Identifying the effects of market imperfections for a scale biased agricultural technology: Tractors in Nigeria

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Abstract: Growths of mechanization service supply have been considered generally frictionless outside Africa South of Sahara (SSA). However, the dominance of large tractors that are sparsely populated in SSA countries like Nigeria today suggests significant imperfections in tractor hiring service market due to technology indivisibility and low spatial mobility. Empirically testing market imperfections for scale-biased technologies like tractors has been challenging, partly due to the difficulty of separating the effect of marginal technology adoptions from intensive technology adoptions that potentially generate scale effects. We fill this knowledge gap by applying covariate matching, ordinary propensity score matching, as well as generalized propensity score matching methods to Nigerian household data. Tractor hiring service market in Nigeria is found imperfect, potentially due to the supply-side constraints. The effect of this imperfection is also sizeable; in the case of Nigeria, overcoming this imperfection can potentially increase farm households' income by as much as 30%. This effect is from the marginal adoption of tractors alone, even without the potential scale effects from intensive tractor use upon adoption.

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1 Background

Market imperfections lead to economically inefficient allocations and suboptimal uses of resources. Slow agricultural technology adoptions in Least Developed Countries (LDCs) including Africa South of Sahara (SSA) are one of the manifestations of such imperfections in modern inputs / services markets. Under the perfect market conditions, marginal technology adoptions should have no effect on the overall profit for the agents, because marginal benefits of adoptions equal their marginal costs. Any positive effects of a marginal technology adoption should therefore reflect some type of market imperfections, overcoming of which brings positive rents.

How imperfections in agricultural technologies markets affect the technology adoptions depends on scale biases of technologies. For scale-neutral technologies like improved seeds and fertilizer, intensive adoptions (how intensively to adopt) may be more constraining than marginal adoptions (adopt or not). For example, using 10g of fertilizer may be less constraining than using 50kg of fertilizer which requires larger cash payment up front. On the other hand, for scale-biased technologies, if indivisible, their marginal adoptions may be constrained, due to market imperfections for either technologies suppliers or technologies adopters, or both. While literature on technology adoption is enormous, it often does not distinguish two separate effects – the effect of overcoming the market imperfections in technology access (associated with marginal adoptions), and the effect of intensively using technologies (associated with intensive adoptions), despite that these two have different policy implications.

Empirically distinguishing these two effects of technology adoption is challenging for scale-biased technologies. It is less so for scale neutral technologies since intensive adoptions in theory may not significantly increase profits as marginal returns remain constant and equal marginal costs; significantly positive impacts of the binary adoption variables are likely to be attributed to the overcoming of barriers for marginal adoptions rather than intensive adoptions. Complications arise for scale-biased technologies; their intensive adoptions can add rents accumulated as economies of scales are exploited. Significant effects of binary adoption variables in such case cannot easily be attributed solely to the effect of marginal adoptions. Adding variables that measure adoption intensity is an option but potential endogeneity of the adoption variables complicate the empirical specifications.

These issues can be particularly relevant for agricultural mechanization technologies like tractors that are potentially scale-biased. Earlier literature on mechanization has had relatively mixed views on this aspect. Some strands of literature broadly suggest that historical tractor adoption processes have been fairly frictionless, with supply responding through private tractor investments into relatively divisible smaller tractors, supply of mechanization services, machinery quality improvements, adaptive research, and repair services in response to growing demand (Herdt 1983; Binswanger 1986; Yang et al. 2013; Manuelli & Seshadri 2014). Many recent studies also assume perfect machinery rental markets (Foster & Rosenzweig 2011). If markets for tractor hiring is perfect on the supply side, a positive effects of tractor adoptions is interpreted as the rents from intensive adoptions, rather than marginal adoptions. However, in SSA including Nigeria, conditions seem different. As is illustrated below, average horsepower (hp) of tractors (and thus average price of tractors) in Nigeria appear relatively high given the scarcity of tractors, compared to past patterns elsewhere. Joint ownership of tractors as well as provisions of formal credit are rare in Nigeria due to the risk of damage and high transactions costs. Consequently, indivisibility and liquidity constraints may be more severely restrict tractor investments and supply of hiring services in Nigeria, than elsewhere. Furthermore, these patterns seem to be driven by private sectors' own initiatives.[1] Prevalence of large, high hp tractors in sparsely populated manner in Nigeria suggest that, both market imperfections in custom hiring services can be severe, and when used, tractors may be exhibiting significant economies of scales. Since the conditions in Nigeria appear different from those suggested in the mechanization literature, it is important to empirically test the presence of market imperfections in tractor hiring service supply there.

Exploiting recent developments in econometric methods and focusing on tractor rental uses data in Nigeria, we provide some indirect evidence of supply side market imperfections in two ways; first, we show that tractor rental is significantly affected by the presence of large farmers within the district, who are more likely to own tractors and hire them out to the neighbors. In doing so, we use pseudo-panel datasets and various spatial datasets to control

[1]This is based on the fact that the demand generally exists for smaller-scale machineries in Nigeria or similar environments in the West Africa, including motorized irrigation pumps (Takeshima & Yamauchi 2012; Takeshima et al. 2010), draft animals (Takeshima 2015) or growing power tiller use in Ghanaian rice irrigation schemes (Takeshima et al. 2013c). The dominance of large tractors in Nigeria is not because larger types of machinery are always preferred in Africa.

partly for the heterogeneous factor endowments and agro-ecological environments that are common in SSA, and minimize the omitted variable biases. Second, we provide a conceptual framework to discuss how the impact of technology adoptions on general outcome variables can be used to assess the presence of market imperfections. Third, using ordinary and generalized propensity score matching methods (Hirano & Imbens 2004) on "marginal" tractor users, we show that marginal tractor adoption alone has significant impacts on key outcome variable (real per capita household expenditures), which is consistent with the hypotheses of substantial supply-side imperfections of tractor custom hiring market in Nigeria.

In addition to methodological contributions, this paper also fills important broader knowledge gaps on agricultural mechanization, an important parallel process of agricultural transformation which has been slow in Africa despite the transformation in non-agricultural sectors (African Economic Transformation Center 2014). The linkages of our findings with low mechanization levels in Nigeria also have important relevance to the on-going debate about the low agricultural labor productivity in SSA (McMillan et al. 2014; Gollin et al. 2014). Evidence of supply side market failures can also be important in rethinking the roles of mechanization policies for transforming agricultural sector in SSA that is becoming increasingly land scarce (Jayne et al. 2014) with limited potential for private investment in large tractors.

2 Indivisibility, limited mobility of tractors in Nigeria

Historically, agricultural mechanization started with the gradual adoptions of cheaper, lower hp tractors. In the United States (US), average tractor hp was around 10~20 in the 1910s when the adoptions of tractors began (Olmstead & Rhode 2001). Early tractorizations in the US were more gradual processes, often substituting a few horses with one small tractor, while maintaining remaining stock of horses (Clarke 1991). In many Asian countries, not only there have been widespread adoptions of two-wheel tractors (2wt) with typically less than 15 hp, but four-wheel tractors (4wt) have been generally in 30 hp range. In Nigeria today, it is typically 50 – 70 hp (Takeshima et al. 2015). Tractor hp largely determines its optimal operational scale and required fixed investment. Historically, tractors have been a relatively scale-neutral technology around the world, compared to those in Nigeria today. Where large, high hp tractors were relatively popular, such as in Latin America, while tractors were expensive, farm households were wealthier. Take 1950 Brazil as an example. While tractors of 40 hp or above were fairly common in Brazil in the 1950s (Stitzlein 1974), close to 40% of farm households were on average cultivating 16 ha of land in 1950 (author's calculations based on Barraclough & Domike (1966)), which is almost ten times larger than those in Nigeria today. They needed less credit / subsidy to invest in tractors, and their relative large sizes might have facilitated the targeting of subsidy provision or monitoring of loan payments if credit / subsidy was provided. In the US, the trend toward fewer but larger farms increased demand for larger hp tractor (Hlavacek & Reddy 1986), as there are economies of size for farm machinery (Fulton et al. 1978). The patterns in Nigeria are contrasting. Dominant types of tractors in Nigeria are quite large (high hp) despite the fact that country's mechanization level is still very low, which is contrasting to the past trajectory of many other countries (Figure 1).

[Insert Figure 1 here]

In Nigeria, liquidity constraints are likely to much more seriously constrain the investment into tractors, and mobility of tractors owned is often low (Takeshima et al. 2015), potentially leading to a substantial market failure in tractor custom hiring service market. This motivates our study to test empirically the existence and consequences of such market imperfections.

3 Indirect evidence of supply-side imperfections of tractor custom hiring market

We empirically test in two ways whether there are supply-side imperfections in Nigerian tractor custom hiring markets. First, we examine the determinants of tractor use and its intensity, and whether a supply side factor affects the tractor adoption. Second, using matching methods, we assess whether marginal adoptions of tractors have significant income effects, which is consistent with the hypothesis of supply-side market imperfections.

3.1 Tractor adoption patterns based on a double hurdle model

3.1.1 Specifications and data

Farm households' decisions to use tractors and how much to use can be modeled as,

$$d^0 = f(Z,X)$$
$$d^1 = f(Z,X) \quad \text{if } d^0 = 1 \tag{1}$$

$$T = f(X) \qquad \text{if } d^1 = 1$$

where $d^0 = 1$ if the farm household has access to custom hiring market (= 0 otherwise), $d^1 = 1$ if the farm household actually hires in tractor services (= 0 otherwise), and T is the hiring-in intensity (areas tractored). Z are a set of factors affecting the access of a farm household to tractor hiring service market, while X are a set of factors that affect all of d^0, d^1 and T.

In our data, only d^1 which is nested within d^0, is observed, while d^0 is unobserved. Under an assumption that the factors affect d^0 and d^1 in the same way (same signs and statistical significance), the two-steps of d^0 and d^1 can be approximated by a reduced form probit in which the dependent variable $d^* = d^0 \cdot d^1$ is regressed on Z and X. A statistically significant coefficient for Z in the reduced form probit is then a weak indication of its statistically significant effect on d^0. The third stage can be estimated using a truncated regression model, making (1) equivalent to Cragg's (1971) double-hurdle model.[2]

Our data consist of two rounds of Living Standard Measurement Study – Integrated Survey of Agriculture (LSMS) (LSMS 2011, 2013), which are nationally representative household data as well as community data collected jointly by the National Bureau of Statistics of Nigeria and the World Bank in 2010/11 and 2012/13, combined with various spatial data. LSMS 2011 and 2013 are pseudo-panel data. Since many determinants of agricultural mechanization are likely to be time-invariant (such as factor endowments) between 2011 and 2013, we use the pooled cross section specification to estimate (1). We, however, also apply the idea of correlated random effects (CRE) model (Chamberlain 1984) and its pseudo-panel extension (Takeshima & Nkonya 2014) to control for some of the potentially unobserved cohort-specific effects. Specifically, we use as such cohorts the local government area (LGA), an administrative unit under Federal and State governments in Nigeria. We assume that LGA sample averages of certain time-variant variables across two rounds of LSMS are correlated with the unobserved household specific effects. Note that, this modified pooled cross section specification is different from standard CRE methods. We assume that time-invariant variables such as factor endowments are identified separately from the unobserved LGA fixed effects once

[2]If factors affect d^0 and d^1 differently, partial observability probit can be used to overcome partly the unobservability of d^0 (Abowd & Farber 1982). Their results are, however, often susceptible to the specifications of each stage.

they are approximated by the LGA time average of time variant variables described above. Inclusions of these cohort variables reduce the potential bias in the pooled cross-section method.

Two rounds of LSMS contain 10,000 observations in total. Out of them, we focus on approximately 6,000 farm households who reported at least one plot they cultivated. Not all these farm households, however, reported the plot sizes, including the GPS based measurements. These observations are excluded because total farm sizes and individual plot sizes are important determinants of tractor uses and their intensities in our study. After further dropping missing observations and outliers, a total of 5,119 observations are used for the analyses. Descriptive statistics of variables used in the analyses are presented in Table 1.

[Insert Table 1 here]

Variables X and Z are identified based on the literature for farming system evolutions and agricultural mechanization. They are generally categorized into (a) factors affecting the demand for intensification (agro-ecological conditions like soil, water access, as well as socio-economic conditions like market access); (b) factors affecting household's constraint (such as assets used to liquidate for credit or insurance purpose, or access to these services, as well as information constraint on production practices, and household demographics and head's characteristics, land tenure); (c) factors specifically affecting demand for tractors (such as human capital, wages that affect labor endowment, availability of substitutable inputs like fertilizer, draft animal endowment, farm land endowment, as well as the access to tractor hiring services). Note that variables may capture more than one of these effects jointly.

Endowments of cultivable land are calculated at the enumeration area (EA) level of LSMS as the sum of cropped areas and pasture (Ramankutty et al. 2008). Pasture is relatively easily converted into farmland compared to the forest (Binswanger & Donovan 1987). Per capita figure is obtained using the population of the corresponding LGA based on the Nigeria 2006 Population Census (National Population Commission 2010). An EA soil workability dummy variable is constructed, which equals 1 (workable) if the soil exhibits no or slight constraints for tillage, and 0 (not workable) if moderate, severe, or very severe constraints. Constraints levels are defined in Fischer et al. (2008) based on how soil management is constrained by the soil texture, effective soil depth or volume and soil phases. The local soil heterogeneity is also captured at EA level by 1km by 1km grid data on soil bulk density and clay contents indicators from ISRIC (2013), as these affect the type of tractors used in Nigeria (Takeshima et al. 2014).

EA level distance to water resources, which can affect the irrigation costs, are proxied by the Euclidean distances to the nearest dams and the nearest rivers, each obtained from FAO (2012) and FAO (2000). EA level distance to the nearest town with the population of 20,000 or more (20k town), which proxies market access, is calculated from Harvest Choice (2012).

Real farm wage is proxied by the daily wage of hired male labor for land preparation reported in the LSMS community survey, and averaged across the communities within each LGA. Similarly, average prices of Urea and NPK are LGA-median prices. Euclidean distances to the centroid of the nearest state governor district-of-origin in 2010 are calculated at the EA level, which is found to affect the access to subsidized fertilizer in Nigeria (Takeshima & Liverpool-Tasie 2015).

All other socio-economic variables are calculated at the household levels from the LSMS (2011, 2013). Variables measured with monetary values have been converted into real values, deflated by the average of the district median prices of local staples (rice and *gari*, a type of processed cassava). Farm land holdings of households are the area of farm land obtained through outright purchase or distributed by the community chief, as the latter is also a common exogenous determinant of land endowments for farm households in Nigeria. Farm wealth is captured by the values of assets owned, except farmland which is rarely marketed in Nigeria. One of the variables in Table 1, real household earned income per year, is used only in the next section as a dependent variable, where its detailed definition is provided.

The variable Z is the sample maximum within LGA of owned- or community distributed-farmland area. This variable is expected to proxy the likelihood of the existence within LGA of tractor owners, who are typically found among large farm owners because of land endowments and wealth that allows tractor investments. The existence of larger farm households within the LGA is likely to affect the supply of tractor service within the LGA (Takeshima et al. 2014, 2015), but not the potential demand for it. The significance of this variable on tractor use therefore indicates the supply side market imperfection of the tractor hiring services.[3]

[3] Ideally, the number of tractor owners within the LGA should be used to assess the level of access to tractor hiring service. Such information is, however, unavailable in neither our data nor government statistics office in Nigeria to the author's knowledge. Nevertheless, presence of large-scale farmers in the sample in the LGA indicate that (based

3.2.2 Determinants of tractor uses

Table 2 presents the results of CRE pseudo-panel double hurdle model. The figures shown are marginal effects on the probability of using tractors, and the areas tractors are used, evaluated at the mean values of each variable. Some variables are log-transformed to improve the goodness of fit of the model. Following Michalopoulos & Papaioannou (2014), some log-transformed variables are converted as $x = x + 0.01$, so that observations with x = 0 can be included. Results are robust to different adjustments. We omit the results for LGA time averages of time variant variables since their coefficients have no relevant meanings other than controlling for unobserved LGA fixed effects. Standard errors are adjusted for potential serial correlation within EA level clusters.[4]

[Insert Table 2]

Results are generally intuitive. Doubling of cultivable land per capita raises the likelihood of tractor service adoption by 0.6 percentage points. A greater land endowment relative to labor induces tractor uses. Importantly, from the farming system evolution perspective, much of Nigeria has already reached the level where overall demand for intensive farming is high, where cultivable land per capita is about 0.5 ha (Table 1), and tractor substitutes labor depending on the level of labor scarcity. The number of male working age household members without education discourages tractor uses, possibly because they are willing to be engaged in manual land preparation. Conversely, a greater number of working-age female members with at least secondary education induces tractor uses. These are consistent with the hypothesis that human capital formation induces the substitution of labor for machinery. Once human capital is controlled, farm labor wages in the area does not seem to affect tractor adoption, indicating that it is the labor costs of family members that induce substitution with tractors.

on the probability sampling theory), the number of such large-scale farmers in the district must be substantial, which also raise the likelihood that sufficient number of tractor owners exist in the district and provide hiring services.
[4]While STATA allows this adjustment, there seems no clear consensus regarding whether it is appropriate to adjust standard errors for heteroskedasticity or serial correlation in the case of probit or truncated models, because in these models not only standard errors but estimated coefficients are inconsistent as well if disturbance terms are heteroskedastic (Freedman 2006). Though specifications like Tobit, a restricted form of double-hurdle model, are generally consistent under certain regularity conditions if errors are only serially correlated within clusters and homoskedastic (Robinson 1982), the consequences of the violations of such conditions are not well known. However, in our case, unadjusted standard errors are generally smaller and coefficients are more significant. Results in Table 2 therefore provide generally conservative estimates of the statistical significance of coefficients.

Doubling real asset values raise the adoption possibility by 0.02 percentage point, possibly because of the reduced risk aversions toward tractor adoption. A higher real fertilizer price induces tractor adoption, possibly because fertilizer and tractors may be broadly substitutes (while the former is complementary to labor, the latter is complementary to land). Tractor adoption is higher on more workable soil and fewer clay contents, possibly because of lower plowing cost. Tractor adoption is also higher in areas closer to the nearest dams, possibly because of better access to formal irrigation facilities where intensive production including mechanized plowing can have high returns. While the average plot size has no effect, an additional plot given the average plot size increases tractor adoption by 0.2 percentage points.

Upon the adoption of tractor services, the areas cultivated by tractors depend largely on the average plot sizes, as well as the number of plots given the average plot size. A positive effect of the higher bulk density of soil may reflect the use of higher horsepower tractors (Takeshima et al. 2015) that are more appropriate for cultivating larger areas. However, the number of male working age members with Koranic education and other education has a negative and a positive effect, respectively, indicating somewhat complicated effects human capital. Soil workability, lower clay contents and proximity to dams also induce greater tractor use intensity.

Two interesting results are observed. Farm households whose members obtained credit previously tend to use tractors on smaller areas upon the adoption. Credit access may be inducing inputs uses such as labor for off-farm activities, although they may still prefer to cultivate their farm so that credit access does not affect traction adoption. Similarly, those living further away from governor's district-of-origin tend to use tractors on larger areas. As in Takeshima & Liverpool-Tasie (2015), proximity to governor's districts-of-origin raised the access to subsidized fertilizer. Since fertilizer which is land-saving inputs often substitutes labor-saving inputs like tractors, the receipt of subsidized fertilizer may reduce area cultivated by tractors upon the tractor adoption.

Importantly, doubling the size of largest farm size within LGA raises the possibility of tractor adoption by a statistically significant 0.2 percentage point in the Probit model. This indicates that the supply of tractor hiring service is somewhat constrained by the scarcity of large farm households with greater incentives to invest in tractors and serve nearby farmers.

Results suggest that tractor adoption in Nigeria is generally driven by economic factors, and some aspects of the tractor service market are functioning according to economic forces. However, the results also suggest that the adoption of tractor services by farmers is also constrained by some supply-side factors, particularly the presence of owners of large farmland within the district, which can affect the availability of tractor services within the district. The latter effect is consistent with the observations discussed in earlier sections about the large average tractor size in Nigeria, their sparsity and limited mobility, and its potential consequence of tractor service market failures. We investigate this aspect of market failure further in the next section.

3.2 Testing tractor hiring market imperfection by examining the impact of marginal tractor adoption

The empirical analysis in the previous section follows transactions costs literature which tests the presence of hurdles by identifying differentiated mechanisms affecting the entry into certain regime and the economic behaviors within such regimes (ex. Key et al. 2000; Bellemare & Barrett 2006; Takeshima & Winter-Nelson 2012; Takeshima et al. 2011). These studies, however, do not quantify the economic significance of these hurdles and thus provides only limited insights into the importance of market failure. Robustness of the results of supply-side market imperfections in the previous section can be validated by obtaining evidence from yet different angles. Here we focus on testing another condition that is consistent with the existence of market failure. We first illustrate such a condition conceptually. We then empirically test this condition empirically.

3.2.1 Conceptual illustration

We illustrate a household's decision mechanism on adoption of technology whose supply market is imperfect. This is in one way described by a mixed regime model in which a household faces fixed transactions costs in switching from no adoption state to adoption state (Takeshima & Nkonya 2014). A household's profit maximization follows

$$\max_{\mathrm{I_r,L_r,M_r}} \Pi = I_0 \cdot [F_0(L_0;z) - p_L L_0] + I_1 \cdot [F_1(L_1, M_1;z) - p_L L_0 - p_M M_1 - \eta] \quad (2)$$

subject to

$$I_0 + I_1 = 1$$

$$L_s, M_s \geq 0 \quad \forall s.$$

where the profit Π depends on the output F_r, labor costs (= labor use L_r times its unit price p_L), and the cost of mechanization services (intensity M_1 times its unit price p_M). For simplicity, we assume labor and machine are the only inputs. Farmer faces two regimes s; s = 0 is “constrained” where no tractor service is available, while s = 1 is “unconstrained” and tractor service is available. The household starts from regime 0 (I_0 = 1), and decides whether to move to regime 1. If tractor hiring market is imperfect, positive transactions costs η are associated with switching to regime 1, due to the various constraints including limited mobility of tractors discussed in earlier sections.

If market is perfect and $\eta = 0$, decisions on I is irrelevant and the model reduces to

$$\max_{I_s, C_s, X_s} \Pi = F(L, M; z) - p_L L - p_M M. \tag{3}$$

Since $\partial F / \partial M = p_M$, $\partial F / \partial L = p_L$, and

$$\left.\frac{\partial \Pi}{\partial M}\right|_{\frac{\partial F}{\partial M} = p_M} = \frac{\partial F}{\partial M} - p_M = 0, \tag{4}$$

a marginal increase of M from M = 0 has no effect on Π.

When tractor hiring market is imperfect, $\boldsymbol{\eta} > \mathbf{0}$. In this case, a marginal increase in M increases $\boldsymbol{\Pi}$ by

$$-\int_{L^*}^{L_0} \left(\frac{\partial F(L, M_0)}{\partial L} - p_L\right) dL + \int_{M_0}^{M^*} \left(\frac{\partial F(L^*, M)}{\partial M} - p_M\right) dM \tag{5}$$

where L^* and M^* are global optimal solutions under both regimes. (5) is a “wedge” arising due to inefficient resource allocations due to imperfection of tractor hiring market. Based on the linear integral theory, the first term represents the loss due to using less labor (as a result of substitution with the use of M) measured at the initial condition $M = M_0$ = 0. However, the whole term is non-negative because the second term, which represents the benefits from tractor use, is positive and offsets the loss in the first term. The wedge (5) is positive under marginal increase in M from M = 0. In other words, marginal tractor adoption leads to an increase in the profit, if $\eta > 0$ due to the failure in tractor hiring market.

Importantly, a positive η is likely to be due to the imperfection in tractor hiring market, rather than any other causes. For example, tractor hiring service suppliers may also address other market imperfections by providing information on improved production practices, or providing goods (such as fertilizer) and services (credit and insurances) that are otherwise unavailable to the farmers. If hiring service suppliers are the sole suppliers of such information, goods and services, inaccessibility to hiring services can lead to positive η and wedge (5) even if hiring service market is perfect. However, given the heterogeneity of production environments, information on production practices is less transferrable across farmers particularly for rice (Munshi 2004), which is one of the most tractorized crops in Nigeria (Johnson et al. 2013; Takeshima et al. 2013a; Takeshima et al. 2013b; Takeshima et al. 2014). Given the low mobility, tractors may be less effective than motorcycles or trucks in transporting goods to remote areas where their supplies are limited. Hiring service suppliers are therefore less likely to address imperfections of other goods for the farmers. Similarly, while hiring service suppliers may provide services on credit, which can partly address credit market failures for the farmers, similar arrangements may more or less exist for other inputs like fertilizer or hired labor which are more widely adopted in Nigeria.[5] Access to tractor hiring service is therefore unlikely to be the sole source of credit to farmers, and therefore unlikely to reduce η that is associated with credit market imperfection. These conditions suggest that a positive η is more likely to be due to the market imperfections in tractor hiring supply.

We further illustrate how the wedge (5) can be substantial depending on the shape of the production function, particularly substitutability of labor to machine. If the production function F follows a Constant Elasticity of Substitution (CES) form, profit is

$$\Pi = A[aM^{\rho} + (1-a)L^{\rho}]^{\beta/\rho} - p_M M - p_L L \tag{6}$$

where M and L are mechanical and labor power, respectively. a is the share parameter, $\rho = 1/(1-\varepsilon)$ in which ε is the elasticity of substitution between M and L. β is the scale parameter, where $\beta < 1$, $\beta = 1$ and $\beta > 1$ indicates decreasing, constant, and increasing returns to scale, respectively. For simplicity, we assume A = 4, a = 0.33, and p_L/p_M = 2. These values are

[5] Close to 40% of farm households in Nigeria use fertilizer (Takeshima & Nkonya 2014), while only around 4% use tractors (Table 1).

selected solely for illustrative purpose. Using the standard profit maximization conditions of Π and applying the first order conditions, we calculate as the proxy of wedge (5) the increase in profit from removing barriers to tractor adoption, under various level of labor-tractor substitutability and β (Table 3). If the technologies exhibit fairly constant returns (high β) and substitutability between machine and labor is low (low ε), the wedge is larger. For example, while the wedge is only 3% when β = 0.6 and ε = 20, it is 100% if β = 0.8 and ε = 3.3. Depending on the technology characteristics, the effect of imperfections in tractor hiring market can be substantial,[6] which further motivates empirically testing the presence of imperfections.

[Insert Table 3 here]

3.2.2 Impact of marginal tractor adoption: matching methods

Empirical challenges

The conceptual framework in the previous section suggests that, if a marginal adoption of a tractor leads to increase significantly household's overall profit, it can indicate the failure of the tractor hiring market. However, for scale-biased technologies like tractors, treating the adoptions as binary as in conventional technology adoptions studies cannot distinguish the effects of marginal adoptions from intensive adoption (Figure 2). If the increase in M from M = 0 is large (intensive adoption of tractors), the term (5) can be positive even if the market is perfect and $\eta = 0$. This is because the first order condition (4) that is based on a marginal change in M breaks down if the increase in M is large enough.

[Insert Figure 2 here]

A possible specification is to include both binary variable indicating the adoption and the continuous variable that measures adoption intensity, and separate out the effects of an intensive adoption from a marginal adoption. However, in many cases both marginal and intensive technology adoptions are potentially endogenous to the outcome variables. Instrumental variables methods such as two-stage least squares (2SLS) are challenging because continuous endogenous variable depends on the binary endogenous variable. Literature is thin on how such

[6]While the estimates of the elasticity of substitution are not available for Nigeria, it is estimated rather low, 1.7 in the US between 1910 and 1960 (Manuelli & Seshadri 2014 p1380).

mechanisms can be modeled in 2SLS. Also, finding good instruments for both marginal and intensive adoptions variables are likely to be difficult.

In addition, 2SLS may be sensitive to the violation of linearity assumption. Imbens & Rubin (2009) suggest that if normalized differences of covariates between treatment and control group are greater than 0.25, then assessing the treatment effects based on linear regression is likely to be susceptible to specification, and alternative models like matching methods are more suitable. In our case, the normalized differences often exceeded 0.25 for approximately half of the covariates.

We address this issue in the following way: first, we use matching estimators such as Propensity Score Matching method (PSM) (Rosenbaum & Rubin 1983) as well as Mahalanobis covariate matching to test if marginal adoptions of tractors have significant effects on a key outcome variable by excluding from the sample of intensive users of tractors, and check the sensitivity of results to the potential bias due to the exclusion of intensive adopters. Matching estimators have been used in the contexts other than project interventions (for example, the impact of market participation by Takeshima & Nagarajan 2012). We then use Generalized PSM (GPSM) methods (Hirano & Imbens 2004) to confirm that the effects of adoption intensity are insignificant among these marginal adopters, so that the significant effects from matching estimators are due to the marginal adoption of tractor, rather than due to the adoption intensity.

Covariate matching and propensity score matching

We define marginal adopters as those using tractors to relatively small areas of land. Limiting the analyses to marginal adopters, however, also limits the size of the treatment group. For this purpose, we use 3 ha as thresholds. In Nigeria, these are fairly small among tractor users who often cultivate 10 ha or more (Takeshima et al. 2014 as well as personal communication with local experts).

Although there are three groups (a) marginal tractor users; (b) those with access to tractor services but not using tractors; (c) those without access to tractor services, we only observe d^1 and not d^0, as was mentioned above. The matching estimators therefore compare (a) and (b) + (c). Under the discussions in the conceptual framework in the previous section, (b) should have the same outcome as (a), while (c) has lower outcome than (b). Therefore, a significant difference in outcome variable between (a) and (b) + (c), which we estimate, is a sufficient condition for the significant difference between (a) + (b) and (c), which is the hypothesis of our interest.

We use `teffects psmatch` for PSM, and `teffects nnmatch` for Mahalanobis covariate matching methods, as well as `psmatch2` (Leuven & Sianesi 2003) for supplementary analyses for both types of matching.[7] We use both commands because of various reasons. First, `teffects psmatch` and `teffects nnmatch` are likely to provide more consistent estimates of the standard errors of the estimated effects (Abadie & Imbens 2012), while `psmatch2` does not take into account the fact that propensity scores are estimated (Leuven & Sianesi 2003). On the other hand, several built-in commands in STATA such as `rbounds` (DiPrete & Gangl 2004) for estimation of Rosenbaum bounds (Rosenbaum 2002) only work with `psmatch2`. In addition, while `teffects nnmatch` allows the option to adjust for biases that arise when matching is based on more than one covariates (Abadie & Imbens 2011), `psmatch2` does not.

In PSM, matching is based on the estimated propensity scores, while in a Mahalanobis covariate matching it is based on Mahalanobis distance which has been reported to perform well under various conditions (Zhao 2004). Mahalanobis matching are generally robust regardless of sample size. PSM tends to have smaller biases but its small sample properties are sometimes questionable (Zhao 2004). Literature does not seem to agree the optimal number of matches. For example, while Abadie & Imbens (2002) suggests that 4 may be better than 1 match in terms of large sample property, multiple matching may lead to greater biases than a single match (Caliendo and Kopeinig 2008). Therefore, we use both 1 and 4 matches for robustness purposes. Using `pstest` command, all specifications are found to satisfy the balancing properties.

PSM is vulnerable to the violation of ignorability assumption (or "selection of observables" as sometimes phrased), which can be particularly serious in cross-section methods. However, partly controlling for LGA level unobserved fixed effects as discussed above, can partly mitigate the limitation of PSM due to the ignorability assumption. In addition, we assess

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[7]We run teffects psmatch and teffects nnmatch with att option, since average treatment effect on the treated (ATT) often has more direct policy implications (psmatch2 estimates ATT as the default).

the Rosenbaum bounds (Rosenbaum 2002) using the command `rbounds` (DiPrete & Gangl, 2004) to see if there are any hidden bias due to the violation of ignorability assumption.

The key outcome variable Π is the real earned income proxied as household expenditure on relevant categories. Expenditure figures are often more accurate than other measures like income (Deaton 1997). Specifically, Π consists of the values of food consumption (home consumption converted into expenditure values using market prices, as well as eating out expenditure), expenditure on non-durable consumption goods,[8] expenditures in education for household members, health expenditures, net purchase of livestock, net purchase of household assets, housing expenses including utilities (water, electricity, fuels, land and mobile phones, refuse disposal, and rent payments), net cash lending, net purchase of agricultural equipment, net of other unearned incomes as well as remittances received. Other unearned income and remittances receipts are excluded so that Π corresponds to the income from productive activities of the household.

Importantly, by the definition described above, Π corresponds not only the profit from agricultural activities but also non-farm activities. Farm and non-farm activities are often substitutes for the household. Some unobserved shocks like the local weather that are not perfectly captured in our more aggregated data might affect the substitution of within household resource allocations across these activities. In such case, limiting the outcome to profit from agricultural activities can cause omitted variable bias, particularly if the shocks also affect the decisions to use tractors. However, since off-farm income earning activities are often employed to diversify such weather risks, combined income (farm and non-farm) may be less susceptible this type of unobserved shocks.

[8] The values of nondurable consumption goods are aggregated over all items reported in the expenditure modules of LSMS data, each converted into 12 months equivalent amount. Each of LSMS 2011 and 2013 consists of a post-planting survey conducted after the planting season, and a post-harvesting survey conducted after the harvesting season. We combine short-term expenditures (7 days and 30 days) from the post-planting survey and long-term expenditures (6 months and 12 months) from the post-harvesting survey. This is because our interest is on the expenditure immediately following the planting season when tractors are typically used. Using short-term expenditures from post-planting survey instead of post-harvesting survey ensures that these expenditures more clearly reflect the cost savings realized by using tractors instead of labor in the planting season. Using long-term expenditures from post-harvesting survey instead of post-planting survey ensures that the most reference periods are after the planting season, so that long-term expenditure “after” the use of tractors is captured. Real expenditure values are obtained by deflating through the above price index.

Estimated results of PSM are summarized in Table 4. Where effects are statistically significant, critical gammas associated with Rosenbaum bounds are shown in brackets. The effects are statistically significant under various specifications and thresholds of marginal adoptions. Using tractors up to 3 ha of land increases household earned income by the value worth 1000 – 1500 kg of staple foods,[9] compared to the households with similar characteristics but not using tractors. At the median of the sample, this is equivalent to approximately 30% increase in household earned income. Using the thresholds below 3 ha also often leads to statistically significant effects of similar scales. These significant effects of marginal tractor adoptions are consistent with the conditions illustrated in the conceptual framework that can arise as a result of the imperfection in tractor hiring market.

[Insert Table 4 here]

Critical gammas in Table 4 are often in the range of 1.0 to 2.0, indicating that, statistical significance holds even when unobserved covariates cause the odds ratio of treatment assignment to differ by a factor of up to 2 between treatment and control groups (DiPrete and Gangl, 2004). This variation in odds ratio may also arise from selecting marginal adopters samples based on the thresholds. Estimated Rosenbaum bounds suggest that the statistically significant effects found in our PSM are generally robust to the presence of these biases.

Generalized Propensity Score Matching

The effects of adoption intensity can still be contained in the PSM results in the previous section if tractor can exhibit economies of scale even below the thresholds used in Table 4. We show that this is not the case, using the generalized propensity score matching method (GPSM) which is an extension of PSM to the case where treatment is continuous rather than binary. GPSM essentially involves estimating generalized propensity scores (GPS) based on the estimated conditional density of treatment intensity, and use GPS in similar way as PSM uses ordinary propensity score to find suitable matches and estimate the treatment effect. Dose response function estimated with GPSM can inform whether treatment effects vary with

[9] Note that this impact may not be exactly the increased production of staple foods, but whatever the benefit is, it is worth this much staple foods evaluated at the local staple food prices.

treatment intensity, upon receiving the treatment. By showing that effects of adoption intensity are absent, we can attribute all significant effects in Table 4 to the marginal adoption.

Following the expositions by Hirano & Imbens (2004) and Bia & Mattei (2008), GPSM is built around the following framework. For each of a random sample $i = 1, \ldots, N$, there is a set of potential outcomes $\Pi_i(t)$ for $t \in \mathcal{T}$ (referred to as the unit-level dose-response function). GPSM aims to estimate the average dose-response function, $\mu(t) = E[\Pi_i(t)]$. Each *i* is also associated with a vector of covariates X_i, and the level of the treatment received $T_i \in [t_0, t_1]$ where t_0 and t_1 the lower and upper bound of treatment level. The vector X_i, T_i and $\Pi_i(T_i)$ are observed. The unconfoundedness assumption of PSM is generalized to the case of a continuous treatment. Specifically, the weak unconfoundedness of GPS is $\Pi(t) \perp T|X$ for all $t \in \mathcal{T}$ (subscript *i* is dropped for simplicity).

Let a random variable $r(t, x)$ be the conditional density of the treatment *t* given the covariates *x*; $r(t, x) = f_{T|X}(t|x)$. Then the GPS is defined as $R = r(T, X)$. The GPS assumes that within strata with the same $r(t, x)$, the probability that $T = t$ does not depend on x. Tests have been developed to check the balancing property in the case of GPSM as in PSM (Bia & Mattei 2008).

The implementation of the GPSM consists of three steps. First, T_i (or its certain transformation $g(T_i)$) is regressed on X through the maximum likelihood method with normally distributed disturbance term, and GPS for observation *i* is calculated based on the estimated parameters as $\hat{R}_i = \frac{1}{\sqrt{2\pi\hat{\sigma}^2}} \exp\left[-\frac{1}{2\hat{\sigma}^2}\{g(T_i) - h(\hat{\gamma}, X_i)\}\right]$. Second, conditional expectation of the outcome $\Pi(t)$ is estimated as an appropriate polynomial of function of T and $\hat{R}$ as well as their interaction term through the ordinary least square method (since the level of treatment is continuous). Third, dose-response function is obtained by connecting $E\{\widehat{\Pi(t)}\}$ across *t*, where $E\{\widehat{\Pi(t)}\}$ is the sample average of predicted outcome at value *t* obtained from the second stage regression above. We estimate $E\{\widehat{\Pi(t)}\}$ and their 90% confidence intervals for t = 0.1, 0.5, 1.0, 1.5, …, 3.0, and plot them, where confidence intervals are estimated by 200 bootstrap processes that take into account the fact that various parameters including GPS are estimated values. The marginal treatment effects (MTE) are then estimated as $\frac{\partial E\{\bar{\Pi}(\bar{t})\}}{\partial t}$, and their confidence intervals are obtained by the same bootstrap procedure. The MTE shows how the treatment effects depend on the treatment level. In our contest, MTE can be used as a measure of how the income effects of tractor use changes as tractor use intensity increases.

GPSM is run using a STATA command `doseresponse` developed by Bia & Mattei (2008). Estimation focuses on observations where the area (ha) cultivated by tractors are greater than 0 and not greater than 3, and the same set of variables as in PSM. Bia & Mattei (2008) relies on the normality assumption of the conditional density of t (or $g(t)$). In our case, normality assumptions are satisfied at 5% statistical significance level when function g is a natural log, so that the estimated dose response functions are consistent using $ln(t)$ in place of t.

Balancing tests in GPSM are conducted by comparing GPS-adjusted means of covariates across sub-groups that are defined based on treatment levels (ha). Following the standard approach (Hirano & Imbens 2004; Kluve et al. 2007), we conduct this test in the following way; we split the sample into three groups G_j (j =1, 2, 3) by the tertiles of treatment level T ([0, 0.65], [0.65, 1.36], [1.36, 3.0]), divide each group into five blocks G_{jk} (k = 1, 2, 3, 4, 5) based on the quintiles of the GPS $R(T_j^m, X)$ evaluated at the median treatment level within the tertile j (T_j^m), calculate the t-statistics for the equality of means of covariates X's between blocks G_{jk} and $G_{\zeta k}$ ($\zeta \neq j$). We find that approximately 5% of the absolute values of t-statistics exceed 1.96, which is what we expect under the null hypothesis that means of X's are jointly equal across groups, suggesting that the balancing properties given GPS are satisfied.

The conditional expectation of outcomes given the estimated GPS are summarized in Table 5, while dose response function and treatment effect function (MTE) are shown in Figure 3. While coefficients in Table 5 have no causal meaning (Hirano & Imbens 2004), they indicate that treatment intensity may have little effect on the outcome. This is confirmed in the dose response functions in Figure 3; in the left figure, the expected earned income does not increase significantly in response to the increase in area cultivated by tractor (treatment intensity) upon the tractor adoption, which is consistent with the right figure where MTEs are always insignificantly different from zero.[10] Figure 3 is based on regression results of the first column in Table 5, as it provides the narrowest confidence intervals and conservative inference of MTE's insignificance. In other words, there are no significant effects of tractor use intensity up to 3 ha, upon the adoption of tractor use (this is because, as described above, GPS method applies to the impact of treatment *given the treatment being positive*).

[Insert Table 5 here]

[Insert Figure 3 here]

The statistically significant effects of tractor use adoption in Table 4, combined with the results from the GPS method, are consistent with our hypothesis; the significant effect in Table 4 is capturing the effect of marginal tractor adoption, rather than cumulative effects of intensive tractor adoption illustrated in Figure 2. Nigerian farm households' earned incomes increase from the marginal tractor adoption alone, even without the potential scale effects associated with scale-biased technologies like tractors, because the access to tractor service help them overcome certain constraints. One of such constraints is likely to be due to the market imperfections in the supply of tractor service, which is consistent with the accessibility constraints implied by the sparsity as well as the dominance of large, high horsepower tractors in Nigeria in Figure 1, their limited spatial mobility and demand seasonality. Other potential sources of constraints may be equally important. However, the matching analyses employed here compare farm households with similar characteristics associated with those other constraints, including credit availability, land fragmentation, or land tenure. The significant income effects of marginal tractor adoption in our study are therefore unlikely to be contaminated by the variations in these other constraints.

4 Conclusions

The growth of agricultural mechanization through custom hiring is an important process in many developing countries in Asia as well as SSA countries like Nigeria, which allows division of labor in agriculture through out-sourcing (Zhang et al. 2015). A strand of literature argues that the supply of mechanization services has been generally frictionless outside SSA.

[10]Negative MTE is not a concern in our case, unlike positive MTE. Slightly negative MTEs in Figure 3, albeit insignificant, indicates that intensive tractor use may be actually facing diminishing returns, rather than increasing returns. This is possibly because cultivating larger plots of land can still require more labor for weeding or harvesting with higher monitoring costs.

However, if the spatial mobility of tractors and the density of suppliers are both low, accessibility to such services can be significantly limited, leading to market imperfections. The current conditions in SSA countries including Nigeria exhibit such characteristics; it is dominated by sparsely populated large, high horsepower tractors, which is unique from a historical perspective. Gaining insights into the existence of market imperfection is critical since it implies the need in SSA for different forms of mechanization interventions from those implemented elsewhere.

Empirically testing such market imperfections has been challenging for scale-biased inputs like tractors, due to the difficulty of separating the effect of marginal technology adoptions from intensive technology adoptions, potential endogeneity of both dimensions of adoptions, as well as high heterogeneity of agro-ecological environments in SSA. Other possible literature, such as transactions costs literature, while useful, still provides only limited insights on market imperfections including its economic significance. We attempted to fill this knowledge gap using Nigerian data, by combining pseudo-panel, correlated random effects double hurdle model, and covariate and propensity matching estimators, as well as generalized propensity score matching estimators.

We find that, while tractor hiring service market in Nigeria partly responds to the underlying economic conditions that conventionally affect the demand for such service, it is still imperfect with significant consequent welfare loss. Tractor adoptions may be constrained by the absence of large farm households within proximity, who are more likely to own tractors, consistent with the hypotheses that the dominance of sparsely populated large tractors is responsible for the supply side imperfection of tractor hiring market in Nigeria. The evidence is also supported by the significant effects of marginal tractor adoption, separately identified from the effects of intensive adoptions. The effect of imperfection in tractor hiring market is also sizeable, as overcoming this imperfection can potentially increase farm households' income by as much as 30%. This effect is from the marginal adoption of tractors alone, and is not confounded by the potential scale effects from intensive tractor use upon adoption.

References

Abadie A & GW Imbens. (2002). *Simple and bias-corrected matching estimators.* Technical report, Department of Economics, University of California, Berkeley.

Abadie A & GW Imbens. (2011). Bias-corrected matching estimators for average treatment effects. *Journal of Business & Economic Statistics 29*(1), 1–11.

Abadie A & GW Imbens. (2012). *Matching on the estimated propensity score.* Harvard University and National Bureau of Economic Research. http://www.hks.harvard.edu/fs/aabadie/pscore.pdf.

Abowd J & H Farber. (1982). Job queues and the union status of workers. *Industrial and Labor Relations Review 35*, 354–367.

African Center for Economic Transformation. (2014). *2014 African Transformation Report: Growth with Depth.* African Center for Economic Transformation. Accra, Ghana.

Barraclough SL & AL Domike. (1966). Agrarian structure in seven Latin American countries. *Land Economics 42*(4), 391–424.

Bellemare MF & CB Barrett. (2006). An Ordered Tobit Model of Market Participation: Evidence from Kenya and Ethiopia. *American Journal of Agricultural Economics 88*(2), 324–337.

Bia M & A Mattei. (2008). A Stata package for the estimation of the dose-response function through adjustment for the generalized propensity score. *Stata Journal 8*(3), 354–373.

Binswanger H. (1986). Agricultural mechanization: A comparative historical perspective. *World Bank Research Observer 1*(1), 27–56.

Binswanger H & G Donovan. (1987). *Agricultural mechanization: Issues and options.* World Bank, Washington DC.

Caliendo M & S Kopeinig. (2008). Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys 22*(1), 31–72.

Center for Sustainable Agricultural Mechanization (CSAM). (2014). *Country Pages*. Available at http://un-csam.org/cp_index.htm. Last visited, July 2, 2014.

Chamberlain G. (1984). *Panel Data.* In *Handbook of Econometrics*, vol. 2, ed. Z Grilliches & MD Intriligator, 1247–1318. Amsterdam: North-Holland.

Clarke S. 1991. New Deal Regulation and the Revolution in American Farm Productivity: A Case Study of the Diffusion of the Tractor in the Corn Belt, 1920–1940. *Journal of Economic History 51*(1), 101–23.

Cragg JG. (1971). Some Statistical Models for Limited Dependent Variables with Application to the Demand for Durable Goods. *Econometrica 39*(5), 829–844.

Deaton A. (1997). *The analysis of household surveys: A microeconomic approach to development policy*. Baltimore: Johns Hopkins University Press.

DiPrete T and M. Gangl (2004), Assessing bias in the estimation of causal effects: Rosenbaum bounds on matching estimators and instrumental variables estimation with imperfect instruments. *Sociological Methodology 34*(1), 271–310.

FAO (Food and Agriculture Organization). (2000). *Rivers of Africa*. Rome, Italy.

FAO. (2012). *AQUASTAT: Geo-referenced Database on Dams.* Computer Disk. Rome, Italy.

Fischer G, F Nachtergaele, S Prieler, HT van Velthuizen, L Verelst, D Wiberg (2008). *Global Agro-ecological Zones Assessment for Agriculture (GAEZ 2008).* IIASA, Laxenburg, Austria and FAO, Rome, Italy.

Foster AD & MR Rosenzweig. (2011). *Are Indian farms too small? Mechanization, agency costs, and farm efficiency*. Economic Growth Center, Yale University New Haven CT.

Freedman DA. (2006). On the so-called “Huber sandwich estimator” and “robust standard errors”. *The American Statistician 60*(4), 299–302.

Fulton CV, EO Heady & GE Ayres. (1978). *Farm machinery costs in relation to machinery and farm size.* CARD Reports. Book 82.

Gardner BD & RD Pope. (1978). How Is Scale and Structure Determined in Agriculture? *American Journal of Agricultural Economics 60*, 295–302.

Gollin D, D Lagakos & ME Waugh. (2014). The Agricultural Productivity Gap. *Quarterly Journal of Economics 129*(2), 939–993.

Harvest Choice. (2012). *Average Travel Time to Nearest Town over 20K (hours) (2000).* Accessed October 10, 2014. http://harvestchoice.org/.

Herdt, R. (1983). *Mechanization of rice production in developing Asian countries: Perspective, evidence and issues.* In IRRI (Ed.), *Consequences of small farm mechanization.* Los Banios, Laguna, Philippines.

Hirano K & GW Imbens. (2004). *The propensity score with continuous treatments.* In *Applied Bayesian modeling and causal inference from incomplete-data perspectives,* A Gelman & XL Meng (eds), John Wiley & Sons.

Hlavacek JD & NM Reddy. (1986). Identifying and Qualifying Industrial Market Segments, *European Journal of Marketing 20*(2), 8–21.

Imbens GW & D Rubin. (2009). *Causal inference in statistics, and in the social and biomedical sciences.* New York: Cambridge University Press.

ISRIC (International Soil Reference and Information Centre). (2013). *Soil Property Maps of Africa at 1 km.* http://www.isric.org.

Jayne TS, J Chamberlin & D Headey. (2014). Land pressures, the evolution of farming systems, and development strategies in Africa: A synthesis. *Food Policy 48*, 1–17.

Johnson M, H Takeshima & K Gyimah-Brempong. (2013). *Assessing the potential and policy alternatives for achieving rice competitiveness and growth in Nigeria.* IFPRI Discussion Paper 01301.

Key, N., Sadoulet, E., & de Janvry, A. (2000). Transactions costs and agricultural household supply response. *American Journal of Agricultural Economics 82*(2), 245–259.

Kienzle J, JE Ashburner & BG Sims. (2013). *Mechanization for Rural Development: A review of patterns and progress from around the world.* FAO.

Kluve J, H Schneider, A Uhlendorff & Z Zhao. (2007). *Evaluating continuous training programs using the generalized propensity score.* IZA Discussion Paper 3255, Institute for the Study of Labor (IZA), Bonn.

Leuven E and B. Sianesi. (2003). *PSMATCH2: Stata module to perform full Mahalanobis and propensity score matching, common support graphing, and covariate imbalance testing*. http://ideas.repec.org/c/boc/bocode/s432001.html.

Manuelli RE & A Seshadri. (2014). Frictionless Technology Diffusion: The Case of Tractors. *American Economic Review 104*(4), 1368–91.

McMillan, M., Rodrik, D., & Verduzco-Gallo, Í. (2014). Globalization, Structural Change and Productivity Growth, with an Update on Africa. *World Development 64*, 11–32.

Michalopoulos S & E Papaioannou. (2014). National Institutions and Subnational Development in Africa. *Quarterly Journal of Economics 129*(1), 151–213.

Munshi K. (2004). Social Learning in a Heterogeneous Population: Technology Diffusion in the Indian Green Revolution. *Journal of Development Economics 73*(1), 185–213.

National Population Commission. (2010). *Population Distribution by Sex, State, LGAs, and Senatorial District: 2006 Census Priority Tables. Vol. 3.* Abuja, Nigeria.

Olmstead AL & PW Rhode. (2001). Reshaping the landscape: the impact and diffusion of the tractor in American agriculture, 1910–1960. *Journal of Economic History 61*(03), 663–698.

Ramankutty, N., Evan, A. T., Monfreda, C., & Foley, J. A. (2008). Farming the planet: 1. Geographic distribution of global agricultural lands in the year 2000. *Global Biogeochemical Cycles, 22*(1).

Robinson P. (1982). On the asymptotic properties of estimators of models containing limited dependent variables. *Econometrica 50*, 27–41.

Rosenbaum PR & DB Rubin. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrica 70*, 41–55.

Rosenbaum, P.R. (2002), *Observational Studies*, New York: Springer.

Roy KC & G Singh. (2008). Agricultural Mechanization in Bangladesh. *Agricultural Mechanization in Asia, Africa and Latin America 39*(2), 83–93.

Stitzlein JN. (1974). *The economics of agricultural mechanization in southern Brazil.* PhD Dissertation. The Ohio State University.

Takeshima H. (2015). Onset risks and draft animal investment in Nigeria. *Journal of International Agricultural Trade and Development 9*(2), 137–163.

Takeshima & Salau (2010). *Agricultural mechanization and the smallholder farmers in Nigeria.* IFPRI NSSP Policy Note 22.

Takeshima H & A Winter-Nelson. (2012). Sales location among semi-subsistence cassava farmers in Benin: a heteroskedastic double selection model. *Agricultural Economics 43*(6), 655–670.

Takeshima H & L Nagarajan. (2012). Minor millets in Tamil Nadu, India: Local market participation, on-farm diversity and farmer welfare. *Environment and Development Economics 17*(5), 603–632.

Takeshima H & F Yamauchi. (2012). Risks and farmers' investment in productive assets in Nigeria. *Agric. Econ. 43*(2), 143–153.

Takeshima H & E Nkonya. (2014). Government fertilizer subsidy and commercial sector fertilizer demand: Evidence from the Federal Market Stabilization Program (FMSP) in Nigeria. *Food Policy 47*, 1–12.

Takeshima H & LS Liverpool-Tasie. (2015). Fertilizer subsidy, political influence and local food prices in sub-Saharan Africa: Evidence from Nigeria. *Food Policy 54*, 11–24.

Takeshima H, A Adeoti, S Okoli, S Salau & V Rhoe. (2010). Demand Characteristics for Small-scale Private Irrigation Technologies: Knowledge Gaps in Nigeria. *IFPRI NSSP Working Paper 18.*

Takeshima H, A Adeoti & S Salau. (2011). Measuring the effect of transaction costs for investment in irrigation pumps: Application of unobserved stochastic threshold model to the case of Nigeria. *African Journal of Agricultural and Resource Economics 6*(2), 118–143.

Takeshima, H., Nin Pratt, A., Diao, X., (2013a). *Agricultural Mechanization Patterns in Nigeria: Insights from Farm Household Typology and Agricultural Household Model Simulation.* IFPRI DP 01291.

Takeshima H, A Nin Pratt & X Diao. (2013b). Mechanization and agricultural technology evolution, agricultural intensification in sub-Saharan Africa: typology of agricultural mechanization in Nigeria. *American Journal of Agricultural Economics 95*(5), 1230–1236.

Takeshima H, K Jimah, S Kolavalli, X Diao & R Funk. (2013c). *Dynamics of transformation: Insights from an exploratory review of rice farming in the Kpong Irrigation Project*. IFPRI Discussion Paper 01272.

Takeshima H, H Edeh, A Lawal & M Isiaka. (2014). *Tractor owner operators in Nigeria: Insights from a small survey in Kaduna and Nasarawa states.* IFPRI Discussion Paper 01355.

Takeshima H, E Edeh, A Lawal & M Ishiaka. (2015). Characteristics of private-sector tractor service provisions: Insights from Nigeria. *The Developing Economies 53*(3), forthcoming.

Thorbecke E & T van der Pluijm. (1993). *Rural Indonesia: socio-economic development in a changing environment (No. 3).* NYU Press.

Ugwuishiwu BO & AP Onwualu. (2009). Sustainability and Cost of Agricultural Mechanization in Nigeria as affected by Macro-Economic Policies. *Journal of Agricultural Engineering and Technology 17*(2), 44–56.

Yang J, Z Huang, X Zhang & T Reardon. (2013). The Rapid Rise of Cross-Regional Agricultural Mechanization Services in China. *American Journal of Agricultural Economics 95*(5), 1245–1251.

Zhang X, J Yang & T Reardon. (2015). *Mechanization Outsourcing Clusters and Division of Labor in Chinese Agriculture*. IFPRI DP 01415.

Zhao, Z. (2004) Using matching to estimate treatment effects: data requirements, matching metrics, and Monte Carlo evidence. *Review of Economics and Statistics 86*(1), 91–107.

Table 1. Descriptive statistics of variables among farm households used in the analyses[a]

Variables	Mean	Median	Standard deviation
Use tractors (1 = yes; 0 = no)	.04	.00	.19
Own some of the farm land (1 = yes; 0 = no)	.20	.00	.40
Average area (ha) of owned or distributed land per plot	.55	.21	2.02
Number of owned or distributed plots	1.32	1.17	.76
Household size	6.19	6.00	3.20
Age of household head	51.21	50.00	14.89
Age squared	2844.51	2500.00	1618.78
Gender of household head (1 = female)	.12	.00	.32
# of working age household members with different education level			
No education, M	.32	.00	.64
Primary education, M	.29	.00	.55
Secondary education or above, M	.70	.00	1.08
Koranic education, M	.10	.00	.39
Any other education, M	.00	.00	.05
No education, F	.68	.00	.89
Primary education, F	.31	.00	.58
Secondary education or above, F	.49	.00	.89
Koranic education, F	.12	.00	.46
Any other education, F	.00	.00	.07
Real asset value excluding land	857.93	292.73	3080.83
Own draft animals (1 = yes; 0 = no)	.13	.00	.34
Real values of draft animal	355.71	.00	2031.72
Credit obtained by at least household member in the past 6 months	.40	.00	.49
Extension contact by at least household member since January	.13	.00	.33

Real price of one kg of fertilizer (average of Urea and NPK)	1.03	.87	1.96
Real district average farm wage per day	5.91	5.00	1.96
Cultivable land per capita (ha)	.51	.36	.58
Soil with high workability (1 = workable, 0 = otherwise)	.62	1.00	.49
Bulk density of the soil (tons per m^3 of soil)	1.34	1.30	0.98
Clay contents of the soil (clay content (<2 μm) in %)	17.47	17.00	5.44
Distance to the nearest town with population of 20,000 (hours)	2.70	2.41	1.51
Euclidean distance to the nearest dam (geographical minute)	.96	.79	.69
Euclidean distance to the nearest river (geographical minute)	.02	.02	.01
Euclidean distance to the governor district-of-origin in 2010	.42	.33	.37
Sample maximum owned/distributed land within enumeration area (ha)	4.02	1.76	16.60
Real earned income per year	4588.68	2444.30	38351.91

Source: Author based on LSMS (2011, 2013).

[a]Real values are measured in average values of equivalent amount (kg) of rice and gari. M = Male, F = Female.

Table 2. Determinants of the area cultivated by tractors (pseudo-panel double hurdle model; marginal effects evaluated at the mean of observations)

	Double hurdle model	
Dependent variable	Probability of using tractor	Area cultivated by tractors (ha)
Model	Probit	Truncated Regression
Own some of the farm land (yes = 1)	.004	.247***
Average area (ha) of owned or distributed land per plot	-.0002	.156***
Number of owned or distributed plots	.002**	.048*
Household size	.0004	.012
Gender of household head (female = 1)	.001	-1.038
Age of household head	-.0006	.022
Age squared	4.08e-06	-.0002
# of working age household members (no education, M)	-.003	-.124
Primary education, M	.001	.020
Secondary education or above, M	-.001	.015
Koranic education, M	-.002	-.239**
Any other education, M	-.019	.617**
# of working age household members (no education, F)	-.001	-.014
Primary education, F	.001	-.063
Secondary education or above, F	.003**	-.067
Koranic education, F	.001	.040
Any other education, F	-.002	-.376
Ln (real asset value)	.0002***	.025
Own draft animals (yes = 1, no = 0)	.002	-.402
Obtained credit (yes = 1, no = 0)	.001	-.187**
Had extension contact (yes = 1, no = 0)	-.002	-.068
Ln (real values of draft animal)	-.0001	.083
Real price of one kg of fertilizer (average of Urea and NPK)	.0007*	-.010*
Real LGA average farm wage	.0004	.033
Ln (cultivable land per capita)	.006***	.057
Soil with high workability (1 = workable, 0 = otherwise)	.012***	.538**
Bulk density of the soil (tons per m^3 of soil)	.034*	.529
Clay contents of the soil (clay content (<2 μm) in %)	-.001***	-.026

Distance to the nearest town with population of 20,000 (hours)	.0002	-.073
Euclidean distance to the nearest dam (geographical minute)	-.004**	-.289*
Euclidean distance to the nearest river (geographical minute)	-.144	-2.676
Euclidean distance to nearest 2010 district of origins of state governors (geographical minute)	-.002	.372*
ln (sample maximum owned/distributed land within enumeration area, ha)	.002*	
Time dummy (year 2012 = 1)	Included	Included
Sector dummy (rural = 1, urban = 0)	Included	Included
Correlated random effects components	Included	Included
Zonal dummies	included	Included
Constant	included	Included
σ		4.292***
Number of observations	5119	223

Source: Author. *** 1%, ** 5%, * 10%.
[a]M = male, F = female.

Table 3. Effects of removing barrier to tractor use – illustrative exercise (% change in profit)

Elasticity of substitution between labor and machinery services (ε)	$\beta = 0.9$	$\beta = 0.8$	$\beta = 0.7$	$\beta = 0.6$
$\rho = 0.95$ ($\varepsilon = 20$)	21	9	5	3
$\rho = 0.9$ ($\varepsilon = 10$)	50	20	11	7
$\rho = 0.8$ ($\varepsilon = 5$)	149	50	27	16
$\rho = 0.7$ ($\varepsilon = 3.3$)	374	100	50	30

Source: Authors.

Table 4. Results of propensity score matching method among marginal adopters (dependent variable = real household earned income measured in kg of staple foods)

Matching methods	Upper thresholds of areas cultivated by tractors (ha)				
	1.0	1.5	2.0	2.5	3.0
Sample size of control group	4862	4862	4862	4862	4862
Sample size of treated group	79	105	121	131	145
Nearest neighbor matching (n = 4)	1564* [1.00]	1524** [1.02]	1164* [1.00]	1271* [1.00]	1239* [1.00]
Nearest neighbor matching (n = 1)	904	1266	991	344	1531** [1.13]
Covariate matching with bias adjustment (Mahalanobis) (n = 4)	1385* [1.26]	1056* [1.35]	988* [1.34]	1025** [1.58]	912* [1.56]
Covariate matching with bias adjustment (Mahalanobis) (n = 1)	-1444	664	1375** [1.69]	1361** [1.93]	1513*** [1.86]

Source: Author's estimation. Asterisks indicate the statistical significance; *** 1%, ** 5%, * 10%.

Table 5. Conditional expectation of outcome estimated with generalized propensity scores

Dependent variables	Real household earned income per year (1,000 kg of staple foods)		
Treatment	-.381 (.592)	-.321 (1.389)	-2.007 (2.594)

GPS	-2.395 (2.764)	-2.227 (4.489)	-5.278 (13.537)
Treatment*GPS		-.153 (3.223)	-.249 (3.241)
Treatment squared			.608 (.789)
GPS squared			5.419 (17.001)
Constant	7.560*** (1.474)	7.495*** (2.003)	8.358*** (2.745)
R^2	.008	.008	.013
p-values of overall fit	.546	.751	.868
Number of observations	149	149	149

Source: Author.

[a]Numbers in parentheses indicate the standard errors of estimated coefficients. GPS = generalized propensity score.

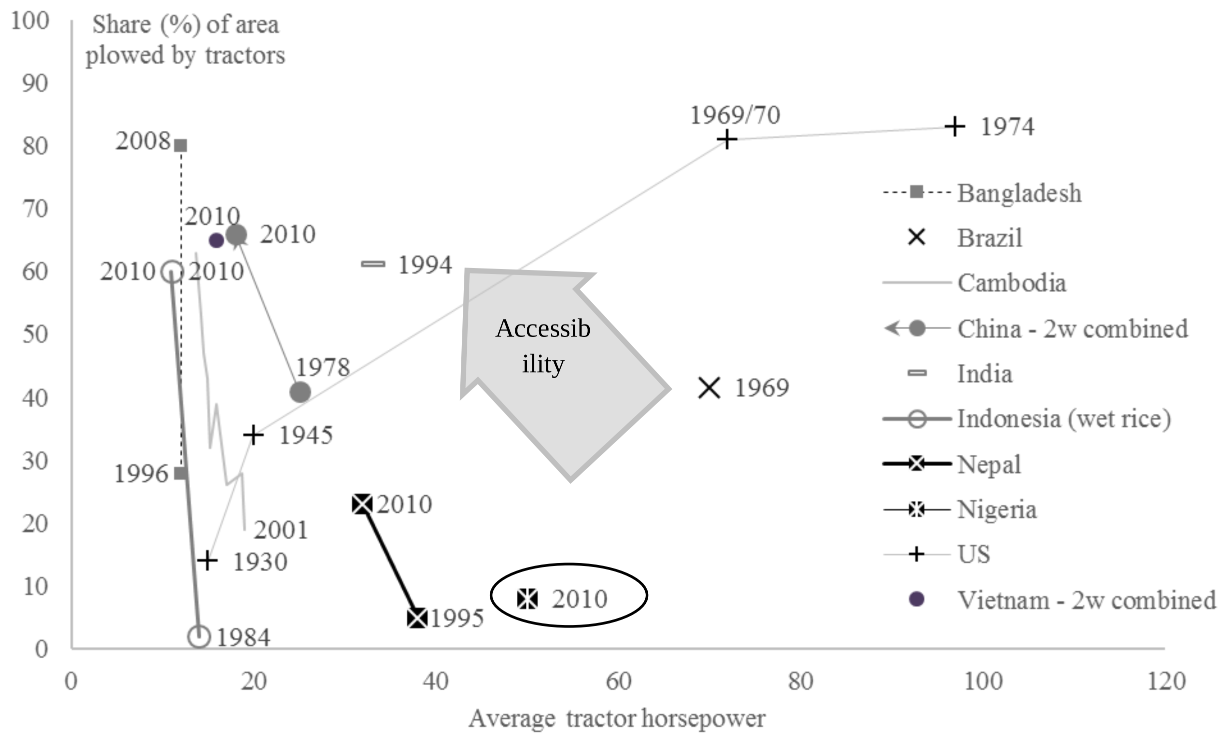

Figure 1. Average tractor horsepower and the level of mechanization (years vary)[abc]

Source: Author's calculation based on the following sources; China and Vietnam, CSAM (2014); Bangladesh, Kienzle et al. (2013), Roy & Singh (2008), Brazil, Stizlein (1974), India, Ugwuishiwu and Onluwal (2009, Table 2.1), United States, Olmstead and Rhode (2001), and US Census of Agriculture, Indonesia, Thorbecke & van der Pluijm (1993 p111) and CSAM (2014), Nigeria, Takeshima & Salau (2010), Takeshima et al. (2015) as well as informal communications with local experts for Nigeria.

Note: [a]Figure for Vietnam is for rice area only. Figures for the United States are the share of farmers using tractors. Figure for Brazil is for wheat only, and the average of the Rio Grande du Soil and Santa Katarina reported by Stizlein (1974, Table 7).

[b]Average horsepower for the US is Gardner & Pope (1978 p.298) for 1970 and 1975. Average horsepower for tractors are calculated assuming that horsepower for 4w tractors and 2w tractors are 42 and 11, respectively, adopting the definitions in China.

[c]Numbers within the figure are corresponding years.

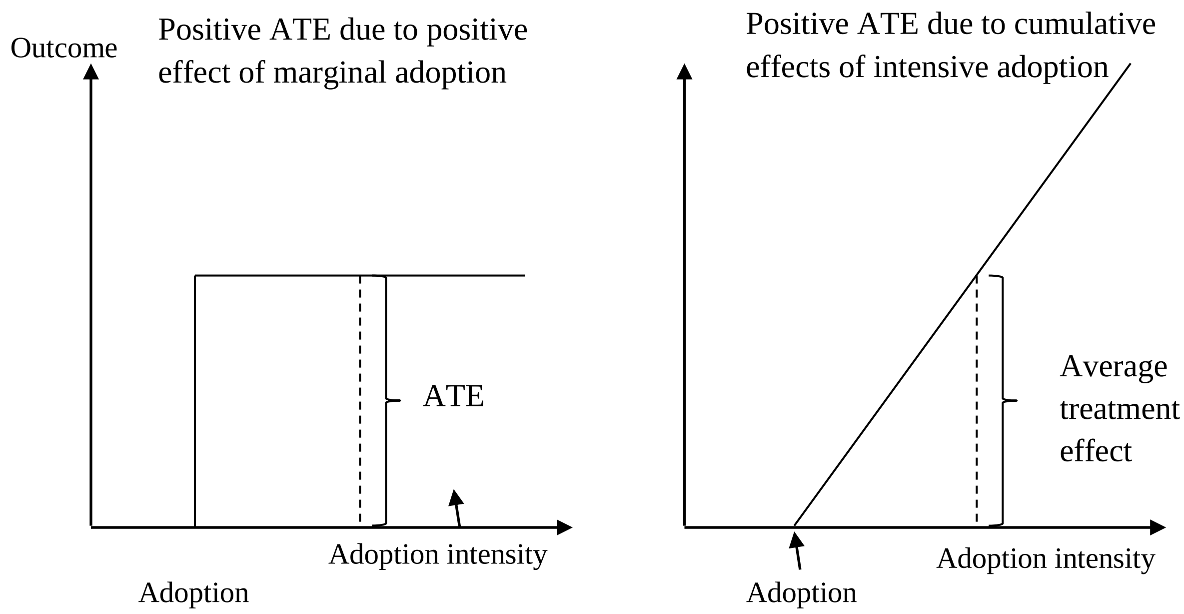

Figure 2. Distinction between the impact of marginal adoption and intensive adoption[a]

Source: Author.

[a] ATE = Average treatment effect

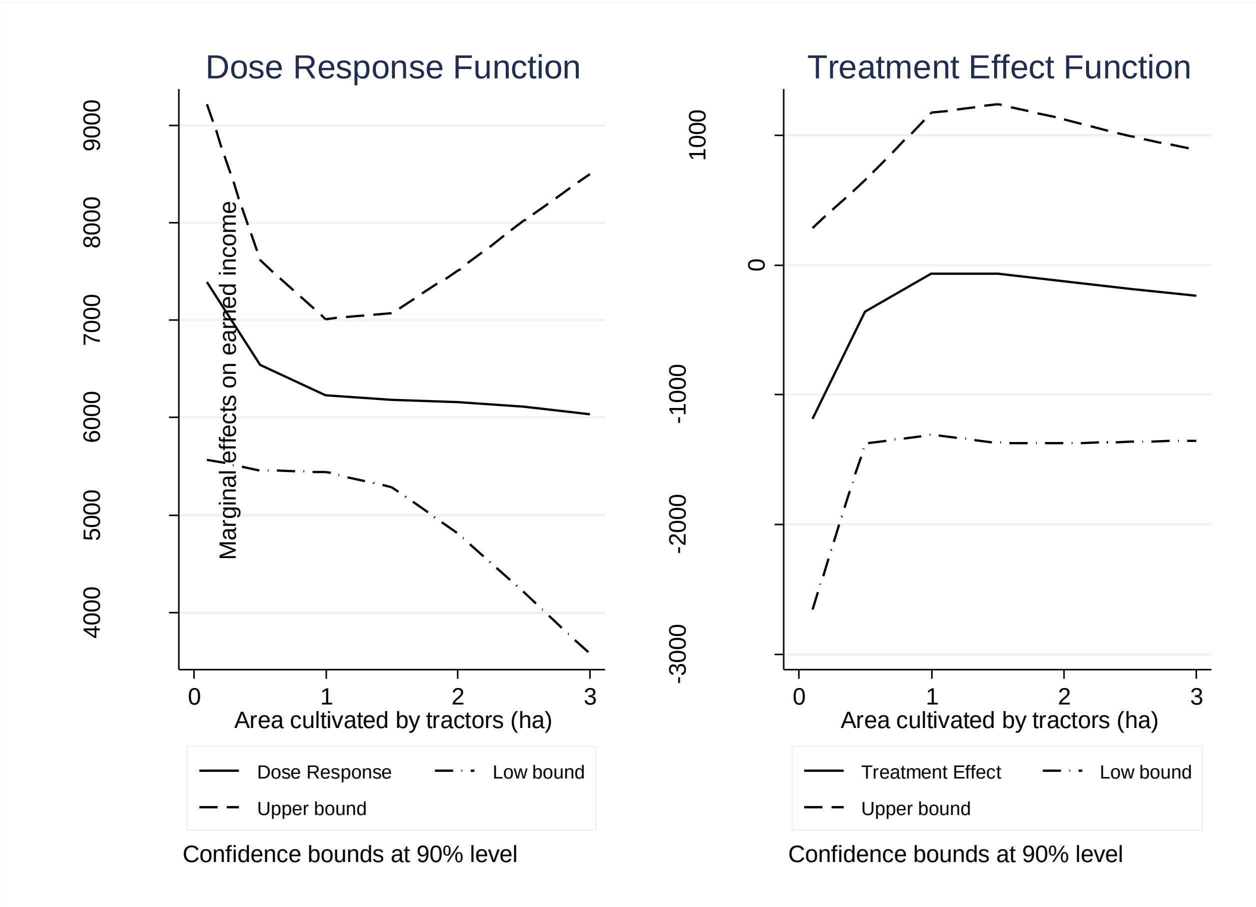

Figure 3. Insignificant marginal treatment effects of tractor use intensity estimated by generalized propensity score method

Source: Author.