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Review Paper

The determinants of banana market commercialisation in Western Uganda

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Increasing crop market participation has the potential to help agricultural households unlock the well known benefits of trade. In this article a double hurdle model and a tobit model are used to identify factors that influence market participation decisions among Ugandan banana growers. This article is motivated by the need to better understand the drivers of commercialisation for a perishable crop. Data for the econometric analyses come from a household survey conducted in Southwestern Uganda. Policies focused on improving banana-growing productivity, increasing prices and reducing the economic costs of distance to market appear important in helping the Ugandan government achieve its goal of a more commercialized agricultural sector. Increasing land size does not help generate larger marketable surpluses when distance to markets increase. Thus, gains in crop productivity appear important in facilitating more market exchanges.

Key words: Uganda, market participation, bananas, econometrics.

INTRODUCTION

Increasing smallholder market participation is dynamically linked to economic development. Limitations to market participation are imposed by market imperfections that give rise to transactions costs, and by heterogeneity of household resource endowments (de Janvry and Sadoulet, 2006). Barrett (2008) highlights the need to establish when barriers to market participation are related to household assets or technologies that can be used to generate surpluses large enough to induce crop sales, and when barriers have stronger linkages to deficiencies in physical infrastructure and market structures. Determining these connections will help assess the relative merit of different crop productivity and infrastructure policies.[1] While the Ugandan government does not directly control banana prices it can indirectly influence prices by implementing policies that lower transaction costs, for example, government expenditure on roads. The crucial role agricultural commercialisation plays in fostering development has been recognized in the Ugandan government's Plan for Modernisation of Agriculture (MFPED 2000). A priority of the Plan is ''eradicating poverty by transforming subsistence agriculture to commercial agriculture''. Statistics from UBOS (2006) show a lack of market orientation, with more than 75% of agricultural households selling less than 25% of their total crop output. While this is an aggregate figure, little is known about specific crops. Recent survey data collected in western Uganda show that approximately 65% of banana production is consumed on-farm, while only 35% is sold (Smale and Tushemereirwe, 2007).

A large empirical literature in eastern and southern Africa suggests that transaction costs have adverse effects on household crop market participation (Barrett, 2008). Additional evidence on perishable-crop market participation is needed as the literature in Sub-Saharan

[1] Crop productivity can be endogenously determined by rural infrastructure development, for example, better roads can increase input application rates. However, in many parts of rural Uganda modern inputs are not used and the discrete choice to adopt new inputs may not occur given a marginal improvement in infrastructure as the threshold level of infrastructure that will commence adoption has not been reached.

Africa focuses on grain and high-valued cash crops, for example, maize, vegetables and cotton. Drivers of marketing decisions may differ based on crop perishability. For example, there could be a high portion of net sellers among growers as storage options are limited, and seasonal conditions could result in large supply variations. Moreover, price could have a limited impact on the decision making of perishable-crop sellers as these crops cannot be stored for long periods and once consumption needs have been met.

Bananas are examined in this article as they occupy 38% of all agricultural land (Smale and Tushemereirwe, 2007) and they contribute significantly to household food consumption and labour allocations. East African highland bananas (*Musa* AAA-EA) are studied in this article as they are the predominant genomic group in Uganda (Tushemereirwe et al., 2006). Furthermore, growers in western Uganda are targeted as an estimated 61% of the Ugandan banana crop comes from this region. The challenge of generating a livelihood using low production technologies is compounded by the high marketing costs banana growers face (Spilsbury et al., 2002). Large marketing margins exist with trader margins for bananas destined for Kampala from western Uganda being 50% of farm gate prices (Smale and Tushemereirwe, 2007). This indicates imperfect competition could be a problem. Retail prices in Kampala are often double those received by farmers in southwestern Uganda (Smale and Tushemereirwe, 2007; Benson et al., 2008). Despite long transportation distances, the margins appear high for a crop that undergoes little product transformation. Uganda is one of the world's largest producers and consumers of bananas: annual banana production is approximately 7205 million kg and Ugandans consume 0.7 kg/capita/day (Smale and Tushemereirwe, 2007).

Daily per capita banana consumption of 1.2 kg among surveyed households in this study exceeds the national average by 70%. While many growers in Southwestern Uganda have a comparative advantage in banana production and rely on own production for home consumption, these high levels of consumption suggest more sales could occur. With banana being a perennial tree crop, the area planted is fixed in the medium term with input usage and climate variations producing inter annual yield fluctuations. Benin et al. (2008) report banana yields of 6.1 t/ha. When supply exceeds demand households have two main options: sell the surplus at the offered price or consume more bananas. There may be room to sell more, and decrease on farm consumption, if market access improves. Increasing crop sales is one of the most important income enhancement strategies given the often found difficulties associated with finding off-farm sales among growers is important in helping formulate development strategies. Transaction costs affect market access, and hence influence market participation decisions. In Figure 1, P^s is the effective sales price—the market price (P) net of transaction costs incurred in selling (t_s)—and P^b is the effective purchase price - including the transaction costs incurred in buying (t_b)—of the food product. If a household's shadow price exceeds the purchase price, the household will purchase the crop until the shadow price that equates supply and demand for home production falls to the purchase price.[2] When the household's internal equilibrium is below P^s, the household will have a crop surplus. Shifting food crop supply to the right, lowering transaction costs and raising market prices all have potential to increase market entry and participation intensity.

Additional empirical evidence on the role prices, quantities, isolation and land endowments play in determining market participation and sales volumes is provided in this article through using household survey data. These four factors all have different influences on marketing decisions. For example, price has a sharper effect on participation decisions than quantity produced, while production has a larger impact on sales volumes. Greater per capita land availability does not positively influence sales volumes when distance to market increases. This finding implies land size alone cannot boost marketable surpluses; land productivity needs to be addressed in conjunction with reducing the economic costs of accessing markets.

Two questions are answered in this article: what factors induce households to become net banana sellers, and how can sales volumes increase for market participants? The findings underscore the need to address not only transaction costs but also household crop production abilities.

ECONOMETRIC APPROACHES TO MODELING MARKET PARTICIPATION

Heckman sample selection models, double-hurdle models and tobit models have been used to examine crop market participation. When sample selection is a problem, Heckman (1976) should be followed, for example in Goetz (1992), Heltberg and Tarp (2002) and Alene et al. (2008). Heckman's model first uses a probit analysis with all available data to estimate the probability of market participation. Then the inverse Mills ratio, computed from the probit regression, is used with other explanatory variables to help explain variation in the continuous, non-zero dependent variable (normally sales volumes).[3] A double-hurdle model is a variant of the Heckman model used when data are drawn from a random sample. Double-hurdle models have been

[2] The shadow price is the implicit value of the crop to the household.

[3] The inverse Mills ratio controls for the probability of market participation so that the remaining regressors provide unbiased estimates of volume sold conditional on a given probability of market participation.

applied to consumer demand (Burton et al., 2000), agricultural input adoption (Shiferaw et al., 2008) and off-farm labour supply (Matshe and Young, 2004) decisions. A handful of studies have used variants of the model for participation in output markets (Newman et al., 2003; Dong et al., 2004; Holloway et al., 2005).

The tobit model contrasts the double-hurdle model as a single mechanism determines the choice between positive and zero sales, and the amount of sales given market participation. When fixed transaction costs are expected to influence participation decisions, and not traded volumes, a double-hurdle model appears more appropriate than the restrictive tobit model. Tobit models assume that zero values traded are because of rational choice, although it may be prohibitive entry barriers that are limiting market entry. The tobit model imposes the restriction that the same factors have the same effects upon the decisions to participate in the market as they do on the quantity sold. Therefore, to test the appropriateness of using a tobit model the hypothesis from Lin and Schmidt (1984) is tested.

Both a double-hurdle model and a recursive simultaneous equations tobit model, described in Greene (2002), are used in this study.[4] Despite double-hurdle models not being common in the market participation literature, the methodology is justified for two reasons. Firstly, sample selection is not a problem in this study.[5] Secondly, the Lin and Schmidt (1984) hypothesis test rejects the tobit model specification. The tobit model is fitted as unresolved endogeneity issues exist in the truncated model, and thus the tobit estimates are compared to the truncated model.

DATA

The data in this article come from a household survey executed by the author in 2006. The survey covered a stratified sample of 131 farm households with the sample domain spanning the Ntungamo and Masaka districts of Southwestern Uganda. A random sample was obtained from subsets within the larger Ugandan agricultural household population. The subsets included those households that grow bananas as their main crop and have different levels of geographical remoteness and commercialistion. Data on agricultural production, prices and marketing were collected. Definitions of variables and summary statistics are in Table 1. Ntungamo households have the highest production, marketable surpluses and crop incomes. While the majority of households have a crop marketable surplus, the value of the surplus has a large standard deviation. Market participation rates in the survey area are high; 90% in Ntungamo and 50% in Masaka, however, the study has a focus on regions where banana growers have a comparative advantage and higher rates of participation are expected. Despite Ntungamo households being located on average the furthest from the district headquarters, they are the most commercialized. Household production is 10 times greater in Ntungamo than in Masaka. Although yields appear high in Ntungamo, large productivity gaps exist between average growers, commercial growers and demonstration sites in Southwestern Uganda (Van Asten et al., 2008).

Following Heltberg and Tarp (2002) and Renkow et al. (2004), transaction costs are captured through three proxy variables: distance to market, education and population density. Distance to market is a proxy for proportional transaction costs and education and population density are proxies for fixed transaction costs. Distance to market reflects isolation, and is defined as the kilometers a household is from its district headquarters. A dummy variable for the education of the household head reflects the ability of the household to process information. The population density variable attempts to capture the density of information and marketing networks.

The average sub-county price was used as an explanatory variable instead of farm-gate prices. If individual farm-gate prices are used, those households with zero sales will be excluded from the analysis. In this case, the modelling procedure would simplify into an ordinary least squares regression. The average sub-county price is inclusive of marketing costs. It represents the price received by the average grower, the market price minus marketing costs. Thus, as prices change so will marketing costs. Transport costs account for 10% of farm-gate prices in Ntungamo. Information on market prices was known by 88% of households in Ntungamo and 90% of households in Masaka.

Household size represents the total number of individuals in the household. Larger households have more labour but greater consumption demands than smaller sized households with the net effect of household size on marketable surplus being unclear. Thus, the dependency burden is also included as an explanatory variable. Access to price information is captured through a dummy variable for households who state having access to price information Price information is perceived to be important when bargaining with traders and guiding marketing decisions. Price information may also help decrease price risks by avoiding trips to the market that would not have occurred if price information were available. Farm endowments are accounted for with a variable representing acres of land per adult to test if a relationship exists between land endowments and commercialisation. Off-farm employ-

[4]A simultaneous equations model is estimated to control for potential endogeneity of crop yields.

[5]Heckman's sample selection model is not applicable in this study as a non-random sample was not used; a selected sample generally describes a non-random sample (Wooldridge, 2002). Observing positive quantities sold only when a household participates in a market is not a sample selection problem. Observation of the volume traded is not a function of the value of another regression equation, as in Heckman (1976). Quantity sold is always observed regardless of whether a household participates in a market or not.

Table 1. Variable definitions and summary statistics.

Variable	Description	Ntungamo		Masaka	
Sample size		70		61	
		Mean	SD	Mean	SD
Marketable surplus	Kg sold/ year	27555	24348	940	1406
Yield	kg/year	30553	39395	3020	2015
Crop income	million Ush/year	7.1	6.9	1.1	1.4
MSD	1 = have marketable surplus	0.9	0.1	0.5	0.5
Price	average sub-county banana price (Ush/kg)	154.4	23.7	144.9	8.6
Adults	Number in household	3.3	1.4	3.0	1.1
Distance	Km to district headquarters	24.0	9.4	7.6	5.8
Household members	Number of people in family	5.7	2.0	6.3	1.8
Dependency burden	Number of persons in household (>65 and <15 years)/household members	0.3	0.2	0.5	0.1
Area	Area of crop planted (acres)	4.7	3.2	1.0	0.8
Off-farm Income	% of income derived off-farm	41.9	11.9	45.2	21.1
Farm size	Household farm size (acres)	7.5	4.8	4.0	2.0
Education	1 = education of household head above primary school level	0.3	0.5	0.5	0.5
Population density	People/km^2 (district level)	200.0	0	196.2	0
Manure	Kg applied/year	530.0	798.6	199.1	400.0
Hired labour	Hours/year	1811	1294	147	333
Family labour	Hours/year	2269	1198	839	814
Experience	Household head's years of crop farming experience	23.2	10.9	28.1	12.9
Improved seed	1 = uses improved seed	0.07	0.2	0.01	0.1
Producer group	1 = household involved in a producer group	0.5	0.5	0.3	0.4

Note: SD denotes standard deviation.

ment and banana sales are income substitutes. When there are limited off-farm employment opportunities household reliance on meeting consumption needs from crop sales rises. The average household derives more than 40% of its income from off-farm sources, thus tradeoffs between off-farm income and time devoted to agricultural activities will be present.

It is proposed that crop output is determined by a number of factors, including area planted, manure application and the usage of hired and family labour. The usage of improved seed varieties is captured through a dummy variable. The number of years the household head had been crop farming captures the impact of experience. A variable of interest when examining crop yields is the involvement of households in a producer group. These groups collectively market crops and receive better access to extension services than individuals. The benefits of producer group membership are well known in East Africa (Bernard and Spielman, 2009). To avoid potential multicollinearity problems, a dummy for access to extension services is not included; rather involvement in a producer group is used as an explanatory variable for crop yield.

MODEL SPECIFICATION

The double-hurdle model was implemented first by estimating a probit model of banana market participation. A truncated model was then used to explain sales volumes when a marketable surplus exists. A truncated model was used as observations with a zero quantity sold are not included in the analysis. Thus, the sample comes from a restricted part of the survey. The truncated model incorporates the inverse Mills ratio as an additional explanatory variable. The probit model takes the following form:

$$y^* = \beta X^k + \alpha y_1 + u_1 \quad (1)$$

$$P(y = 1 | X^k, y_1) = \Phi(\beta X^k + \alpha y_1) \quad (2)$$

In which: y^* = an underlying latent variable, where $y=1 | y^* > 0$;

y = 1 if the household sells the crop, y=0 otherwise;

y_1 = kg of crop produced;
X^k = vector of variables (k = price, distance, size, dependency, price information, land, off-farm income, education, population and distance×land);

Price = average sub-county price Ush/kg;
Distance = distance to crop selling market in km;
Size = number of residents in the household;
Dependency = dependency burden;
Price information = a dummy variable for receiving price information (1/0);
Land = total farm size in acres/number of adults (aged 15–65 years);
Off-farm income = % of income derived off farm;
Education = a dummy variable if the household head has attained an education level more advanced than primary school (1/0);
population = district population density people/km^2;
Φ = the cumulative density function;
β and α = the coefficients to be estimated; and
u_1 = an error term, symmetrically distributed around zero.

The truncated model applies to the non-limit observations of quantity sold and is given as

$$E[y_2 \mid y_2 > 0, X^k, y_1] = \beta X^k + \alpha y_1 + \sigma \frac{\phi(-(\beta X^k + \alpha y_1)/\sigma)}{1 - \Phi(-(\beta X^k + \alpha y_1)/\sigma)} \quad (3)$$

In which y_2 is the kilograms of bananas sold and ϕ is the probability density function. The last term on the right-hand-side of equation (3) is the inverse Mills ratio. The lower truncation of sales is zero.[6]

To have the participation equation convincingly identified requires that at least one regressor not in the quantity equation appears in the participation equation. Deaton (1997) believes that this condition will rarely be met in practice. Although the explanatory variables in the probit and truncated regressions are identical, nonlinearity of the inverse Mills ratio allows the identification condition to be met (Wooldridge, 2002).
The recursive simultaneous equations tobit model is specified as follows:

$$y_2^* = \delta X^k + \kappa y_1 + u_2 \quad (4)$$

$$y_2 = \max\ (0, y_2^*) \quad (5)$$

$$y_1 = \pi X^l + v \quad (6)$$

In which: X^l = vector of variables (l = manure, area, farm labour, hired labour, experience, producer group and seed); Manure = kg manure applied to the crop;
Area = acres of banana grown;
Farm labour = hours of family labour used for the crop;
Hired labour = hours of hired labour used for the crop;
Experience = years of crop experience;
Producer group = dummy variable for involvement in a producer group (1/0);
Seed = dummy for using improved seed (1/0);
δ, κ and π = the coefficients to be estimated; and u_2 and v = the errors terms, symmetrically distributed around zero.

RESULTS

Both models were estimated using LIMDEP version 8.0 with the results presented in Tables 2 and 3. Results are reported in sub-sections related to specific variables. The truncated model appears an appropriate estimator for volume sold as $\sigma \neq 0$. When $\sigma = 0$ crop sales can be estimated using a least squares estimator. Factors of production potentially influence quantity sold, thus making quantity produced endogenous to the volume traded decision. Therefore, prior to estimation, testing for endogeneity of quantity produced was carried out in both models using the test proposed by Smith and Blundell (1986). The instruments used to explain crop yield are in the X^l vector. The null hypothesis of exogeneity was rejected in the tobit model (t statistic = –3.58 with a p-value = 0.00).[7] As u_2 and v are correlated, single equation tobit estimates of the quantity sold equation will be biased. This supports the usage of the recursive simultaneous equations tobit model, as this estimation procedure controls for the endogenous relationship between quantities sold and quantity produced. The model provides consistent estimates of δ, κ and π with asymptotically valid standard errors. In the double-hurdle model, exogeneity of yield was rejected in the truncated model but not in the probit model. Coefficients in the truncated model are consistent as the error term from the yield regression on instruments and other independent variables is used as a control function. An unresolved issue is correcting their standard errors, with the literature providing little guidance on how this can be achieved.
The hypothesis that the likelihood value of the tobit model equals the sum of the likelihood values of the probit and truncated models, against the alternative that different

[6] As logarithms are used for continuous variables, and given log (0) is not defined, the lower truncation becomes –3, log (0.001).

[7] Instruments appear valid (F statistic = 23.89 with a p-value = 0.00). The F statistic is calculated using the sum of squares residuals from a restricted and unrestricted model, with the restricted model not including the X^l vector of variables.

Table 2. Double-hurdle model results.

Explanatory variable	Dependent variable (estimation technique)			
	Whether bananas are sold (Probit)		Quantity sold by net sellers (Truncation)	
	Coefficient	**Standard error**	**Coefficient**	**Standard error**
Constant	-33.15	264.56	-24.00	31.02
Price (log)	13.95	3.71***	0.33	0.17*
Yield (log)	1.48	0.71**	1.25	0.08***
Distance (log)	-6.95	2.27***	-0.24	0.24
Size (log)	3.20	2.82	0.38	0.27
Dependency (log)	-0.42	0.50	0.02	0.02
Off-farm income (log)	-0.51	0.57	-0.11	0.05**
Land (log)	1.66	1.06	0.28	0.11**
Price information	1.51	0.42***	-0.12	0.05***
Distance (log) × Land (log)	-1.67	2.50	-0.64	0.25**
Population (log)	-19.36	104.02	8.27	12.24
Education	-0.54	0.42	0.00	0.03
σ			0.18	0.11***
Exogeneity test for yield: *p*-value	0.12		0.00	
Outcomes correctly predicted (%)	94.29			
Pseudo R-squared	0.85			
Log likelihood not	-93.83			
Log likelihood ratio (113.67): *p*-value_ 0.00	0.00			

Note: the symbols *, **, *** denote the 90, 95 and 99% levels of confidence, respectively.

sets of parameters determine the probability of a limit observation and the density of the non-limit observations, was rejected.[8] This rejection validates using the double-hurdle model in addition to the tobit model. Heteroscedasticity was tested for using the Lagrangian multiplier test proposed by Greene (2000), with homoscedastic errors not being rejected in all cases. To test for multicollinearity, a variance inflation factor was computed for each explanatory variable, with none exceeding nine. Greene (2000) suggests values in excess of 20 indicate multicollinearity could be a problem.

Prices

Higher sub-county prices encourage market participation and increase traded volumes. The finding is consistent with *a priori* expectations and has also been observed in grain markets by Alene et al. (2008). A rise in market prices can be viewed as a fall in marketing costs or a change in economic conditions, for example, changing consumer demand. The price variable's magnitude in the probit model suggests prices are an important driver of market entry. With rising prices the gap between the selling price and the household's subjective valuation of bananas diminishes until a threshold is reached in which market entry occurs. In Figure 1, rising sales prices result in more household internal equilibrium points being outside the self-sufficiency band. Higher prices have the two-fold effect of influencing market participation decisions and raising incomes (even without a rise in volumes sold). Lowering transaction costs raises prices and increases commercialisation.

Crop yields

Higher yields have a positive effect on market participation and marketable surplus sizes. Yield has the greatest explanatory power in determining quantity sold,

[8] The Lagrangian multiplier test devised by Lin and Schmidt (1984) is used to distinguish between the double-hurdle and tobit model. The test statistic is 2×(likelihood probit + likelihood truncation − likelihood tobit) > χ^2_{13}. The test statistic equals 58.6, which exceeds the 1% critical value (22.36).

Table 3. Recursive simultaneous equation tobit model results.

Explanatory variable	Dependent variable			
	Quantity marketed		Quantity produced	
	Coefficient	Standard error	Coefficient	Standard error
Constant	213.79	175.02		
Price (log)	2.57	1.12**		
Yield (log)	2.56	0.45***		
Distance (log)	-2.06	2.02		
Size (log)	2.46	1.45*		
Dependency (log)	-0.07	0.19		
Population (log)	-92.50	69.23		
Off-farm income (log)	-0.47	0.26*		
Land (log)	1.20	0.59**		
Education	-0.15	0.18		
Price information	1.20	0.19***		
Distance (log) × Land (log)	-2.39	1.30*		
Constant			2.99	0.09***
Manure (log)			-0.00	0.12
Area (log)			0.67	0.09***
Hired labour (log)			0.02	0.01**
Family labour (log)			0.01	0.01
Experience (log)			0.04	0.05
Producer group			0.12	0.05**
Seed			0.07	0.21

Note: the symbols *, **, *** denote the 90, 95 and 99% levels of confidence, respectively.

in contrast to the probit model in which price was a more significant variable. The determinants of crop yield are given in Table 3. Hired labour usage and producer group participation both positively affect yields. These findings are broadly consistent with Smale and Tushemereirwe (2007) who find labour and access to extension services are both significant drivers of production. Growers in producer groups have better access to extension services and this access to technical advice on crop management helps increase yields. Higher yields shift the supply curve to the right in Figure 1, with household adjustments to marketing decisions following.

Distance to market

Geographical remoteness, as proxied by distance to market, reduces the likelihood of market participation, but has no marginal effect on quantities sold. Isolation can increase the cost of exchange either implicitly or explicitly. For example, the cost to pay a porter to transport bananas to a market increases with distance, while with greater isolation traders may be more rigid in price negotiations and, as a result, offer growers lower prices. These factors widen the self-sufficiency band in Figure 1 and reduce the horizontal distance between the demand and marginal cost curves for net sellers. It would be expected that prices fall with increasing isolation, however, no multicollinearity problems were detected between the two variables. When distance to market is interacted with land area, the terms take on a negative and statistically significant sign. Increasing remoteness renders land size less effective at boosting marketed quantities. Greater per capita land availability does not offset the effects of distance to markets in increasing sales volumes; as per capita land endowments and distance increase simultaneously, quantity sold falls. This implies land size alone cannot boost marketable

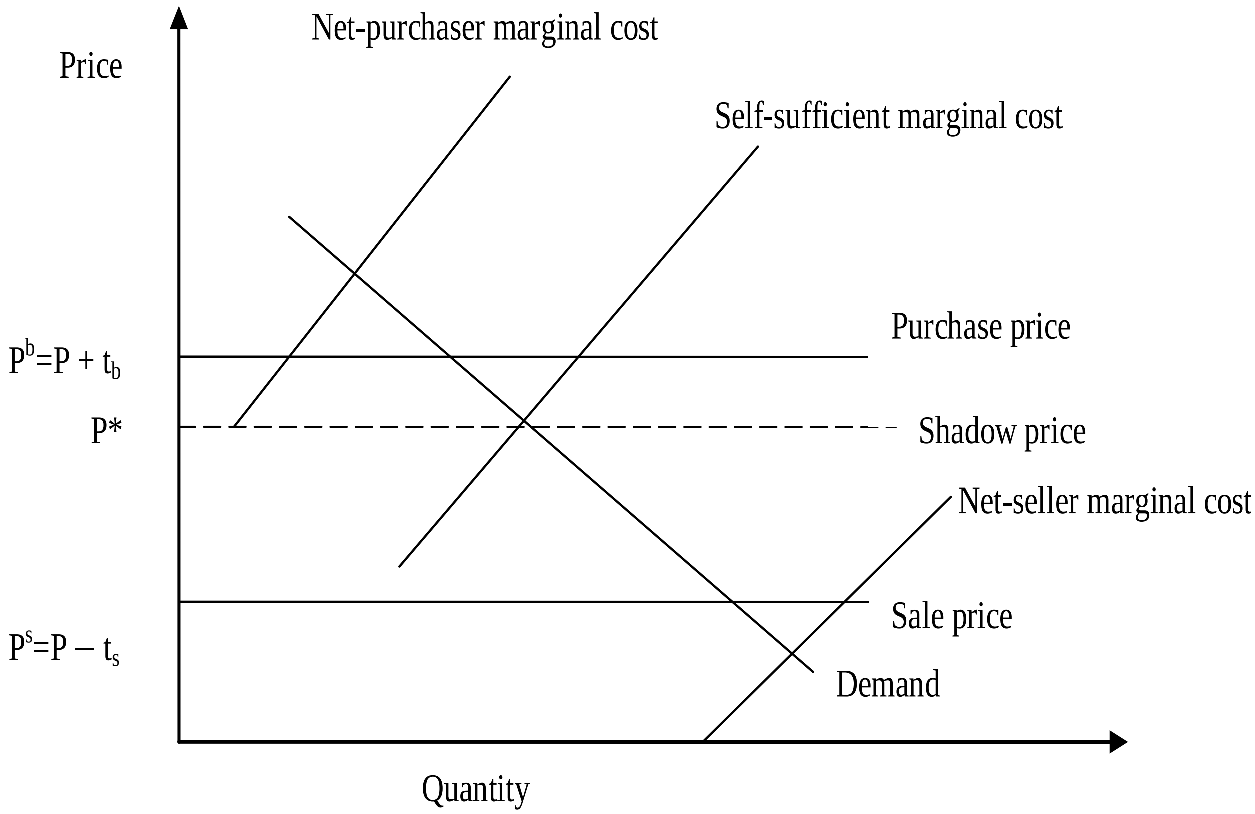

Figure 1. Transaction costs and market participation.
Source: de Janvry and Sadoulet (2006).

surpluses, with land productivity also needing to be addressed.

Price information

Price information influences the initial hurdle of market entry and has a significant positive effect on traded quantities. The variable has a negative effect in the truncated model, as possibly households with price information sell less as they know prices are low and decide not to engage in exchange. The conceptual issue of how price information influences sales volumes requires further development.

Land

Farm size measured as land per household worker is positively related to quantity sold, and is consistent with the observation that Ntungamo growers sell more bananas. Being relatively well-endowed with agricultural land has a positive impact on commercialisation, but has no explanatory power in predicting market participation decisions. Yield, not the area of operation, helps explain participation.

Education and population density

Education and population density are unconvincing proxies for fixed transaction costs in this study. Neither variable is significantly different from zero. A trade-off exists in the modelling approach; the Lin and Schmidt (1984) test implies that the tobit model is not relevant and that the truncated model's standard errors need correction. Variables in the tobit and truncated model are similar in sign and significance, however, price information in the double hurdle model has a positive sign in the first stage and a negative sign in the second. This indicates that the tobit model will not be accurate, as explanatory variables have different effects on participation and sales. There are ample opportunities for future research to improve on the econometric estimation techniques.

DISCUSSION AND CONCLUSION

The results highlight the need to increase yields and prices and reduce distance to market costs. Those households closer to markets have a higher likelihood of being a net seller and generating larger sales volumes. Sub-county prices have a stronger influence on initial market entry decisions and quantities have a larger impact on volumes traded. This suggests marketing barriers linked to infrastructure and institutional deficiencies are keeping prices below household shadow prices to induce self sufficiency. Once households enter markets, crop productivity programs are vital. Results imply increasing per capita land availability alone cannot help boost sales volumes as households become more isolated from markets. This suggests with increasing isolation larger growers have no advantage over smaller growers in being able to sell more crops. This finding is consistent with results in Smale and Tushemereirwe (2007) that state that labour contributes more to crop productivity than land area.

Households often have a primary goal of meeting subsistence needs, with any excess supply, after accounting for storage, being sold for cash income. However, self sufficiency in food production is not always necessary. Higher prices can play a role in shifting households from being food self sufficient to self reliant, with extra income from sales being used to buy in part of their food requirements. This requires the effective sales price to exceed the household's subjective valuation of bananas. Even without meeting subsistence needs from own production price rises can lead to higher incomes, which in turn increases purchasing power. Extra income from sales, resulting from reduced banana consumption, can help diversify diets. Diversification of household diets into potatoes, rice and other carbohydrates could follow if a goal of food self reliance not self sufficiency was pursued. Lowering market exchange costs that appear to encourage high consumption rates appears critical in providing households with more opportunities to trade.

The findings provide useful information for developing better targeted policies, for example, in areas where many households are already market participants focusing on crop productivity appears more important than addressing transaction costs (price factors). Yield improvements are critical to ensure the commercialisation of food crop markets occurs, with superior household technical abilities being an important method to increase sales volumes in the absence of better prices. Mitigating the effects of Banana bacterial Wilt and improving nutrient management are the two technology scenarios flagged by Smale and Tushemereirwe (2007) that have the greatest net benefits to growers.

Fostering the development of producer groups appears a vital element in a crop productivity improvement program. The dissemination of technology and new crop management techniques will rely on effective extension programs being developed. A critical aspect of research and development is the distribution of new technologies that are being developed by the National Agricultural Research Organisation (NARO) aimed at addressing the crippling yield loses associated with banana weevil, banana bacterial wilt, nematodes, Black Sigatoka and low soil fertility (Smale and Tushemereirwe, 2007). Trial samples of new technologies should be distributed along with a better dissemination of banana technologies to regions that require them the most. Improved banana plantlets have been distributed widely to banana-growing households by NARO. Laurence (2003) reports the majority of plantlets have been distributed in Uganda's central region. This regional strategy is puzzling given that the majority of banana-dependent households are located in Southwestern Uganda. Better targeted programs and a decentralisation of NARO activities could play a complementary role in spreading new plantlet varieties.

The results in this study add credence to support government policies that mitigate the impacts of household isolation. Reducing the affect of distance to market can be viewed as reducing the economic costs of distance to market. In particular, in terms of reduced travel times, less quality deterioration and less damage to means of transport. Furthermore, spill over effects exist between reducing the economic cost of accessing markets and crop prices. Better rural infrastructure should lead to more traders penetrating rural areas, and this increased competition could benefit growers through higher prices. Investment in rural road infrastructure emerges as an area of government intervention that could provide benefits to agricultural households. Jagwe et al. (2008) highlight that increased public expenditure on rural roads can help reduce transaction costs in Rwanda and Burundi, thus fostering market participation. Government spending on feeder roads in western Uganda has a low opportunity cost; spending has a benefit-cost ratio of 9.2, compared to 3.8 for education, however the importance of agricultural research and extension should not be overlooked as it has a ratio of 14.7 (Fan and Zhang, 2008).

Since the data for this analysis are cross-sectional, measuring long run trends in market participation are beyond the scope of this article. Yet results clearly indicate increasing quantities via improved science, and increasing prices through government policies aimed at improving infrastructure and market competition will help smallholder households become more market focused. Price and production policies can play complementary roles, however, rising prices can drive up production and the general equilibrium effects of this require measuring.

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