Emergent large traders in smallholder grain markets and their role in enhancing adoption of sustainable agricultural intensification practices in Kenya

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Abstract

Pervasive threats of climate change and land degradation have compounded the low farm productivity problem inherent in sub-Saharan Africa. Though sustainable agricultural intensification practices have been shown to improve resilience of farm production in the face of these emerging threats, they suffer low adoption rates typical of technology adoption in these regions. Recent evidence shows the emergence of large grain traders in the smallholder farm output markets. Given established correlation between contractual farm arrangements and technology adoption, the hypothesis is that these traders can incentivize technology adoption at scale at the farm level, given their financial capacity. This study tests this hypothesis using a large panel dataset from Kenya spanning a decade. A dynamic random effects Probit model is used to evaluate how past adoption of sustainable inputs influence subsequent adoption behavior, while a control function approach is used evaluate how sales to large grain traders affect the adoption of sustainable inputs at the farm level. Results indicate that sales to large grain traders lead to higher adoption of inorganic fertilizer but not improved seed and manure, and that land ownership is a key success factor in explaining sales to these market actors. The adoption of improved seed and organic manure is persistent across time, indicating state dependence in the use of these inputs. These results suggest that strategies to foster engagements between large grain traders and farmers can enhance uptake of inorganic fertilizer; such strategies should also be accompanied by efforts to enable resource-poor farmers access to these markets.

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1 Introduction

Farm yields in sub-Saharan Africa (SSA) remain low despite decades of efforts to enhance intensification in the region. This problem is amplified by increasing land degradation and the emerging threat of climate change. Consequently, there has been renewed calls for sustainable agricultural intensification aimed at increasing productivity without adverse effects to the environment (Pretty and Bharucha, 2014; Pretty et al., 2011).

Sustainable agricultural intensification practices (SAIPs) in many areas of SSA may include *inter alia*, the use of inorganic and organic fertilizers, improved seeds, measures to conserve soil and water, and farm management practices such as crop rotations involving legumes, re-incorporation of crop residues, and selective agro-forestry practices (Manda et al., 2016; Pretty et al., 2011). These are however highly location-specific and may vary greatly by agro-ecological conditions and relative prices of factors such as land, labor and capital.

Finding new or less utilized channels for bolstering SAIP use remains a topical issue for development economists given the ubiquitous low technology adoption problem in SSA. For the most part, policy has focused on how intervening directly into agricultural input and output markets (e.g., input subsidies and crop price supports) can nudge technology adoption. Yet it is often overlooked how changes in the broader food system can indirectly encourage intensification at the farm level.

This study examines how new marketing actors in Kenya's grain value chains have affected the incentives and wherewithal of farmers to intensify their production patterns. Traditionally, most smallholder farmers have sold their outputs informally to rural assembly traders and local households (Sitko and Jayne, 2014). While these actors provide market outlets for otherwise excluded farmers' in remote rural areas, their capacity and marketing model does little to directly support sustainable intensification practices by smallholder farmers. Similarly, selling to big marketing parastatals, another option for farmers in high production areas, presents a challenge to the small farmer as they often do not pay in cash thus discouraging liquidity-constrained farmers with small volumes to sell (Olwande et al., 2015; Sitko and Jayne, 2014). The entrance of new market actors with access to big capital in the smallholder farm markets has significant implications for food production systems given their capacity to intervene in the production process, to guarantee access to enough grain supply (Sitko et al., 2017).

There is a dearth of evidence on the implications of these changes in the agro-food industry on the production systems especially in the adoption of SAIPs in SSA. Most extant studies view the problem as unidirectional; how farm-level production affects marketing behavior. Emerging literature investigating effects in the opposite direction focus on how small contract farming arrangements between farmers and a particular contracting marketing actor affect farm level production decisions. Our study contributes to this emerging literature by investigating how the entry of large grain traders (LGTs) in smallholder grain output markets in Kenya affect the adoption of sustainable intensification inputs at farm level. To achieve this, we utilize a rich panel dataset spanning a decade (2000 to 2010), during which the role of LGTs in markets has substantially changed in some areas but not others, which enables us to examine the dynamic links between grain output marketing and farm production behavior.

2 Context and data

2.1 *Literature review*

The functioning of output markets, including the attributes of marketing actors, may influence farm behavior in numerous ways. For example, reliable and timely cash payments for farm outputs may relax future binding liquidity constraints that otherwise dampen adoption of intensification inputs. Evidence indicates that under favorable conditions, outgrower cash crop programs have encouraged greater farmer use of inputs in food crop farming Govereh and Jayne, 2003). This is through exploitation of the synergy between the two crop types, such that even though food crops may not be highly marketed, farmer exposure to the market through cash crop overcomes liquidity constraints on the purchase of cash inputs for food production too.

A key pathway for leveraging the markets for farm-level productivity is contract arrangements. Aversion to risks has been shown to inhibit adoption of technologies that require substantial capital outlays with a risk of loss in case of weather-induced crop failure (Brick and Visser, 2015; Jumare et al., 2018; Mulwa and Visser, 2018). A contract guarantees recovery of costs in case of crop loss thus helping farmers overcome risks involved in investing in technologies like improved seed and inorganic fertilizer (Barrett et al., 2012; Liu, 2013). Across SSA, buyers of cash crops like coffee, tea and horticultural crops provide farmers with inputs and advisory services and in return are guaranteed quality output Minten (2010) found that smallholder farmers in Madagascar receiving inputs from processors through contract arrangements increased their yields significantly when this was combined with advice from technical assistants. In Ethiopia, potato farmers were found to prefer contract arrangements since these insured them against uncertainty in the input markets (Abebe et al., 2013).

While presenting a conceptual framework for the analysis of contract farming arrangements, Barrett et al. (2012b) observed that the dearth of empirical literature on these production-marketing arrangements was due to methodologocal challenges. Since then however, studies have emerged that look into the issue. Several recent studies find that contract farming arrangements lead to enhanced intensification and an improvement in welfare for the participating farmers (Bellemare, 2012; Maertens and Vande Velde, 2017; Ton, et al., 2018). A few however point to possible drawbacks to contract farming arrangements (Lambrecht et al., 2018; Ragasa et al., 2018). For example, Ragasa et al. (2018) evaluate different maize-based contract farming schemes in Ghana and find that though these contract farming arrangements improve technology uptake, the resulting yield increase is not enough to compensate for the technology costs.

While giving evidence on the benefits of contract farming arrangements, Ton et al. (2018) also advocates for a price premium in the contract schemes, to prevent side-selling.

Much of the literature reviewed in this subsection relates to small scale - low volume contract arrangements between a producer(s) and a group of farmers, where farmers are engaged one project and village at a time. For meaningful welfare impacts across farming households, this needs to be scaled up. Recent evidence indicates that large-scale grain traders (LGTs) have rapidly expanded their operations and become an important direct and indirect buyer of grain for smallholder farmers in many parts of the region (Sitko and Chisanga, 2016; Sitko et al., 2017).

These LGTs are similar in scale to the market actors entering into contract farming arrangements with smallholder farmers in reviewed studies above. It is interesting to assess how the LGTs operations may be transforming the food production systems over time. Using a panel dataset spanning a decade, this study adds to the literature on the role of market actors in enhancing farm production by looking at how LGTs affect take up of sustainable intensification inputs.

2.2 Data

2.2.1 Data sources

Data used in this study comes from the Tegemeo Agricultural Monitoring and Policy Analysis (TAMPA) project, a collaborative effort between Egerton University's Tegemeo Institute and Michigan State University. The dataset runs from 2000 to 2010 and covers 24 Districts in Kenya within which there are 39 Divisions and 120 villages. A stratified sampling technique was used to take into account the ecological diversity in the country where all the districts were classified into eight agro-regional zones based on agro-climatic conditions, agricultural activities and rural livelihoods. Using standard proportional sampling, 1,500 farm households were then sampled randomly from the 24 districts. Attrition across the waves was relatively small and re-interview models conducted show that this is largely random (Jin and Jayne, 2013).

A standard question put to the respondents across the four waves regarded where the household had sold their largest part of their grain (maize, wheat and rice) output after harvesting, with large traders being one of the options under consideration. This question was used to construct the key treatment variable of whether a household sold a large share of their maize to a large trader or not (=1 if the household sold to a LGT, and 0 in otherwise). The outcome variables considered in the study are the sustainable agricultural intensification inputs (SAIPs) which include inorganic fertilizer, improved seed and organic manure. Again, these variables were constructed from standard questions in all survey waves about household use of the SAIP. Data for manure use in the 2000 wave is however missing and only three waves were used in the analysis of the demand for this particular SAIP.

2.2.2 Descriptive statistics

The proportion of households using the various sustainable agricultural intensification inputs (SAIPs) and participating in LGT markets are presented in Table 1, as well as summary statistics of all other explanatory variables and controls used in the study. The results indicate few LGT sales in earlier years of the panel but these rise sharply in 2007 to 2010. While the proportion of households using the SAIPs seem high, a key concern on the uptake of these inputs has been the low rates of use in SSA, especially fertilizer application (Sheahan, Black, and Jayne, 2013). To reflect this, the analysis used in this study analysis both adoption and intensity of adoption.

2.2.3 Household transitions in and out of LGT markets across the panel waves

The transition matrix in Table 2 shows how farmers enter and exit the LGT market across the waves. The results show significant movement in the proportion of farmers entering and exiting the LGTs market. Of the farmers who were selling to LGT in 2000, only 4.6% of these were still selling to LGTs in 2004 with the rest exiting the market (95.4%) in same time period. These initial LGT sellers however come back to the market with 22.7% and a further 42.9% of the farmers who sold to LGTs in 2000 doing so again in 2004 and 2007, respectfully. Likewise, 0.6% of the farmers who did not sell to LGT in 2000 entered the market in 2004 and the proportion grew to 8.2% and 8.9% of new entrants in 2007 and 2010, respectfully.

A large proportion of the initial non-LGT sellers in 2000 still does not enter the market, 99.4% of these still remaining outside the market in 2004 which reduces to 91.8% and 91.1% in 2007 and 2010, respectfully. The results show some stability in later waves, where 31.8% of the farmers who sold to LGTs in 2007 still do so in 2010; only 68.2% of these exit over same time period. This is significant especially since the proportion of new entrants is growing in the same time period.

3 Estimation strategy and empirical models

This study investigates the effect of LGT sales on farmers' likelihood of adopting a sustainable agricultural intensification input (SAIP). The decision to adopt a SAIP is partly explained by unobserved idiosyncratic factors like risk attitudes and ambition, which could also be correlated with the explanatory variables like in this case, the decision to sell to LGT. Access to panel data presents an opportunity to study important dynamics in input adoption. For example, the role of intensification inputs on productivity enhancement is uncontested in the literature. Thus the adoption of a SAIP in one season can lead to higher incomes, which potentially relaxes liquidity constraints and enhance SAIP take up in subsequent periods. Likewise, some treatment effects are persistent. For example, Sitko et al (2018) found that farmers selling maize to a LGT obtained 6% higher farm-gate price for maize than farmers selling to other types of buyers, controlling for market access conditions and month of sale. Households selling to a LGT may therefore obtain greater revenue from their output, enabling them to purchase more cash inputs or hire labor in subsequent seasons to utilize labor-intensive SAIPs, and/or foster formal or informal CFAs that enable them to get inputs on credit in subsequent seasons

Model selection in panel data analysis is guided by researcher assumptions regarding unobserved heterogeneity. In the case where there is correlation between the explanatory variables at time $t(\mathbf{X}_t)$ and the error term at time t (μ_t), or explanatory variables at time t $(\mathbf{X}_t)$ are correlated with past period's error term (μ_{t-1}), a pooled OLS estimator will be inconsistent. If only the latter is assumed to hold, a random effects (RE) estimator will be consistent but if the first and/or second case is assumed, only the fixed effects (FE) estimator will be consistent (Wooldridge, 2002). The FE method is problematic to use with non-linear models though since it involves subtracting the means of time-varying variables across $T\,(1\dots T)$ for each individual from the observed variable values at t.Time-invariant variables like gender and education of head also drop out of the analysis when using this method.

We adopt various models and functional forms that control for these issues, discussed in following subsections. First, we use a dynamic Probit model that analyzes the dynamic process of SAIPs adoption, while controlling for unobserved characteristics and initial conditions problem. This model assumes that there is no endogeneity between our key variable, LGT sales and the outcome variables, sustainable agricultural intensification inputs (SAIPs) adoption. This naïve assumption is used to test for dynamism in SAIPs adoption, and not causation between LGT sales and SAIPs adoption. Next, we make a more reasonable assumption of non-randomness in treatment (LGT sales) and adopt the control function approach to account for this. Lastly, we recognize the fact that demand for certain SAIPs like inorganic fertilizer is not necessarily linear; first, a farmer decides whether to use or not, given prevailing circumstances, then decides on how much to use. We thus adopt a Double Hurdle functional form to account for this corner solution problem.

3.1 The dynamic random effects Probit model

The conceptual model for SAIPs adoption can be represented as;

$$y_{it}^* = \alpha_i LGT_{it} + \beta_i \mathbf{X}_{it} + k_i + u_{it} \tag{1}$$

where y_{it}^* is a latent indicator of SAIP adoption (y_{it} =1 if adopted and 0 otherwise) by household$i$ in time period t; LGT is the indicator variable of interest i.e. if the household had LGT sales in year t; X_{it} is a vector of exogenous variables that explain SAIP adoption like gender, access to information, employment status etc.; k_i is a unit-specific time-invariant unobserved effect; and u_{it} is an idiosyncratic error term.

To capture the dynamic adoption process, we include lags of dependent variables and key explanatory variable as additional regressors;

$$y_{it}^* = \gamma y_{it-1} + \varphi_i LGT_{it-1} + \alpha_i LGT_{it} + \beta_i \mathbf{X}_{it} + k_i + u_{it} \tag{2}$$

where y_{it-1} represents past SAIPs adoption decisions; LGT_{it-1} is an indicator variable for a household's LTG sales in the previous year. Even if we assumed that $Cov\ (\mu_t,\, X_t) = 0$ from equation 1, this cannot hold in equation 2. This is since errors in past time periods u_{it-1} are correlated with current ones u_{it}, by inclusion of the lagged variables. A pooled OLS would be inconsistent in this case.

In the case where key explanatory variables are not expected to vary much, FE estimators lead to imprecise estimates (Wooldridge, 2002 pp 286). The key determinants to SAIPS use are hypothesized to be age, gender and education of household head, all of which are time constant across the panel. Also, as our earlier results on transition of LGT sales show, at some point most farmers will keep selling to LGTs when they start doing so, thus the within variation may be limited. A fixed effects estimator may therefore not be best suited for our analysis due to the incidental parameter problem. Likewise, it's not plausible to assume that the unobserved heterogeneity in our model is orthogonal to all the explanatory variables (thus satisfying the exogeneity assumption), based on the preceding discussion earlier in this section. Thus, a random effects estimator would also yield inconsistent estimates. Empirical studies facing this issue (for example Muyanga et al., 2013) use the correlated random effects (CRE) framework to overcome the shortcomings of both the FE and RE estimators.

In the CRE framework, the unobserved heterogeneity is modelled as;

$$k_i = \alpha_0 + \alpha_1 L\bar{G}T_i + \alpha_2 \bar{X}_i + a_i \tag{3}$$

Where k_i is the time-invariant household-specific unobserved heterogeneity; $L\bar{G}T_i$ and $\bar{X}_i$ represent the means of time-varying explanatory variables across $T(t = 1, \ldots, T)$; and a_i is the household-specific error term. Our analysis follows this framework to correct for unobserved effect.

By including lagged depended variable to study dynamics in sustainable agricultural intensification inputs (SAIPs) adoption, we introduce a potential bias where the unobserved heterogeneity as modelled above could be correlated with the initial observation, y_{i0}. The assumption being made here is that the stochastic dynamic process started when the households in the sample were observed in the first period (t_0). This is unreasonable since if we are assuming a dynamic process with previous behavior informing subsequent decisions, then adoption of SAIPs prior to t_0 should also affect adoption decisions within the panel period. Similarly, past LGT sales prior to t_0 presumably affect adoption decisions within the panel period. These effects will be captured in the unobserved heterogeneity and need to be controlled for, for a genuine estimation of state-dependency in SAIPs adoption.

Controlling for initial conditions in the unobserved heterogeneity

Rabe-Hesketh and Skrondal (2013) show that Wooldridge's (2005) simple solution of modelling the distribution of the unobserved heterogeneity conditional on the initial values might result in serious bias when used with constrained models that includes the means of time-varying explanatory variables, like the CRE above. The solution suggested by Rabe-Hesketh and Skrondal (2013) was that of including the initial-period explanatory variables as additional regressors in modelling the unobserved heterogeneity. This solution was shown to be more efficient in the case of short panels, like in our case.

This study thus adopts the CRE framework where the unobserved heterogeneity is modelled by including within-means of time-varying variables, then adding the values of the explanatory variables at the first wave of the panel, to control for the initial conditions problem following Rabe-Hesketh and Skrondal (2013). From equation 3, the unobserved heterogeneity is thus adjusted to:

$$k_i = \alpha_0 + \alpha_1 y_{i0} + \alpha_2 L\bar{G}T_i + \alpha_3 LGT_{i0} + \alpha_4 \bar{X}_i + \alpha_5 \mathbf{X}_{i0} + a_i \tag{4}$$

where y_{i0}, LGT_{i0}, and $\mathbf{X}_{i0}$ represent values for sustainable agricultural intensification inputs (SAIPs), LGT sales, and other time-varying explanatory variables at t_0, respectfully; $L\bar{G}T_i$ and $\bar{\mathbf{X}}_i$ are the means of the time-varying explanatory variables across $T(t = 0, \ldots T)$ for each i such that $L\bar{G}T_i =^1 /_T \sum_{i=0}^{T} LGT_{it}$ and $\bar{\mathbf{X}}_i =^1 /_T \sum_{i=0}^{T} X_{it}$; and a_i is the normally distributed household-specific error term with zero mean and variance δ_a^2.

Replacing for k_i in equation 2 and holding the assumption that the term captures the unobserved heterogeneity, y_{it-1} can then be interpreted to capture the genuine state dependence of SAIPs adoption on past adoption behavior. The equations are then estimated in STATA using the command developed by Grotti and Cutuli (2018). For comparative purposes, we also estimate equation 2 (where we assume there is no unobserved heterogeneity in our model) and report these results.

3.2 Non-random selection into large-grain-trader markets

The dynamic model described above explains how marketing behavior may influence SAIPs adoption decisions, controlling for time-invariant unobserved characteristics and the initial conditions problem in dynamic models. It could also be the case that there are time-varying unobserved variables that cannot be controlled for by the above procedure. A valid concern may be whether this adequately controls for the obvious self-selection problem; farmers endowed with assets like land are able to generate high outputs, thus have the economies of scale to sell to LGTs. While our hypothesis is that selling to LGTs enable farmers to utilize SAIPs more, it could as well be the case that using SAIPs enables a farmer to generate higher outputs, which then enables them to participate in markets where volume of sales may matter, like LGT markets.

The control function approach has been used in studies similar to ours to solve this problem (Asfaw, Pallante and Palma, 2018; Ricker-Gilbert, Jayne, and Chirwa, 2011). We thus adopt this approach to analyze the effect of LGT sales on farmer adoption of SAIPs. In this study, we use the non-self-proportion of farmers in a district selling to LGTs as an instrument in the first stage of the control function approach. Our assumption is that this variable is correlated with a farmer selling to LGTs, but not with the farmers' likelihood of using a particular SAIP. Tests conducted in this study confirm the validity of the instrument for this type of analysis.

Unlike in the previous dynamic random effects Probit model where we adopted a binary indicator of SAIPs adoption, we now shift the analysis to consider continuous dependent variables for manure and inorganic fertilizer. The literature indicates that sub-optimal use of fertilizer leads to yield stagnation (see for example Sheahan, Black, and Jayne, 2013). Thus, while a farmer may be using the input, they might be using less than the optimal quantity resulting in low yields. This motivates the shift from binary indicators of organic and inorganic fertilizer use to total quantities used in kilograms.

We implement the following equation in the first stage;

$$LGTs_{it}^{*}{=}\Omega_i PrLGTs_{dt}{+}\beta_i\mathbf{X}_{it}{+}\sigma_i\bar{X}_i{+}\varepsilon_{it} \tag{5}$$

where $LGTs_{it}^{*}$ is the latent indicator if a household i sold to LGTs in year t; $PrLGTs_{dt}$ captures the non-self-proportion of farmers selling to LGTs in district d at year t; $\mathbf{X}_{it}$ is a vector of exogenous explanatory variables; $\bar{X}_i$ are the Mundlak augmenting means of time-varying explanatory variables; and E_{it} is the idiosyncratic error term.

Residuals from the first stage are included in the following second stage regression;

$$y_{it}^{*}/y_{it}{=}\alpha_i LGT_{it}{+}\theta_i L\hat{G}T_{it}{+}\beta_i\mathbf{X}_{it}{+}L\bar{G}T_i{+}\sigma_i\bar{X}_i{+}\varepsilon_{it} \tag{6}$$

Where y_{it}^{*}/y_{it} is binary indicator of improved seed use and quantity of fertilizer or manure in kilograms, respectively; $L\hat{G}T_{it}$ is the residual term obtained from equation 5; and E_{it} is the idiosyncratic error term; the other terms are as defined before.

3.3 The corner solution problem in fertilizer adoption

The control function approach discussed above, and the inclusion of Mundlak means of time-varying variables as additional covariates, control for endogeneity issues in estimating SAIPs adoption. An additional challenge in analyzing sustainable agricultural intensification inputs (SAIPs) demand is the issue of separate decisions on whether to use a particular SAIP, and how much of the SAIP to use. This is especially so in the case of inorganic fertilizer where a large percentage of farmers do not use the input, hence a non-trivial number of zero outcomes in the dependent variable.

Functional forms that account for this nonlinearity in demand of inorganic fertilizer include the Double Hurdle and Type 1 Tobit models. While the former is more flexible in the assumptions of the decision process in the two hurdles (i.e. whether to use fertilizer or not, and how much to use), the latter is more restrictive and assumes the two decisions are determined by the same process, hence giving less attention the first hurdle. We follow Croppenstedt, Demeke and Meschi (2003) and Ricker-Gilbert, Jayne, and Chirwa (2011) in using the double hurdle model to analyze fertilizer demand in our study.

Equation 6 for fertilizer demand is thus broken into two for the two hurdles; hurdle 1 is a Probit estimation of the probability of a household using fertilizer i.e.

$$Fert_{it}^{*}=\Omega_i DExt_{it}+\alpha_i LGT_{it}+\theta_i L\hat{G}T_{it}+\beta_i \mathbf{X}_{it}+L\bar{G}T_i+\sigma_i \bar{\mathbf{X}}_i+\varepsilon_{it} \tag{7}$$

where $Fert_{it}^{*}$ is the latent indicator of fertilizer use; $DExt_{it}$ is household i distance to extension advice, which is used as the selection instrument for the identification of the model; and the other terms are as defined in equation 6.

The second hurdle is specified as;

$$Fertkg_{it}=\alpha_i LGT_{it}+\theta_i L\hat{G}T_{it}+\beta_i \mathbf{X}_{it}+L\bar{G}T_i+\sigma_i \bar{\mathbf{X}}_i+\delta IMR+\varepsilon_{it} \tag{8}$$

where $\mathrm{Fertkg_{it}}$ is quantity of fertilizer used in kg; *IMR* are the inverse mills from the first hurdle; and the other terms are as defined in equation 6.

4 Results

In this section, results from the described models in section 3 are presented. First, we present the dynamic random effects Probit results, followed by results from the first stage of the control function approach. The second stage results are presented next, starting with the double hurdle estimation of fertilizer demand, followed by those from a Probit and OLS estimation of improved seed and manure adoption, respectively.

4.1 Dynamic random effects Probit model results

For comparative purposes, we present results from pooled Probit regressions (equations 1) and the random effects dynamic Probit model (equations 2). Only results from the random effects dynamic Probit model are discussed in this section. The results show that previous adoption of improved seed and manure affect current adoption status implying state dependency in the adoption of the two SAIPs. Past use of fertilizer is not significant in explaining current use. This could be because improved seed is relatively cheaper than fertilizer, hence low dis-adoption rates once farmers start using the SAIP. Similarly, once a farmer has livestock that can provide the manure, there is no reason to stop using the SAIP in subsequent periods.

LGT sales are positively correlated with fertilizer use but not that of improved seed or manure. This result could imply the significant role that LGTs play in enabling households to access relatively expensive inputs like fertilizer. Interviews with LGTs within maize growing areas in Kenya identified credit and information provision as key services these market actors gave to farmers Sitko et al., 2017). Our result above is in line with this assertion by the LGTs. This result is explored further in the control function results in a subsequent section.

Among the socio-demographic variables and consistent with many others studies, the results show that female-headed households are less likely to adopt fertilizer and improved seed while more educated household heads are more likely to use fertilizer. Distance to extension advice is negatively correlated to fertilizer use, and so is credit constraint variable. Specifically, an extra km away from extension decreases the probability of adopting fertilizer by 0.02 while being credit constrained decreases this probability by 0.45. On the other hand, a percentage increase in the value of assets owned increases the probability of adopting improved maize and manure by 0.18 and 0.32, respectfully. Finally, an increase in the area of own cultivated land by 1 acre increases the probability of using fertilizer by 0.04.

4.2 Results from the control function approach

4.2.1 *First stage results- Determinants of LGT market participation*

The results from the first stage of the control function approach are presented in Table 4. The second equation (column 2) includes Mundlak augmenting means as additional regressors; these results are interpreted. The results show that the instrumental variable, non-self-proportion of farmers selling to LGTs in the district, highly explains a farmer's sale to LGTs. Specifically, a one percentage point increase in the non-self-proportion of farmers selling to LGTs in a district increases a farmer's probability of selling to LGTs by 0.07. The result is highly significant.

Among other explanatory variables included in the model, age of the household head and area of own land cultivated highly explain sales to LGTs. An additional year in the age of the household head increases the probability of selling to LGTs by 0.02, while an extra acre of owned cultivated land increases this probability 0.08. This result highlights the self-selection issue in the type of farmers who sell to LGTs; farmers owning larger land areas for cultivation can take advantage of economies of scale to produce enough surplus and sell to LGTs, since these mostly buy in bulk.

4.2.2 *Determinants of fertilizer adoption*

As discussed in section 3, we apply the double hurdle model to analyze fertilizer demand and control for unobserved variables through the inclusion of means of all the time-varying variables as additional regressors. The second equation in Table 5 estimates a second version of this model with Inverse Mills Ratio (IMR) controlling for potential correlation of error terms in the two hurdle equations (Engel and Moffatt, 2014). This term is highly significant indicating correlation in the error terms, and these results are discussed in this section. The term correcting for selection into selling to LGTs is also highly significant in the second hurdle equation (amount of fertilizer used) but insignificant in the first hurdle i.e. the decision to use fertilizer. This implies that characteristics important in informing LGT sales matter in determining how much fertilizer is used, and not whether a farmer uses fertilizer or not. This is intuitive since one such important characteristic is quantity of land owned. While this may affect how much fertilizer a farmer uses, it is unreasonable to assume that it also affects the decision of whether to use fertilizer or not, controlling for income and asset ownership.

The results show that sales to LGTs significantly affect the amount of fertilizer a household uses, but not the decision on whether to use fertilizer or not. This is a departure from earlier result obtained from the dynamic random effects Probit model which indicated sales to LGTs matter in the decision to participate in fertilizer market, and confirms the appropriateness of modelling fertilizer demand as a two-hurdle problem. Specifically, farmers who sell to LGTs on average use about 145kg of fertilizer more, compared to those that do not. Given that land size has been found to be positively correlated to fertilizer use, this high amount of fertilizer is not surprising. Selling to LGTs thus increases the rate of fertilizer used, through either of the channels discussed earlier; mitigation of market risks through forward contracts hence inducing more fertilizer use, offering higher output prices hence more incomes to buy more fertilizer, facilitating acquisition of inputs on credit, and information provision.

Sociodemographic variables important in explaining fertilizer use include: age, education and gender of the household head. An extra year of age and education of the household head increases the probability of using fertilizer by 0.14 and 0.16, respectfully. Conversely, being a female household head decreases the amount of fertilizer used by the household by 76kg. In terms of quantity of the input used, an extra year of age and education of the household head increases the amount of fertilizer used by about 1kg and 8kg, respectfully. On the other hand, being credit constrained decreases the amount of fertilizer used by 105kg, while a percentage increase in value of assets owned increase fertilizer use by 42kg. Curiously, the variable is significantly and negatively correlated with the probability of using fertilizer. As expected, quantity of owned cultivated land is positively correlated with amount of fertilizer used, with an extra acre of owned-cultivated land increasing amount of fertilizer used by about 10kg. These results are in line with others obtained from the dynamic random effects Probit model.

4.2.3 *Determinants of improved seed and manure adoption*

Table 6 presents results on the estimation of the determinants of improved seed and manure adoption. The selection correction residuals from the first stage of the control function model is highly significant, indicating the appropriateness of this approach to correct for the endogeneity in the adoption of these sustainable intensification inputs. After controlling for unobserved time-invariant variables in equation (2), sales to LGTs are shown to be insignificant in explaining the adoption of both improved seed and manure. This result is similar to one obtained from the dynamic random effects Probit model and confirms that in our study, sales to LGT explain fertilizer demand, but not that of improved seed or manure.

Other results from this analysis indicate that age of the household head is negatively correlated with both improved seed and manure use, with an extra year of age decreasing the likelihood of using improved seed by 0.01, and the amount of manure used by 14kg. Similarly, being a female household head decreases the probability of using improved seed by 0.2, and the amount of manure used by over 300 kg. On the other hand, education and asset ownership variables are positively correlated with the adoption of the two SAIPs; an extra year of education of the head increases the probability of using improved seed by 0.02, while a percentage increase in the value of assets owned increases this probability by 0.1 and the amount of manure used by 151kg.

5 Discussion and conclusions

The effect of farm productivity on commercialization is unequivocally established in the literature, and so is the effect of commercialization on welfare. Emerging literature assess the duality of the problem i.e. whether commercialization can induce farm productivity through incentivizing technology use and demand for extension. Most of this literature however is based on case studies of contractual arrangements between particular market actors and groups of farmers. This study extends this emerging literature by looking at how entry of large grain traders (LGTs) into smallholder farm markets may incentivize the use of sustainable agricultural intensification inputs (SAIPs) namely, inorganic fertilizer, improved seed, and organic manure.

The study uses a large dataset spanning a decade that permits the use of innovate methods to investigate the dynamic process of technology adoption, as well as, control for unobserved effects that confound most cross-sectional analyses. This not only allows us to interrogate the effect of past SAIPs adoption on current adoption behavior, but also the correlation between past and current sales to LGTs and SAIPs adoption. The study then uses a control function approach to investigate the effect of sales to LGTs on SAIPs adoption. The results show that sales to LGTs affect fertilizer demand but not that of improved seed or manure. This result is robust across all the analytical methods used in the study. Results from the dynamic random effects Probit model also show that use of improved seed and manure is persistent across years, unlike fertilizer whose past use does not affect current use.

The results imply the importance of the link between LGTs and SAIPs adoption (especially fertilizer) at the farm level. Given the critical role played by inorganic fertilizer in improving land productivity and the documented soil degradation in SSA, this linkage has important implications. Studies have already shown that farmers in the region are under-utilizing fertilizer (e.g. Sheahan et al., 2013). Policies that aim to strengthen and scale-out these LGTs-farmer engagements are desirable and should be pursued, as alternative interventions to enhance not only adoption but also the use rates of fertilizer.Another important issue regards the factors identified in the study as key to explaining sales to LGTs, for example land ownership. Poorer farmers who face barriers in accessing these LGT markets may further be marginalized if these market actors crowd-out other smaller traders, who are the primary source of market for land-poor farmers. Strategies to improve the competitiveness of these smaller traders may thus be desirable in the short-run. On the production side, efforts to aggregate output from low-output producing farmers through formation of producer associations would mitigate the output barriers to accessing LGT markets, thus enabling the trickle down of the benefits of these engagements, even to land-poor farmers. LGTs may also be subsidized for their costs in engaging with lowly-producing farmers, in a Public-Private Partnership (PPP) type of approach.

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Table 1: Summary statistics

Variables	2000		2004		2007		2010	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Dependent variables								
Fertilizer use (1=Yes)	0.66	0.473	0.71	0.453	0.76	0.428	0.75	0.434
Fertilizer intensity (kg)	206	398.6	190	333.9	200	340.1	169	263.8
Improved seed use (1=Yes)	0.66	0.473	0.67	0.472	0.73	0.445	0.82	0.381
Manure use (1=Yes)	-	-	0.74	0.438	0.77	0.422	0.78	0.415
Manure intensity (kg)	-	-	1815	3146.7	1463	2494.6	1251	2002.4
Explanatory variables								
Large Grain Trader sales (LGTs) (1=Yes)	0.015	0.1197	0.007	0.0843	0.085	0.2789	0.095	0.2929
Distance to extension (Km)	5.7	7.01	5.3	5.81	4.6	5.07	5.4	5.13
Age of hh head (years)	53.1	13.97	56.4	13.57	58.6	13.42	60.5	13.22
Gender of hh head (1=Female)	0.13	0.332	0.21	0.404	0.24	0.426	0.27	0.444
Education of hh head (years)	6.0	4.48	6.7	5.48	8.0	3.99	8.1	4.02
Credit constrained (1=Yes)	0.04	0.197	0.08	0.266	0.02	0.138	0.02	0.140
HH income (‘000 Ksh)	56.6	93.69	78.1	160.6	85.2	175.3	116.8	228.6
Log of total asset value (Ksh)	11.3	1.29	11.6	1.29	11.9	1.15	12.0	1.17
Own cultivated land (acres)	3.52	4.655	3.57	7.602	3.29	7.017	2.82	4.278
Agro-ecological zones controls (%)								
Coastal Lowland	5.95		6.30		6.26		6.34	
Lowland	7.94		3.58		3.58		3.44	
Lower Midland 3-6	19.11		19.97		19.67		19.56	
Lower Midland 1-2	10.98		11.24		11.18		11.23	
Upper Midland 2-6	18.92		19.40		19.52		19.56	
Upper Midland 0-1	16.87		17.75		18.26		18.49	
Lower Highland	17.53		18.83		18.48		18.26	
Upper Highland	2.71		2.93		3.06		3.13	

Table 2: A transition matrix of LGT sales across the panel

		LGT seller (%)			Non- LGT seller (%)		
		2004	2007	2010	2004	2007	2010
LGT seller (%)	2000	4.6	22.7	42.9	95.4	77.3	57.1
	2004		11.1	11.11		88.9	88.9
	2007			31.8			68.2
Non-LGT seller (%)	2000	0.6	8.2	8.9	99.4	91.8	91.1
	2004		8.5	9.5		91.5	90.5
	2007			7.4			92.6

Table 3: Results from Pooled and random effects dynamic Probit models

	Equations 1			Equations 2		
	Fertilizer	Improved seed	Manure	Fertilizer	Improved seed	Manure
Lag. dependent	1.535***	1.206***	0.956***	0.217	0.339***	0.556***
variable	(0.0712)	(0.0680)	(0.0756)	(0.170)	(0.129)	(0.174)
Lag. LGT	-0.241	0.0666	-0.0988	0.247	-0.0379	0.166
sales	(0.222)	(0.239)	(0.168)	(0.351)	(0.358)	(0.228)
LGT sales	0.309	0.573***	-0.287**	0.910***	0.355	0.0283
	(0.193)	(0.212)	(0.118)	(0.320)	(0.298)	(0.209)
Distance to	-0.0143**	-0.0104**	-0.00998	-0.0175**	-0.00574	-0.00881
extension	(0.00601)	(0.00517)	(0.00643)	(0.00892)	(0.00716)	(0.00676)
Age	0.00528**	-0.00789***	-0.00129	0.00373	-0.0126	-0.00940
	(0.00269)	(0.00245)	(0.00294)	(0.00964)	(0.00854)	(0.00980)
Gender	-0.249***	-0.219***	-0.138	-0.356***	-0.286***	-0.129
	(0.0788)	(0.0719)	(0.0877)	(0.135)	(0.110)	(0.0933)
Education	0.0316***	0.00992	-0.0108	0.0373**	0.0129	-0.00703
	(0.00901)	(0.00769)	(0.0102)	(0.0148)	(0.0114)	(0.0107)
Credit	-0.196	-0.0741	-0.244	-0.451**	-0.125	-0.253
constrained	(0.159)	(0.139)	(0.231)	(0.224)	(0.184)	(0.239)
Income	-7.75e-05	0.000181	0.000188	-3.47e-05	0.000410	5.01e-05
(‘000 Ksh)	(0.000233)	(0.000242)	(0.000233)	(0.000423)	(0.000416)	(0.000333)
Ln assets (Ksh)	0.0365	0.135***	0.222***	0.0906	0.177***	0.322***
	(0.0324)	(0.0305)	(0.0361)	(0.0820)	(0.0646)	(0.0732)
Cultivated land	0.0156	0.0164	-0.0140**	0.0428*	-0.00147	-0.0252
(acres)	(0.0124)	(0.0112)	(0.00627)	(0.0243)	(0.0224)	(0.0185)
AEZ controls	YES	YES	YES	YES	YES	YES
Year controls	YES	YES	YES	YES	YES	YES
Mundlak means	NO	NO	NO	YES	YES	YES
Initial conditions	NO	NO	NO	YES	YES	YES
Observations	3,430	3,430	2,094	3,430	3,430	2,094
Number of HHS	1,379	1,379	1,139	1,379	1,379	1,139

Table 4. Drivers to LGT sales - First stage of the control function approach results

	Equation 1	Equation 2
	LGT sales	LGT sales
% LGT sellers in district	0.0424***	0.0671***
	(0.00424)	(0.00799)
HH age	-0.000846	0.0227*
	(0.00359)	(0.0122)
HH gender	0.0270	-0.253
	(0.118)	(0.368)
HH education	0.0209*	0.00340
	(0.0108)	(0.0154)
Credit constraint	-0.100	-0.618
	(0.258)	(0.390)
Income (‘000 Ksh)	-0.000126	0.000480
	(0.000183)	(0.000349)
Ln assets (Ksh)	0.156***	-0.00530
	(0.0427)	(0.110)
Cultivated land (acres)	0.00977**	0.0823***
	(0.00429)	(0.0175)
AEZ dummies	YES	YES
Year dummies	YES	YES
Mundlak means	NO	YES
N	4,928	4,928
Number of HHs	1,495	1,495

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 5. Drivers to fertilizer use – results from the Double Hurdle approach

	Equation 1		Equation 2	
	Hurdle 1 Probability of purchasing fertilizer	**Hurdle 2** Fertilizer used (kg)	**Hurdle 1** Probability of purchasing fertilizer	**Hurdle 2** Fertilizer used (kg)
LGT sales	0.485	155.2***	4.318	145.3***
	(0.721)	(30.64)	(137.8)	(30.29)
Distance to extension	-0.0242**	-	0.0556	-
	(0.0117)		(0.0624)	
HH age	-0.0256***	1.683***	0.144***	1.362***
	(0.00791)	(0.499)	(0.0371)	(0.478)
HH gender	-0.171	-75.32***	-0.339	-75.92***
	(0.261)	(16.64)	(0.612)	(15.23)
HH education	0.0468	10.67***	0.160***	8.324***
	(0.0326)	(1.608)	(0.0483)	(1.479)
Credit constraint	-0.156	-111.4***	-0.925	-105.3***
	(0.424)	(36.37)	(0.950)	(34.76)
Income (‘000)	-0.000333	-0.0960**	0.000597	-0.0822*
	(0.000530)	(0.0458)	(0.000553)	(0.0452)
Assets	0.168	40.11***	-1.328***	42.05***
	(0.117)	(11.05)	(0.320)	(10.50)
Own cultivated land	-0.00582	9.360***	0.0208	9.598***
(Acres)	(0.0159)	(1.790)	(0.0205)	(1.758)
AEZ control	YES	YES	YES	YES
Survey year control	YES	YES	YES	YES
Mundlak means	YES	YES	YES	YES
Selection correction	0.616**	75.94***	-0.439	80.22***
residual	(0.264)	(12.97)	(0.383)	(12.71)
Inverse Mills ratio				-474.3***
				(32.65)
N	4,908	4,908	4,908	4,908

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 6. Drivers to improved seed and manure adoption

	Equations 1		Equations 2	
	Improved seed use	Manure (kg)	Improved seed use	Manure (kg)
LGT sales	0.620**	-287.9	0.294	36.52
	(0.251)	(196.2)	(0.256)	(214.9)
Distance to extension	-0.00900	-8.014	-0.00423	-2.428
	(0.00592)	(8.390)	(0.00588)	(8.247)
HH age	-0.00637**	-7.543*	-0.00799**	-13.72***
	(0.00313)	(4.093)	(0.00316)	(4.078)
HH gender	-0.237**	-277.9**	-0.247***	-304.6**
	(0.0966)	(124.2)	(0.0955)	(122.0)
HH education	0.0193*	-3.002	0.0179*	-18.96
	(0.0105)	(12.05)	(0.0102)	(12.21)
Credit constraint	0.0159	-442.3**	0.0491	-225.6
	(0.143)	(207.7)	(0.160)	(233.1)
Income (‘000)	0.000153	0.0774	0.000368	0.278
	(0.000270)	(0.253)	(0.000313)	(0.318)
Assets	0.183***	635.3***	0.100**	151.3*
	(0.0450)	(50.01)	(0.0488)	(77.64)
Own cultivated land	-0.0101	-6.270	-0.0142	16.61
	(0.00626)	(7.739)	(0.00951)	(12.27)
AEZ dummies	YES	YES	YES	YES
Year dummies	YES	YES	YES	YES
Mundlak means	NO	NO	YES	YES
Selection correction residual	-0.699***	219.1*	-0.447***	194.6*
	(0.189)	(132.7)	(0.0977)	(110.4)
N	4,908	3,465	4,908	3,483
Number of HHs	1,495	1,390	1,495	1,390

Standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$