample size	287			413		
R-squared						
p value						
H_0: Significant difference in RTS	.063					
H_0: model is not overidentified	.629			.382		
H_0: model is underidentified	.000			.000		

Source: Authors.

Note: Standard errors are estimated through 200 paired-bootstrap to account for the fact that probability weights are estimated. Similarly, the coefficients are bias-corrected estimates (Efron and Tibshirani 1993) obtained from the original and the bootstrapped estimates. RTS = returns-to-scale.

Asterisks indicate the statistical significance: *10 percent. **5 percent. ***1 percent.

Table A.5 Production function estimates with generalized propensity score on tractor values (among tractor owners only)

Variable	Coefficient	Standard error
LN_LAND	.877***	(.102)
LN_LAB	.131	(.127)
LN_EXP	–.110	(.084)
LN_CAP	.034	(.133)
LN_LAND × *VT*	–.404***	(.079)
LN_LAB × *VT*	.233***	(.083)
LN_EXP × *VT*	.204***	(.054)
LN_CAP × *VT*	–.044	(.031)
HYBRID	–.166	(.147)
RAIN4M	.000	(.000)
AGE	.024*	(.013)
AGE2	.000	(.000)
FEXP	.002	(.003)
Other controls[a]	Included	
District dummy	Included	
Intercept	Included	
Effects of 100 percent increase in tractor values on RTS (sum of coefficients for all variables interacted with *VT*)	–.012	(.064)
Sample size	322	
R-squared		
p value		
H_0: significant difference in RTS	.857	
H_0: model is not overidentified	.538	
H_0: model is underidentified	.000	

Source: Authors.

Note: Standard errors are estimated through 200 paired-bootstrap to account for the fact that probability weights are estimated. Similarly, the coefficients are bias-corrected estimates (Efron and Tibshirani 1993) obtained from the original and the bootstrapped estimates. RTS = returns-to-scale.

[a]Other controls are variables that are not part of the structural form production function but are included as part of regression adjustment because inverse-probability-weighting through generalized propensity score alone is found insufficient in eliminating the significant differences in these variables across households with different tractor values.

Asterisks indicate the statistical significance: *10 percent. **5 percent. ***1 percent.

Table A.6 Reduced form equations of the effects of tillage intensity on maize production, generalized propensity score─inverse-probability-weighting

Dependent variable = *ln*(value of maize production)	Tractor owners		Nonowners	
Explanatory variable	Coefficient	Standard error	Coefficient	Standard error
LN_TILLAGE	0.720***	0.065	0.812***	0.045
LN_CAP	–0.042	0.087	0.293**	0.122
RAIN4M	0.000	0.000	0.000	0.000
RAIN2M	0.000	0.000	0.000	0.000
RUG	–0.110	0.137	–0.254**	0.127
SOILBULK	–1.834**	0.891	–1.188	0.771
SOILSAND	–0.024	0.017	0.014	0.011
SOILCLAY	0.011	0.024	0.001	0.018
AGE	0.024	0.023	0.012	0.016
AGE2	0.000	0.000	0.000	0.000
FEXP	–0.002	0.006	0.008*	0.005
EDUAVE	–0.002	0.010	0.023***	0.008
HHSIZEM	–0.055	0.082	0.063	0.073
HHSIZEF	0.185**	0.087	0.182***	0.052
HHSIZEC	0.003	0.021	–0.016	0.018
LN_LANDOWN	0.266***	0.065	–0.115**	0.055
POPDEN	–0.001	0.001	0.001	0.001
WG	–0.002	0.002	0.000	0.001
WG2	0.000	0.000	0.000	0.000
PFERT	–4.987	7.528	–4.109	4.362
PFERT2	3.229	4.133	2.212	2.358
PTRH	0.139	0.726	–3.089	2.428
PTRH2	0.000	0.002	0.000	0.000
VARIETY_V	0.850	0.521	0.721**	0.332
ASSTGSEED	0.303	0.209	–0.241	0.133
MEMBER	–0.036	0.089	0.147**	0.072
D20K	0.018	0.088	0.111**	0.055
LN_ASSET	0.046	0.059	–0.251*	0.129
District dummies	Included		Included	
Intercept	Included		Included	
Sample size	282		367	
p value (H_0: model jointly insignificant)	.000		.000	

Source: Authors.

Note: Asterisks indicate the statistical significance: *10 percent. **5 percent. ***1 percent.

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