Working paper

International Growth Centre

Food crop production in Tanzania

Evidence from the 2008/09 National Panel Survey

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December 2014

When citing this paper, please use the title and the following reference number:
F-40110-TZA-1

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Food crop production in Tanzania: Evidence from the 2008/09 National Panel Survey

Research report to IGC Tanzania

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December, 2014

Abstract

An earlier scoping study showed that the Tanzania National Panel Surveys (NPS) of 2008/09 and 2010/11 provide useable data to address productivity and supply response in agriculture. This report provides analysis of long season food crops for the first wave of the NPS (2008/09) concentrating on supply response, the price and non-price factors determining production and how responsive farmers are to these factors. The report highlights important limitations in the NPS data for analysis of supply response, notably the absence of market prices and that few farmers report using purchased inputs. Nevertheless, we identify certain core determinants of production and show that farmers are responsive to prices.

Contents

JEL Classifications:
Keywords: Agricultural Productivity, Supply Response, Panel Surveys, Tanzania

1 Context: Agriculture in Tanzania

After 50 years of independence, despite apparent commitment to policies and strategies to transform the agriculture sector, performance in agricultural output and productivity has been disappointing. Policies and plans, such as ‘agriculture is the mainstay of the economy’ and *Kilimo Kwanza* (agriculture first), have remained slogans to the public as there is so little experience of reforms that have improved livelihoods and millions in the agriculture sector remain in poverty. Tanzania is endowed with considerable fertile agricultural land and inland fresh water resources that can be utilized for irrigation, but much of the land is underutilized and what is utilised often exhibits very low productivity. In this sense Tanzania has yet to achieve the traditional ‘structural transformation’ whereby increasing agricultural production provides a platform for manufacturing and economic growth. Balanced growth is achieved if agriculture becomes increasingly commercialized while the manufacturing sector grows. Initially manufacturing may be based on agriculture, through processing and agri-business, but ultimately manufacturing and the economy will become diversified. This has not happened in Tanzania, and the economy remains essentially agriculture-based, mostly a peasant economy with low productivity. Understanding the factors that can expand production and enhance agricultural productivity in Tanzania is critical for ensuring ‘structural transformation’ and economic growth, boosting development and reducing poverty (given that the majority of the poor are in rural areas and in agricultural activities).

Although the contribution of agriculture sector to GDP and exports earnings has been falling over time, to around 25 percent of GDP and 20 percent of export earnings in 2012 compared to where it was in 1970s and 1980s where the sector accounted for more than 50 per cent of GDP and 75 per cent of export earnings; the sector remains important as some 80 per cent of Tanzanians depend on agriculture for their livelihood and 95 percent of their food. Consequently, the National Development Vision 2025, the main national development strategy in Tanzania, places considerable emphasis on the sector and envisages that by 2025 the economy will have been transformed from a low productivity agricultural economy to a semi-industrialized one led by modernized and highly productive agricultural activities that are integrated with industrial and service activities in urban and rural areas. Against this background, in the last decade a number of polices and strategies have been formulated to support agriculture in a more systematic way. The Agricultural Sector Development Strategy (ASDS) was adopted in 2001, and gave rise to the Agricultural Sector Development Program (ASDP) of 2005; and the Cooperative Development Policy (CDP) of 2002, complemented by a variety of sector policies. The strategy and the ASDP are embedded in the National Strategy for Growth and Reduction of Poverty (NSGRP), which is a medium term plan to realize Vision 2025. *Kilimo Kwanza* (agriculture first), developed in 2009, provides additional inputs for the implementation of ASDP and other programs favourable for the agricultural sector. It is an assertion of the commitment of the government and the private sector to agricultural development, and it invites all Tanzanians to become part of this commitment. Its ten pillars support the ASDS and the ASDP and strengthen them by adding additional initiatives, in particular in rural finance.

The agriculture sector is therefore seen as a main vehicle in any national economic strategy to combat poverty, enhanced agricultural productivity is crucial to realize the objectives, and the policy statements have at least identified the issues and proposed a strategy. The ASDS emphasized the need to improve the efficiency of input markets and product marketing, increase access to credit, enhance the provision of extension services and increase investment in rural areas (especially for irrigation and transport). The ASDP was in principle the strategy to implement these aims, but had limited impact – the strategies were not a success. Thus, the culmination of these initiatives was the formulation of a belief in the need to 'reintroduce selective subsidies, particularly for agricultural inputs, machinery and livestock development inputs and services' (ESRF, 2005: xii). Thus, by providing some quantitative assessment of the importance of different factors (such as prices, access to credit and other inputs, access to markets and marketing) to output levels for the major crops, this research contributes to understanding why the strategy has failed and providing recommendations of factors to target for an effective strategy.

Despite the CDP, the cooperative sector has failed to respond to the challenge of liberalization. The sector suffers from weak managerial (and advocacy) skills, a lack of financial resources (in particular undercapitalization of cooperative banks, so credit constraints remain), and a weak institutional structure (especially in that they are not accountable to members). Thus, although the cooperative sector remains significant it is not viewed as successful, either in supporting development and growth or in representing the interests of members, giving added impetus to liberalization initiatives.

Agriculture is recognized as integral to the Poverty Reduction Strategy, and agricultural sector growth is essential if Tanzania is to achieve sustained economic development. While this may seem somewhat obvious, it marks a change in emphasis – the whole sector (not only export crops) has attained a higher status on the policy (and political) agenda, and a view is emerging that there is a need for positive support to the sector. In this context, it is timely to attempt to assess the determinants of production and productivity in agriculture using crop and farm level data.

Although there have been many studies of agriculture in Tanzania, there are no recent nationwide studies of production and productivity covering all major crops. As part of the World Bank project on Distortions to Agriculture in Africa (Anderson and Masters, 2009), Morrissey and Leyaro (2009) provided an analysis and discussion of the bias in agriculture policy in Tanzania over the period 1976-2004. They found that reforms implemented since the late 1980s have reduced distortions in agriculture, but certain crops (especially cash crops) have become less competitive due to serious deficiencies in marketing and productivity. The level of distortion against agriculture remained reasonably high for all cash crops up to the early 2000s. Analysing time series data over 1964-1990, McKay *et al* (1999) find that food crop production increased as prices increases relative to export crops, implying aggregate export crop production was not responsive to prices. As producers seem to respond to the relative price and incentives for food crops compared to cash crops, with high relative price elasticity for food crops (McKay *et al*, 1999), one expects increasing food production in the latter half of the 2000s.

Arndt *et al* (2012) use representative climate projections in calibrated crop models to estimate the impact of climate change on food security (represented by crop yield changes) for 110 districts in Tanzania. Treating domestic agricultural production as the channel of impact, climate change is likely to have an adverse effect on food security, albeit with a high degree of diversity of outcomes (including some favourable). Ahmed *et al* (2012) identify the potential for Tanzania to increase its maize exports as climate change scenarios suggest a decline in maize production in major exporting regions. Specifically, climate predictions suggest that some of Tanzania's trading partners will experience severe dry conditions in years when Tanzania is only mildly affected. Tanzanian maize production is far less variable than that of major global producers (no significant growth, but no large declines due to weather shocks), including compared to other SSA producers (Ahmed *et al*, 2012, p 403), so has scope to respond to the adversity other producers will face. However, as shown by Arndt *et al* (2012), Tanzania may itself suffer a decline in production. Addressing the reasons why production in Tanzania has not grown is crucial to create a production environment within which productivity can increase, and maize is a crop worthy of specific attention.

The next section discusses the basic data used in the estimation, and Section 3 presents the empirical strategy. Section 4 presents and discusses the results, with conclusions in Section 5 that tease some policy implications.

2 Data measurement and definitions

The National Panel Surveys (NPS) are a series of nationally representative household panel surveys that assemble information on a wide range of topics including agricultural production, non-farm income generating activities, consumption expenditures and socio-economic characteristics. The 2008/09 NPS is the first in the series conducted over twelve months, from October 2008 to October 2009, implemented by the Tanzania National Bureau of Statistics (NBS) with a sample based on the National Master Sample frame, largely a sub-sample of households interviewed for the 2006/07 Household Budget Survey.

The 2008/09 NPS covered 3,280 households from 410 Enumeration Areas (2,064 households in rural areas and 1,216 in urban areas). The agriculture production data are collected and reported by plot (j) for household (i) and crop (c), recording inter-cropping and allowing for the long and short seasons crops, and perennial (tree) crops.[1] Most variables have to be calculated at the plot level as although over 40 per cent of households have only one plot and fewer than 10 per cent have more than three plots, most plots are used to grow more than one crop either by inter-cropping or sub-dividing the plot. Plot-level data are calculated and aggregated up to the farm (household) level. For the detailed descriptive statistics at the farm-level (mean and median) by crop and agro-ecological zones (or region) to capture the distribution of farm size and of products and inputs prices across farms see the scoping study (Leyaro and Morrissey, 2013).

The data we use in this study is the first wave (2008/09) of the NPS. Except for the number of working adults per household (obtained from the Household questionnaire), all data were obtained from the Agricultural questionnaire. The original sample consists of 3280 households but our final sample size is significantly smaller, due to missing data and exclusion of outliers following graphical and statistical analysis. Further, we focus on annual crops (thus omitting important crops such as coffee) and rely on data for the long rainy

[1] Long season crops data file is appended on top of short season crops data file for the same variables and this new data file is then appended on top of perennial (tree) crops file for the same variables. Variables are then aggregated at farm (household) level for descriptive analysis and estimation.

season only. When referring to 'total harvest', or 'total production', we thus refer to total values for annual crops for the long season. We have in total 1670 households in our sample.

Since we are using only one wave we show that there is enough variation in prices at the farm level to allow for analysis (see Leyaro and Morrissey, 2013). Our analysis aims at understanding what drives supply response in agriculture at the aggregate level. Therefore, total harvest (in Kg) and total value of sales will be our main dependent variables, as well as quantities of variable inputs demanded. Variable inputs considered are total hired labour (defined as the sum of men and women labour days hired for land preparation, weeding, and harvesting), and chemical (inorganic) fertiliser used (in Kg). Those can be treated as variable inputs rather than quasi-fixed inputs, as in Hattink et al (1998), since we have data on wage bills and expenditures on chemical fertiliser. Note that variable inputs use is given at the plot level, that is, it refers to the total harvest realised on that plot, rather than the amount of that harvest which is then sold. Therefore, such variables are only suitable when using harvest as the dependent variable. When using quantity sold as the dependent variable (i.e., a fraction of harvest), we use a weighted version of those variable inputs regressors (weighted by the proportion of the harvest which is actually sold). Not doing so would yield upward biased results for variable input use. Variable input prices are also calculated (daily wage rate and price per kilogram of chemical fertiliser) by dividing total amount hired/used by total expenditure. They are then divided by unit price to normalise them, following the standard approach in the literature. Unit prices are derived by dividing total sales (in Tanzanian shillings) by total quantity sold. Most studies considering total value of sales or total output supplied onto the market as dependent variables would generally normalise them using a market price index, as in Abrar et al (2004a). However, in this case, there is no market price index available, so that no normalisation is made in regressions using total output sold as the dependent variable.

Quantity of organic fertiliser used (in Kg) is considered as a fixed input, and is a proxy for animal power, usually defined as the number of oxen owned, which was not directly available. Following Abrar el al (2004a), organic fertiliser may be seen as capturing a wealth effect. Family labour is also considered as a fixed input, and is defined as the total number of working-age adults (15 to 65 years old inclusive) per farm. Control variables included are total area cultivated (in acres) and average distance to nearest village market (in Km). A `weighted' version of the distance variable is used, where distance is weighted by area. Weighted average distance may be used instead of average distance for greater accuracy as it may capture interactions between land size and distance to the market. Finally, weighted property (the percentage of land cultivated which is owned by the farm/household) is also considered as a control variable in order to capture property rights or incentive effects. We will use these weighted variables throughout and simply refer to them as *Distance* and *Property* for convenience.

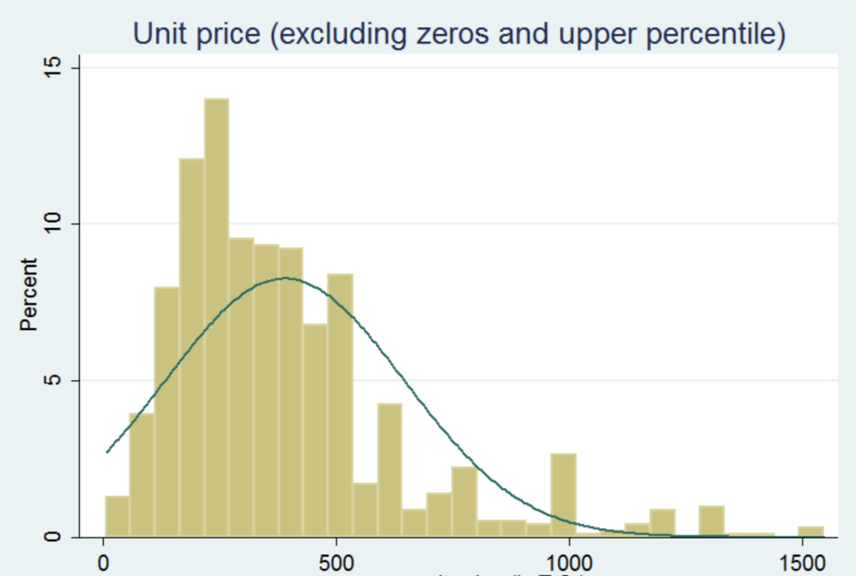
As around 85% of farms in the sample make no use of chemical fertilizer, and around 60% do not hire labour, it is likely that summary statistics for the whole sample are not very informative. We therefore consider four sub-samples: Group 1, the 836 households not using any variable input; Group 2, the 588 households hiring labour only; Group 3, the 107 households buying chemical fertilizer only; and Group 4, the 139 households buying both variable inputs. Thus, about 50% of the total sample does not use any variable inputs, whilst only 8% uses both.

Table 1: Summary statistics for sample and groups

	Whole sample	Group 1	Group 2	Group 3	Group 4
Observations	1670	836	588	107	139
Harvest (Kg)	1058	771	1281	1344	1618
Quantity sold (Kg)	315	161	426	407	698
Marketed surplus (%)	30	21	33	30	43
Sales (TSh)	113769	53378	137946	207982	302187
Unit price (TSh)	231	190	245	342	343
Organic fert. (Kg)	171	51	219	305	579
Adults	2.77	2.80	2.73	2.76	2.81
Area	3.99	3.44	4.62	3.76	4.80
Distance	4.94	5.22	4.84	4.10	4.33
Property	0.57	0.62	0.54	0.43	0.49
Inorganic fertilizer (Kg)	15.6			106	106
Inorganic (weighted, Kg)	5.4			28.8	42.7
Fertilizer price	0.40			2.67	2.72
Labour (days)	11.9		26.7		29.32
Labour (weighted, days)	3.95		8.03		13.46
Wage rate	3.32		7.10		9.78

Source: Author’s own construction based on 2008/09 NPS

Figure 1: Variation in unit prices



Source: Author's own construction based on 2008/09 NPS

Table 1 provides summary statistics for the whole sample and the four groups. Mean values are reported as well as respective sample size (standard deviations are not reported). We also include for convenience the percentage of marketed surplus for each group (quantity sold divided by harvest). A general analysis of agricultural supply response using the whole sample is inappropriate as most households do not purchase any variable input so each group warrants separate statistical treatment. Farms in Group 1 have the lowest average harvest and sales at the lowest unit price, just over half the unit price achieved by the higher producing farms in Groups 3 and 4. There is considerable variation in unit prices across the sample; although almost 90% of prices are around 500 Tanzanian Shillings or less, there is a noticeable skew to the right (Figure 1).

Marketed surplus is only 21% for Group 1, suggesting widespread subsistence farming and sharply contrasting with Group 4 with a marketed surplus of 43%. There is also variation in variable input use and the proportion of non-users of chemical fertilizer and that of non-users of hired labour is particularly high. The disaggregated picture reveals interesting features. In particular, the difference in production variables between Groups 1 and 4 is striking, which confirms our intuition that subsistence farming may be widespread in Group 1, together with a lower degree of market integration than in Group 4. Apart from the fact that both harvest and quantity sold are much greater in Group 4 than in Group 1, it is clear that the proportion of harvest that is marketed is also much greater in Group 4.

While the differences between Groups 3 and 4 are fairly small (except for quantity harvested and sold and organic fertilizer use), Groups 1 and 2 look quite different to Group 4. As expected, average use of organic fertilizer (which may capture a wealth effect) is extremely low in Group 1, in which farmers do not buy any variable inputs, possibly due to financial constraints. Farmers in Group 4 use 11 times as much organic fertilizer as their counterparts from Group 1. The difference is also very marked with Groups 2 and 3, suggesting that constraints faced by farmers in Group 1 may not be faced by those using one variable input only, or at least, not faced with the same intensity. Regarding family labour, the average is very close across groups, while the average total area cultivated is significantly higher in Group 4 than in Group 1. The smallest farms in the sample are located in Group 1, but these have the highest weighted property index with an average of 62% of total area cultivated owned, as opposed to 49% in Group 4.

3 Empirical methodology

Although the NPS are small in sample size (3,280 households), they provide recent farm level household panel data for which econometric analysis is feasible. The analysis presented addresses supply response, the price and non-price factors determining production and how responsive farmers are to these factors. Two fundamental approaches are used in studying production decisions: the production function (primal approach) and the profit function (dual approach). Under appropriate regularity conditions, and with the assumption of profit maximization, both functions contain the same essential information on a production technology. The dual approach has several advantages: prices are specified as the exogenous variables as opposed to input quantities (prices are usually less collinear than input quantities); estimates of output supply, input demand, and the price (and cross-price) elasticities are more easily derived (as derivatives of the profit function); and it is more flexible for modelling multiple outputs and inputs systems (as is the case here).

Following Abrar *et al.* (2004a) a profit, cost, or revenue function is estimated employing a variant specification of the profit function. Assume that farmers attempt to maximise restricted profit, defined as the return to the variable factors, so the profit maximisation problem can be expressed as:

$$\text{Max } \Pi\ (\boldsymbol{p,w;z}) = Ma\ x\ \boldsymbol{p'y} - \boldsymbol{r'x} \tag{1}$$
$$s.t.\ F(\boldsymbol{y, x; z}) \leq 0,$$

where Π , $\boldsymbol{p}$, $\boldsymbol{w}$, respectively, represent restricted profit, and vectors of output and input prices. The variables $\boldsymbol{y}$ and $\boldsymbol{x}$ represent vector of output and input quantities respectively. *F(.)* is the production technology set of the producer, and *Z* is a set of control variables. The restricted profit function represents the maximum profit the farmer could obtain with available prices, fixed factors, and production technology. The profit-maximising output supply and input demand functions are derived as:

$$Y_m(p, w; z) = \frac{\partial \Pi(p, w; z)}{\partial P_m}, \quad \forall\ m = 1, \ldots, M, \tag{2}$$

and

$$-X_n(p, w; z) = \frac{\partial \Pi(p, w; z)}{\partial W_n}, \quad \forall\ n = 1, \ldots, N. \tag{3}$$

where *m* and *n* index the outputs and variable inputs respectively. There are usually four (translog, generalised Leontief, generalised Cobb-Douglas, and the quadratic forms) functional forms of the profit function that have been used in the literature. A choice of a particular specification, in part, depends on the nature of the data set available. The translog profit function is generally preferred if the level of analysis includes a number of crops (i.e. farms are treated as multi-product producers). As we are using an aggregate of food crop production, a Cobb-Douglas production is appropriate.

Due to the nature of the data, and in particular, the very large proportion of farms that do not use any variable inputs, our modelling strategy has two parts. We firstly focus on those farms not buying any variable inputs. A full study of supply response in this context seems inappropriate since those farms may be characterized by subsistence farming and low market integration (in essence, such households may not satisfy assumptions underlying the estimation of a restricted profit function). We will therefore do some preliminary exploratory analysis on this sub-sample. We then consider a more complete analysis of production and supply behaviour using data of farms using at least one variable input.

3.1 Farms with no purchased inputs

A focus on the 835 farms that do not buy any variable inputs is justified to the extent that it is reasonable to assume that these face particular constraints compared to other groups. We explore the behaviour of farmers from this group by estimating first a simple Cobb-Douglas production function, regressing total harvest on fixed inputs and control variables. The model we estimate is (suppressing the *i* subscript for farms):

$$H = \beta_0 + \beta_1 L + \beta_2 A + \beta_3 D + \beta_4 O + \beta_5 F + \varepsilon \qquad (4)$$

All variables are expressed in logs where H is harvest quantity, L is number of adults, A is area, D is distance, O is owned property and F designates organic fertilizer; ε has the usual properties and distance and property are weighted by area. From this we obtain elasticities to assess the importance of fixed inputs and control variables. As the majority of farms in this group do not use any organic fertilizer we estimate several versions of (4). The first version is a benchmark one, where we estimate on the whole group without including organic fertilizer. The second version is only for farms which do not use any organic fertilizer, without the organic fertilizer term, and the third version is for farms using organic fertilizer with the organic term included.

We also estimate a similar model for sales (S, total value of quantity sold in TSh) and include also unit price (*P)*:

$$S = \beta_0 + \beta_1 L + \beta_2 A + \beta_3 D + \beta_4 O + \beta_5 F + \beta_6 P + \varepsilon \qquad (5)$$

We are interested to see if we observe significant responsiveness of sales to output price. In this analysis the data are in levels rather than logs because most of the farmers in this group (are not buying any variable inputs) do not supply anything onto the market (i.e., they have a positive harvest, but no marketed surplus). Taking logs would imply a truncated regression omitting a very large fraction of the sub-sample (as a result, no differentiation between the pooled model and a model based on positive observations only could be made). To account for the censored dependent variable we estimate a standard Tobit model, which also has the advantage of permitting estimation of different types of marginal effects. The dependent variable is thus the limit observations (with value 0) and the non-limit observations (with values above 0). Limit observations are estimated using a probit model.

As the coefficients from a Tobit model do not represent marginal effects of the variable of interest (they represent marginal effects for the unobserved latent variable) those must be computed separately; we use a maximum likelihood (ML) estimator. Average marginal effects conditional on positive sales can then be computed using the inverse Mills Ratio. We also compute average marginal effects of price as total area cultivated varies (to see whether the 'price factor' becomes more important as more land is cultivated, which we expect), and as the quantity of organic fertilizer used varies (which we expect to be increasing reflecting more wealth and market integration).

3.2 Farms with purchased inputs

A different estimation strategy is appropriate for those farms that purchase at least one variable input; farms for which both hired labour and purchased fertilizer is zero are excluded. The approach used is to estimate a restricted profit function derived as total sales (total value of output sold) minus cost of variable inputs following Abrar et al (2004a, 2004b), Hattink et al (1998) and Savadogo et al (1995) by using a quadratic functional form. The basic underlying assumptions are that farmers intend to maximise restricted profits and that markets are competitive. This method is rooted in the dual approach to estimating a profit function rather that the production function directly, as outlined in (1) – (3) above. In essence, information about production and technology can be recovered from the profit function, provided the assumptions of competitive markets and profit maximising behaviour are satisfied. The 18 farms with negative restricted profit are omitted, following Abrar et al (2004b). The quadratic normalised profit function generates specifications of (2) and (3) to be estimated using the quantity of marketed output and quantities of purchased and fixed inputs. Following the standard approach, these are estimated using iterative seemingly unrelated regressions (SUR) with bootstrap standard errors.

Complications arise given the extremely large proportion of farms that do not appear to devote fertilizer to that part of the harvest which is marketed, as well as the large proportion that do not hire labour. This creates 'censored data', which, if not accounted for, will bias results. Standard OLS technique will fail to account for the non-linearity in the data, and will also fail to account for the qualitative difference between censored and non-censored observations. We follow the approach of Hattink et al (1998) and Abrar et al (2004b) to address this problem, using a Heckman 2-step estimator by first estimating a Probit model on all observations, deriving the inverse Mills Ratios and using these as additional regressors in the second stage OLS regression using those observations for which data are available.

4 Econometric results

As noted above we use alternative estimation for the different groups. Section 4.1 reports the results for farms not purchasing inputs, and 4.2 reports estimates for farms that do purchase inputs.

4.1 Results for farms with no purchased inputs

Table 2 presents results from estimating the three versions of (4) as a Cobb-Douglas production function where the dependent variable is the log of total harvest in Kgs. As all variables are in logs, coefficients can be directly read as elasticities. The first point to note is the high significance of the area variable across specifications with similar coefficients; area appears to be the most important factor in affecting total harvest, which is not unexpected since we are focusing on farms which can reasonably be considered as the least integrated to input markets. As a result, their productivity can be expected to be lower than that of farms using variable inputs, so that reliance on total area cultivated matters crucially in determining production. Family labour (adults) is mildly significant except when only farms using organic fertilizer are considered. That may be a preliminary indicator of greater productivity among organic fertilizer users, which could result in less reliance on family labour. The fact that distance appears to be insignificant across specifications may be due to too little variation in that variable. It may also simply reflect the fact that since the dependent variable here is total harvest, distance to village markets matters less than if the dependent variable were marketed surplus. Alternatively, it can also be a sign that rural infrastructure, especially road quality, is uniformly poor.

The weighted property variable is negative but significant (Table 2). Intuitively, one may expect that the greater the proportion of land owned, the greater the incentives for farmers to increase production. The negative sign and high significance of the coefficients seem puzzling. This may reflect a constraint on production; it could be that the land which is owned is of low quality, unlike the land which could be bought or rented, and these farmers cannot buy/rent more land because they are financially constrained and have no access to a properly functioning credit market. The high significance of the (negative) property variable (not just in this Cobb-Douglas estimation, but in the whole analysis) could be an indicator of severe credit market failures and/or farmers' poor financial situation. We favour this view although a proper investigation of the structure of land tenancy and distribution characteristics is required. Further, besides being constrained on production, it might be that poor households own large tract of land not for increasing production but rather safety net reasons. The coefficient on organic fertilizer use is insignificant. This is unexpected since we would expect this variable to capture a productivity and wealth effect. Note however, that results from this specification are to be interpreted carefully due to the small sample size.

Table 2: Cobb Douglas production functions for non-users of variable inputs

	(1) Pooled sub-sample	(2) No organic fertiliser	(3) With organic fertiliser
Adults	0.174*	0.165*	0.0993
	(0.0910)	(0.1000)	(0.231)
Area	0.596***	0.590***	0.560***
	(0.0486)	(0.0534)	(0.126)
Distance	0.000638	0.00193	-0.0265
	(0.0417)	(0.0434)	(0.128)
Property	-0.340***	-0.319***	-0.596***
	(0.0683)	(0.0730)	(0.197)
Organic			0.159
			(0.131)
Constant	5.040***	5.038***	4.327***
	(0.125)	(0.136)	(0.804)
N	667	580	87
R^2	0.271	0.258	0.381

Source: Author's estimation based on 2008/09 NPS

Notes: Robust standard errors in parentheses: * indicates p < 0:10, *** p < 0:01

Table 3 presents the results for estimation of (5). The first two columns give OLS estimates on the whole sample and positive observations only respectively, while the third column reproduces Tobit estimates, with corresponding marginal effects in the last column. Results show that an OLS regression on all observations would give an upward biased estimate of the effect of unit price on sales, while a truncated regression would have a downward bias. The price variable is highly significant in all models, and indicates a degree of responsiveness of output to its own price. Area is also highly significant, although it is worth noting that the Tobit model produces an estimate far lower than any OLS regression. Family labour and distance appear to be insignificant, while property is again significant and negative (thus having both an adverse effect on harvest and marketed surplus). Here too, however, the Tobit model produces coefficients significantly smaller in magnitude than OLS regressions.

In order to get a more refined analysis of how price affects sales decisions, we compute average marginal effects of the price variable varying total area cultivated (from 0 to 20 acres, by increments of 2 acres), and average marginal effects of the price variable varying the amount of organic fertilizer used (from 0 to 3600 Kgs, by increments of 300 Kgs). The intuition is that we expect price to 'matter more' for farmers with greater area cultivated and/or greater amount of organic fertilizer used, since we expect those farmers to be more commercially active and more integrated to distribution circuits. Since the organic fertilizer variable also possibly represents a wealth effect through being a proxy for animal power, we expect wealthier farmers to be more commercial.

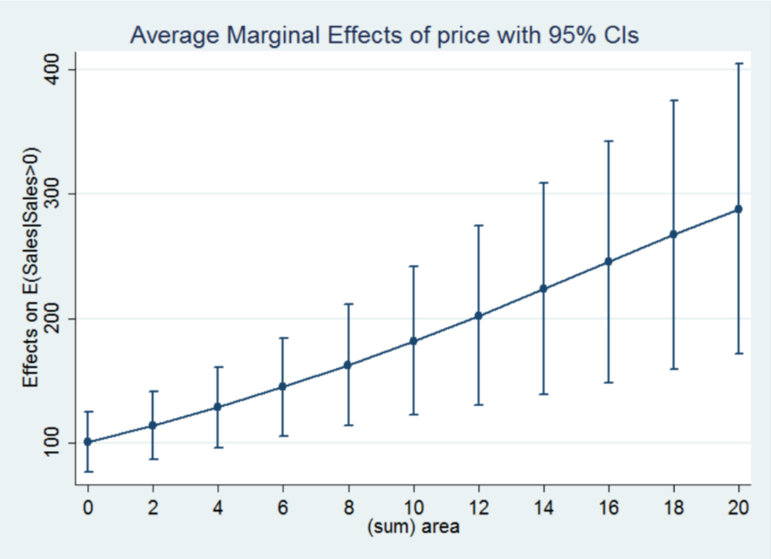
Table 3: OLS and Tobit model for non-users of variable inputs

	(1) OLS (all)	(2) OLS (non-limit)	(3) Tobit model	(4) Tobit margins
Price	166.5***	107.9***	380.7***	127.3***
	(24.97)	39.71)	(47.59)	(16.26)
Adults	-2207.3	-7182.4	-7177.7	-2400.1
	(4229.0)	(8941.7)	(7244.3)	(2418.1)
Area	12623.1***	17264.4***	16888.6***	5647.3***
	(3476.1)	(4149.6)	(4250.3)	(1426.6)
Distance	658.5	1154.0	906.0	302.9
	(780.9)	(1454.6)	(1267.6)	(424.4)
Property	-20644.1**	-46309.8**	-41301.0**	-13810.5**
	(10113.9)	(21459.3)	(18633.6)	(6626.6)
Organic	31.34*	56.15*	56.62**	18.93**
	(18.98)	(30.67)	(25.62)	(8.57)
Constant	-7847.0	31354.8	-134181.7***	-134181.7***
	(14704.0)	(31193.4)	(26376.5)	(26376.5)
Sigma- cons			151504.3***	151504.3***
			(12851.1)	(12851.1)
N	836	404	836	836
R^2	0.362	0.308	0.04	

Source: As for Table 2

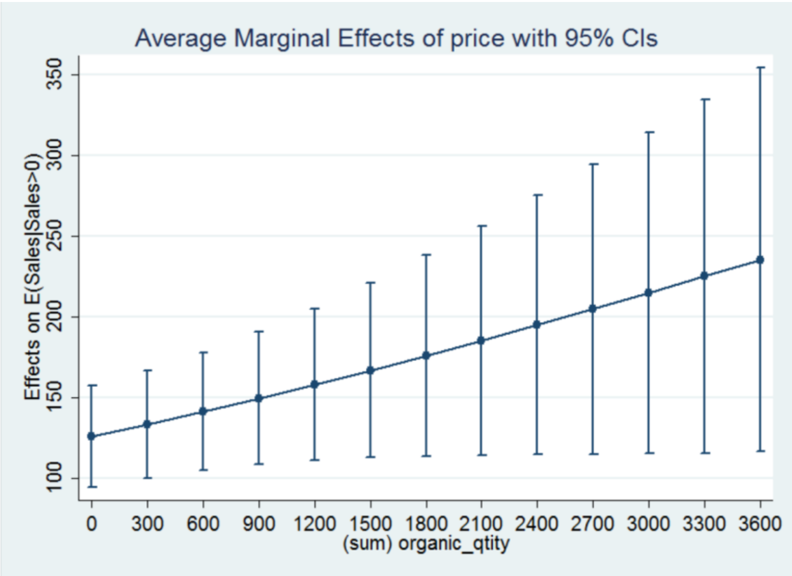
Notes: Robust standard errors in parentheses: * indicates p < 0:10, ** p < 0:05, *** p < 0:01; R^2 refers to pseudo R^2 for the Tobit

Figure 2: Marginal effects of the Tobit: Varying areas



Source: As for Figure 1

Figure 3: Marginal effects of the Tobit: varying organic fertiliser



Source: As for Figure 1

As expected, marginal effects of price get more important as area and organic fertilizer use increase. The increase is particularly steep when varying area, confirming the idea that for farmers not using variable inputs, total area is a crucial factor in determining production decisions, which reflects extensive farming practices and possibly, low productivity. It is reasonable to assume that farmers in this subgroup are the poorest and most constrained financially, so that it is no surprise that total area cultivated has a direct and strongly positive impact on production decisions. Note also that the increase in the size of associated confidence intervals is smaller when varying area than when varying organic fertilizer use. The conclusion to be drawn from these results is that, for farms not using any variable inputs, it is possible to identify crucial non-price factors and fixed inputs that affect production decisions: how much to produce, and how much of the production to be marketed. While insignificant in the Cobb-Douglas production function, organic fertilizer becomes significant and positive in the Tobit model for marketed surplus. The picture that emerges from this analysis is that, among those farmers which do not buy any variable inputs, total area cultivated seems to matter crucially, as well as farm-gate price and organic fertilizer used. Also important is the result that land ownership appears as a constraint on production and sales rather than an incentive. This pattern needs further investigation.

4.2 Farms with no purchased inputs

We use the strategy outlined in 3.2 for three separate cases. First, we model adoption of chemical fertilizer when studying supply response of marketed surplus, so that we focus on the weighted fertilizer use variable. A binary variable is created, equalling 1 if fertilizer use is positive and equal to 0 otherwise, and is regressed on total sales, quantity of organic fertilizer used, total area cultivated, and a weight variable which measures the percentage of harvest which is marketed (as we expect more commercial farmers to be more integrated in inputs markets and more aware of how to apply chemical fertilizer than less commercial or subsistence farmers).

Second, we also use a Heckit technique for the labour demand equation in some specifications (see below) using the weighted version of the input variable. Observations for which labour equals zero are excluded in Abrar et al (2004b), while labour is only treated as a quasi-fixed input in Hattink et al (1998). Here we keep observations for which labour equals zero because they are informative and dropping them would significantly reduce our sample size. Because the proportion of farms not hiring labour is large, a two-step Heckman procedure such as that described above for fertilizer is applied to reflect the imperfect rural labour market in Tanzania (Ogbu and Gbetibouo, 1990). The variables used in the first step (the Probit model), are: total sales, quantity of organic fertilizer used, the output weight variable (percentage of harvest which is marketed), total area cultivated, and the weighted distance variable.

Third, in specification 4 (see below) we use total harvest (*H*) as the dependent variable in place of sales and use the original fertilizer variable rather than its weighted version. We therefore run a probit to model (non-weighted) fertilizer use and then regress *H* on: total value of sales, organic fertilizer used, output weight, area, weighted distance and property.

The elasticities are estimated using a two-step Heckman procedure under four specifications. The first three have total sales as the dependent variable with variable inputs quantities weighted by the proportion of total harvest sold and comprise: 1, a Heckit for weighted chemical fertilizer only; 2, Heckit on both weighted fertilizer and weighted labour; and 3, also including the profit function in the SUR system. The fourth specification uses total harvest as the dependent variable with a Heckit for unweighted fertilizer. Table 4 reports the Probit results.

Regarding the first probit model estimated, for weighted fertilizer, while sales, organic fertilizer use and the output weight (proportion of output which is marketed) are significant and positive; these are the main determinants of adoption of inorganic fertiliser. Sales are expressed in millions of TSh (otherwise the coefficient would be extremely small) and are highly significant, as is output weight. Although significant the quantity of organic fertilizer has a very small influence (even when scaled in thousands). The Probit performs quite well and unsurprisingly the level of sales and proportion of output marketed are the major determinants of ability to purchase fertilizer.

The output weight and area are the only (highly) significant determinants of demand for (weighted) labour (the second Probit). Again the Probit performed well. The probability of hiring labour is largely determined by the amount land (indicating need for extra labour) and the share of the harvest which is marketed (perhaps indicating the ability to pay workers). Note that the determinants for hired labour are different than for inorganic fertilizer, consistent with the observation that relatively few forms purchase both. In both cases share of output marketed is important but whereas area appears to drive demand for labour, sales revenue drives demand for inorganic fertilizer. This suggests some degree of substitution between the two variable inputs.

Table 4: Estimated Probit models

	Fertilizer (w)	Labour (w)	Fertilizer (unw)
Sales (TSh mil)	6.66***	-3.52	7.30***
	(1.86)	(2.60)	(1.86)
Organic ('000 Kg)	0.09**	-0.005	0.10**
	(0.04)	(0.004)	(0.04)
Output weight	1.186***	3.573***	-0.122
	(0.197)	(0.397)	(0.208)
Area	-0.005	0.042***	-0.025**
	(0.010)	(0.016)	(0.012)
Distance		-0.003	-0.009
		(0.009)	(0.009)
Adults		-0.056	
		(0.035)	
Property			-0.366***
			(0.134)
Constant	-1.383***	-0.638***	-0.345***
	(0.082)	(0.125)	(0.111)
N	816	816	816
Pseudo R^2	0.13	0.30	0.04
% 1 correct	61.5	80.5	56.1
% 0 correct	73.3	83.9	62.2
Area under ROC	0.77	0.89	0.63

Source: As for Table 2

Notes: Robust standard errors in parentheses: * indicates p < 0.10, ** p < 0.05, *** p < 0.01. The goodness of fit of the Probit is evaluated by the pseudo-R2, the sensitivity (percentage of correctly estimated 1s), specificity (percentage of correctly estimated 0s), and the area under the Receiver Operating Characteristic (ROC) curves. The greater the explanatory power of the Probit model, the greater the area under the ROC curve.

In respect of unweighted fertilizer use (the third Probit), the output weight is insignificant, while sales (positive) , weighted property and area (both negative) are highly significant; organic fertilizer is also significant but with a very small positive coefficient (perhaps indicating a weak 'wealth effect'). This is the poorest performing Probit in terms of goodness of fit but is adequate for estimating specification 4. Given sales revenue, required to purchase fertilizer, larger farms with higher shares owned are less likely to purchase fertilizer, perhaps because they are somewhat more likely to hire labour.

We now turn to the elasticities estimated using the four specifications, reported in Tables 5-7. The first three specifications are for total sales value (*S*) and the first two only estimate the first order conditions of the profit function in the SUR system, accounting only for censored observations for fertilizer use (80% of farms do not use fertilizer for marketed output) in (1) and also for censored observations of hired labour (43% of farms do not hire labour for marketed output) in (2). In (3) the profit function itself is included in the system under (2), while in (4) total harvest quantity (*H*) is the dependent variable.

Table 5: Estimated Elasticities for Output Supply

	S (1)	*S* (2)	*S* (3)	*H* (4)
Price	0.19 ***	0.18***	-0.55***	0.07**
Wage rate	0.06	0.06	0.05	0.02
Fertilizer price	0.09 ***	0.09***	0.09**	0.04**
Area	0.40 ***	0.42***	0.57***	0.43***
Adults	0.17 *	0.15	0.03	0.28**
Organic	0.03	0.03*	0.03	0.02
Distance	0.07 *	0.07*	0.06	-0.02
Property	-0.32 ***	-0.33***	-0.42***	-0.18***

Source: As for Table 2

Notes: First three columns are for sales (*S*), final column for harvest (*H*). Robust standard errors not reported but significance indicated: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. A Wald test of independence of equations in the SUR system strongly rejects the null hypothesis of independence across equations implying that SUR is more efficient than OLS.

Table 6: Estimated Elasticities for Labour Demand

	S (1)	*S* (2)	*S* (3)	*H* (4)
Price	0.26 ***	0.09	-0.17	-0.01
Wage rate	-0.03	-0.07***	-0.07***	-0.04***
Fertilizer price	0.03	-0.01	-0.01	-0.02
Area	0.48 ***	0.33***	0.39***	0.40***
Adults	-0.01	0.10	0.07	0.12
Organic	0.04	0.05	0.04	0.02
Distance	0.11	0.05	0.05	0.06
Property	-0.36 ***	-0.26***	-0.29***	-0.06

Source: As for Table 2

Notes: As for Table 5.

Table 7: Estimated Elasticities for Fertilizer Demand

	S (1)	*S* (2)	*S* (3)	*H* (4)
Price	1.12 ***	1.11***	1.06***	0.63***
Wage rate	-0.01	-0.01	-0.02	-0.05
Fertilizer price	0.21***	0.20***	0.20***	0.12***
Area	-0.06	-0.06	-0.06	0.25**
Adults	0.35	0.35	0.36	0.23
Organic	-0.03	-0.03	-0.04	-0.08***
Distance	0.12	0.12	0.11	0.08
Property	0.06	0.06	0.43**	0.43***

Source: As for Table 2

Notes: As for Table 5.

With the exception of the own-price elasticity under (3), all supply elasticity estimates are quite similar and generally low (Table 5); the wage rate is the only variable that is insignificant in all specifications. Output supply seems to be most responsive to area, whether considering sales or harvest, with a highly significant elasticity of about 0.4. However, the proportion of land owned by the farmer (property) has a relatively large negative and highly significant elasticity, especially for sales. This is consistent with owned land being of lower quality; we noted that the ownership share was highest (62%) for Group 1 farms, which tended to be smaller and did not purchase inputs (Table 1). In specifications (1) and (2) sales are mildly responsive to fertilizer price and distance to market (the latter is not significant for harvest). Although harvest is responsive to household labour (adults) this is not consistently significant for sales.

Sales do appear responsive to price with an own-price elasticity of about 0.2 that is highly significant (Table 5); total harvest also responds to price but, as expected, the elasticity is much lower. However, in (3) the own-price elasticity of output becomes negative and is highly significant (other coefficient estimates are similar). This shows how sensitive the results are to the estimation technique. It could be that this full estimation is too demanding of the data given our relatively small sample and limited quality data. The fit of the profit equation estimated within the system is extremely poor (R^2=0.03 with only property significant, and negative) suggesting that many farms may not conform to the assumption of profit maximisation.

Labour demand is only consistently responsive to area, positive and highly significant, property and the wage rate, both of which are negative and highly significant (Table 6); property is insignificant for labour demand in the harvest specification and the wage rate elasticity is lower. Specification (1) differs, with significant price elasticity and insignificant wage rate, but this is probably because there is no control for farms that do not hire labour. Specification (2) is the most relevant for labour demand and shows it increases with area but decreases with ownership and the wage rate.

Fertilizer demand seems to be extremely responsive to output price, with an elasticity of above unity in the sales specifications (Table 7). Fertilizer demand is also quite responsive to fertilizer price, with an elasticity of about 0.2; surprisingly perhaps this is positive. This may simply be a feature of the cross-section data, with farmers that are able to afford more fertilizer buying a more expensive variety. Another possibility is inter-linked transactions where farmers using fertilizer are subject to contractual arrangements which tie them to buy fertilizer from traders at an above market price, whilst in exchange traders buy their output at a favourable price. Benson et al (2012) mention the existence of such types of arrangements in Tanzania.

Area is insignificant for fertilizer demand, which does not come as a surprise given the very large proportion of non-users. The exception is in the harvest specification where area has a positive significant elasticity and organic fertilizer is negative and insignificant. This result is consistent with larger farms that do have access to sufficient organic fertilizer being more likely to demand inorganic fertilizer. It may more simply reflect weaknesses in the data, and we noted in table 4 that the Probit for (4) was the weakest of those estimated.

Perhaps the most unusual results is that the property variable is positive and quite significant in (3) and (4). As we have seen that ownership appears to be associated with lower output, why would it be associated with higher demand for fertilizer? It would be mistaken to read too much into this as specifications (3) and (4) are the most weakly performing models. However, the pattern of results for this ownership measure suggest that there are differences between the land that farmers own and land they operate in some form of rental arrangement. It may be that there are multiple differences we have not been able to account for, i.e. some farmers own poor quality land with low levels of (marketed) output and purchased inputs, but there are also some who own higher quality land and purchase fertilizer to increase marketed output. In future research incorporating tree crops and the later NPS wave to increase the sample size we may be able to investigate this further.

5 Conclusions and discussion

This study assessed the extent to which price responsiveness is observed in Tanzanian agriculture using farm-level data for long season food crops from the first wave of the NPS of 2008/09. A significant degree of responsiveness is found and many results are consistent with the existing literature. Marketed output is responsive to price, fertilizer demand is responsive to prices (of output and fertilizer) and labour demand responds to the wage rate. However, non-price factors, especially area cultivated and the weighted property index, are found to be highly significant, confirming that supply response is not simply about prices. We have identified an interesting effect with the ownership variable which may hide serious constraints on land and calls for a deeper analysis of land structure and tenancy.

Fertilizer use is found to be highly responsive to output price but there is a positive fertilizer price elasticity; fertilizer use may be a criterion for differentiation between the more richer commercial farms and more traditional near subsistence farms. An important caveat is that results are highly dependent upon the specification used and there are serious limitations in the data.

Further research should disaggregate the data further (by crops and agro-climatic zones) to get better insights into regional disparities and cropping pattern structures. Using the three waves of the NPS is also desirable so as to include a temporal dimension to the analysis. Although only using part of the data in the first wave, we have identified challenges and constraints shaping the Tanzanian agricultural sector that need to be accounted for if this sector is to achieve a successful development through productivity enhancement, income generation, reducing unemployment (especially youth unemployment) and a decline in rural poverty.

A major finding is that there is something about inorganic fertilizer in Tanzania, in the sense that results show extreme output price responsiveness, and summary statistics clearly show that the discrimination between large and smaller producers is made on the basis of whether fertilizer is used or not. In this respect, fertilizer use appears much more discriminatory than hiring labour. This may hide social characteristics only common to those farmers buying fertilizer. Fertilizer adoption may be linked to social characteristics that have not been captured in the analysis (one possible salient feature is the complex bureaucracy and corruption involved in the supply and distribution chain of fertilizers). It appears that farmers who buy fertilizer do so because they can afford it. According to Minot (2009), 63% of farmers in Tanzania who did not buy fertilizer reported this was due to prices being too high; the source of finance is farm income in 69% of cases, whereas credit is only a source of finance in 2% of all cases, an indicator of barriers faced by poor farmers. Perception of risk is also important, since more risk aversion among poorer farmers may greatly limit adoption. More generally, there may be phenomena of virtuous circles taking place: successful use of fertilizer in a given season will increase yields and generate cash, making it easier to buy fertilizer in the next season. The extent to which such use is successful could be endogenous.

In terms of the groups identified, the households not buying any variable input may not conform to the assumption of profit maximisation (confounding interpretation of the econometric estimates). However, given our results, especially those regarding how important fertilizer adoption is, it could be that farms hiring labour only do not meet this assumption either (which is consistent with the marked differences observed between group 2 and group 3). For these households, a Leontief production function with fixed use of inputs may be more appropriate than the standard profit-maximising flexible production function.

Several policy implications can be derived with considerable caution. Improving the functioning of factor markets is obviously important and not controversial. This is well established for credit markets and the implications for access to fertilizer but our results suggest that there may also be major constraints associated with the operation of land markets. Land ownership is not associated with the positive effects one might expect to see. Our results would not justify advocating subsidies to promote increased fertilizer use but it does seem important to promote knowledge of effective fertilizer use, perhaps through targeted extension services.

Output does respond to prices but area cultivated is the major determinant of sales and output. This does not imply advocating larger scale farming (a more thorough investigation of yields and farm size is necessary for any such recommendations). Given farm size, access to fertilizer and labour can increase output; this is quite well known and our analysis merely confirms the constraints faced in utilising purchased inputs. The more surprising finding is that there is no obvious benefit, in terms of increased sales or output, associated with owning land, suggesting that further analysis of land markets is warranted.

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