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Increasing Returns to Marketing in Zambian Maize Markets

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The article investigates the existence of market externalities due to increasing returns to marketing. Panel data on 198 pairs of maize markets in Zambia and correlated random effects linear and tobit estimators were used to model the relationship between market externalities and producer-to-wholesale marketing margins. This article is one of the first to explicitly account for unobserved local market heterogeneity in a developing country context. The results suggest that Zambian smallholder maize markets are substantially specialized with significant margin-reducing own externality effects and insignificant cross-externality effects. The results also indicate that the unobserved market effects exert a systematic influence on this relationship, a phenomenon that is impossible to measure with cross-sectional data.

1. Introduction

A salient feature of food marketing systems in developing countries is that supplies originate from large numbers of small farmers distributed over wide geographical areas, who individually produce very small surpluses. High transaction costs of trading result when traders must transact with many actors for small volumes. This situation may contribute to a “catch-22” situation whereby smallholder farmers’ incentives to produce surpluses for the market are impeded by a lack of trader presence in the area, and trader presence is limited by small surplus production and hence high transaction costs per unit purchased (Shaffer et al., 1983). A common manifestation of the apparent market-wide inefficiency is the wide margins between consumer and producer prices (see, for example, Ahmed and Rustagi, 1984; Kherallah et al., 2002).

It is widely believed that transaction costs could be reduced by initiatives that facilitate the bulking up of farmers’ surpluses, which would then allow marketing firms to spread their fixed costs over larger volumes. Forms of collective action, such as marketing cooperatives, are often viewed as instruments for resolving marketing problems in developing countries. Often ignored, however, is the fact that the degree to which bulking can reduce transaction costs depends on whether there exist local market externalities and scale economies. Because of high fixed costs in marketing, there often are multiple Pareto-ranked market equilibrium points, some of which are devoid of such market externalities (Emran and Shilpi, 2002). Thus, the existence of market economies is not guaranteed and is largely an empirical issue. If, however, such economies do exist, they can potentially be

passed along to producers and consumers in the form of higher producer prices and lower marketing margins.

While a number of studies have looked at increasing returns in agricultural markets of developing countries (Emran and Shilpi, 2002; Fafchamps et al., 2003), empirical evidence is still scarce on the effects of aggregate supplies on marketing margins. In their cross-country comparative study, Fafchamps et al., (2003) used data generated from trader surveys in Benin, Madagascar and Malawi to measure the presence of increasing returns in agricultural trade. Their framework uses the trader as the unit of observation and the quantities of output that he/she handles as a source of market economies. In this sense, the authors sought to determine if there was scope for concentration of marketing functions among a few efficient firms. This framework, however, does not account for variations across markets in the volume of trade or other local market-specific conditions.

The question of the possible existence of the externality effects of local market surpluses was first addressed by Emran and Shilpi (2002) in their study of the Bangladesh rice and vegetable markets. While recognizing the importance of the relationship between producer and consumer prices in identifying local market externality effects, owing to data limitations, Emran and Shilpi (2002) approached the problem rather indirectly and modelled the relationship between the surpluses in the local markets and the sales decisions of the households located in those market areas. Like Fafchamps et al., (2003), Emran and Shilpi (2002) used cross-sectional data on market participants, which do not lend themselves to comprehensive treatment of unobserved market heterogeneity. Insights from the new institutional economics literature indicate that transaction costs are unique to each market participant and, thus, form a basis for participant-specific heterogeneity (Sadoulet and de Janury, 1995).¹

This article uses the unique opportunity presented by panel data on Zambia's smallholder farmers and district markets to determine the existence of local market externalities and their effects on farm-retail marketing margins. Panel data, unlike the more common cross-sectional data, provide the opportunity to explicitly account for unobserved market heterogeneity. Maize presents an important case study as it is the single most important food and cash crop in many sub-Saharan African countries such as Zambia.

We use the correlated random effects (CRE) linear and tobit frameworks to model the price spread between rural markets and district markets as a function of per capita own and cross externality effects, proxies for cost of trade (distance to nearest district town; and average wage rate), a proxy for the level of activity and dependency on local markets as sources of staples (median household expenditure on staple food crops), and location/district dummy variables. In this framework, the distribution of the price spread is censored at zero because a positive price spread is a necessary but insufficient condition for trade to flow from rural market areas to district centres. Pollack and Wales' (1991) likelihood dominance criterion (LDC) showed that the CRE Tobit formulation was 30 times more likely than the alternative CRE linear regression model that uses a trade dummy variable to specify different

relationships for positive and negative price spreads.

The results indicate that Zambian local maize markets are characterised by significant margin-reducing own externality effects (i.e., higher surplus maize production within a market catchment area is associated with lower spatial price spreads) and insignificant cross-externality effects (i.e., higher surplus production of other commodities has no effect on maize price spreads). The results also suggest the existence of significant unobserved market heterogeneity on the price spread, which is not possible to detect in cross-sectional studies.

The rest of the article is organized as follows. We look at the agricultural marketing policy in Zambia in section 2. We then discuss the methods and estimation procedures in section 3. We analyse the results in section 4 and conclude the article in section 5.

2. Agricultural marketing policy in Zambia

Since Zambia achieved its independence in 1964, a prominent goal of government policy has been to promote smallholder welfare, primarily through the use of maize production incentives. The state initially invested heavily in crop-buying depots, first through the National Agricultural Marketing Board (NAMBOARD) and later through the Zambia Cooperative Federation (ZCF). Government funded extension services, seed research, and fertilizer subsidies (used mainly on maize) which resulted in a continued rise in output and yield per hectare. However, by the late 1980s, treasury costs of state fertilizer and maize marketing operations were so large that they contributed to macroeconomic instability and hyperinflation (Jansen and Muir, 1994). The government was forced to begin to reform the input and crop marketing systems and policies. This was fuelled by increased donor pressure. This included discontinuation of consumer subsidies on maize meal.

With the continuing desire for market stabilization, the Zambian government established the Food Reserve Agency (FRA) in 1995. Unlike its predecessor, NAMBOARD, which was the sole buyer and seller of grain in Zambia, the FRA was originally created to hold buffer stocks in order to dampen price variability. FRA was also to provide liquidity in the maize market during the initial years of liberalisation. Although FRA's original mandate did not include a price support function, it was soon instructed to purchase maize in remote areas where production was unlikely to be profitable under commercial conditions, as well as to distribute fertilizer (Govereh et al., 2002).

FRA involvement in the buying and selling of grain was very limited until the 2000/2001 marketing season, and all purchases and sales were done using a tender process. With an increase in budgetary support from the government and the looming drought of 2001/2002, the FRA progressively became one of the major actors in the maize market. It started announcing maize floor prices and was declared 'buyer of last resort'. Starting in May 2005, the FRA began ramping up its buying activities and has continued to buy a large portion of local production, now approximately 34% of the country's domestically marketed maize. Thus, the government has arguably become the dominant player in the maize market. Although the private sector is encouraged to participate alongside the public sector, in reality it is prevented from doing so by the

unpredictability of government actions. These include discretionary export bans and restrictions, import tariff rates, and government import programmes. Recent assessments of the effects of the enacted marketing reforms have been mixed. Some scholars argue that citing private sector failure in a free market system fails to account for the role that effective, incentive-enhancing governments can and must play. Even the most ardent advocates of liberalisation agree that governments need to perform certain tasks in order for agricultural markets to function effectively. These tasks include providing a stable and transparent policy environment, investing in public goods to reduce the costs and risks of trade and production, providing appropriate institutions for contract enforcement, risk-mitigation, and incentives for investment.

3. Methods and procedures

The net price for a rural market is often computed as the selling price in the destination market, p_j^c , less the purchase price in the local market, p_j , unit transportation costs, and marginal quality verification costs. The quality verification cost is assumed to be a function of the quantity of all other commodities bought, hence representing a possible source of diseconomies to scope. This allows modelling the price spread between the destination markets and the local markets, $p_j^c - p_j$, as a function of distance (d_j), quantity of the commodity in question (q_j), and the quantities of all other surplus commodities in the local market (Q_{-j}):

$$p_j^c - p_j = g(d_j, q_j, Q_{-j}). \quad (1)$$

In this framework, own and cross externality effects exist if the price spread, $p_j^c - p_j$, is inversely and significantly related to q_j and Q_{-j} , respectively (Emran and Shilpi, 2002).

Due to the fixed costs that characterize local markets in developing countries, the intermediary will be able to offer a higher price for commodity j the larger the aggregate supply of the commodity itself (q_j) and the larger the aggregate supply of all other commodities, Q_{-j} , that she can pool together from the local market. According to Emran and Shilpi (2002) the existence of fixed costs and externalities implies that there could be multiple equilibria associated with different levels of market development. Three distinct stages of market development can be discerned in developing countries.

In the first, rural markets are isolated, market clearing occurs at the local level, marketable surpluses are very low and economies are virtually absent. In the second stage, long-range marketing intermediaries are in operation but need to pull together multiple commodities to cover the fixed costs. The third and final stage involves marketable surpluses that are large enough for each commodity to permit commodity-wise specialization. Thus, the last stage is associated only with own externalities. The stage at which a particular market is will directly affect the impacts of the withdrawal of state buying stations from rural areas and other forms of market restructuring that cause price relationships to be influenced by high fixed costs of trading. For most developing countries, this knowledge may be important

in explaining the performance of the market and in arriving at informed and practical policy instruments to accelerate market development.

The price spread can be negative, equal to zero, or positive. Just over 82% of the local-destination market combinations had positive price spreads in our sample. In general, trade will flow from the local market to the destination market if $p_j^c - p_j$ is greater than zero and sufficiently large to offset the marketing costs involved. Equation (1) can be operationalized in two alternative frameworks, depending on the assumptions made about the behaviour of trade flows for the commodity in question when the price spread is negative. Considering that local markets are generally regarded as centres of production and district markets as demand points, it is traditional to assume that no trade will be observed when $p_j^c - p_j < 0$, rendering the dependent variable censored at zero. This fits the description of a variable that can be modelled with a Tobit model. Because of the need to account for unobserved market heterogeneity, we use an unobserved effects Tobit specification.³

$$y_{it} = \max(0, \mathbf{x}_{it}\boldsymbol{\beta} + c_i + \varepsilon_{it}), \quad (2)$$

where $y_{it} = p_{it}^c - p_{it}$ is the price spread between the destination market and the i^{th} local market, or CSA, in time t , $c_i \sim (0, \sigma_c^2)$ is an unobserved, time-invariant local market effect, $\varepsilon_{it} \sim (0, \sigma_\varepsilon^2)$ is the idiosyncratic random error term, \mathbf{x}_{it} is a vector of explanatory variables containing all the relevant elements on the right-hand side of equation (1) plus regional and time dummy variables, and $\boldsymbol{\beta}$ is a parameter vector to be estimated.

Alternatively, if we assume that enough effective demand exists in the rural markets so much so that trade reverses when $p_{it}^c - p_{it} < 0$, then the dependent variable in equation (1) is uncensored, leading to a more traditional unobserved effects linear regression model:

$$y_{it} = \mathbf{x}_{it}\boldsymbol{\beta} + c_i + \varepsilon_{it} \quad (3)$$

where $y_{it} = p_{it}^c - p_{it}$, \mathbf{x}_{it} , c_i , ε_{it} , and $\boldsymbol{\beta}$ are as defined in equation (2). It is important to recognize in this case that the relationship could be different when $y_{it} > 0$, compared to when $y_{it} \geq 0$. Thus, we include a trade dummy variable in \mathbf{x}_{it} equal to 1 if $y_{it} \geq 0$, and zero otherwise. Models (2) and (3) are non-nested as neither is a special case of the other. While equation (3) is linear in the parameters, equation (2) is inherently non-linear.

Two aspects complicate the identification of the own and cross externalities: endogeneity of explanatory variables due to simultaneity; and the omitted variable problem due to unobserved individual effects. Endogeneity is not expected to be a big problem because our model is at a level higher than the household – at the local market or CSA level. However, care was taken to ensure that the right-hand-side variables were appropriately defined (see variable construction sub-section below; and Table 1).

Panel data models are based on the premise that most of the omitted variables are individual-specific and time-invariant, represented in the standard panel data model by an unobservable variable, c_i . Two frameworks can be used to

operationalize models that include unobserved heterogeneity. One assumes that c_i is a random variable that adds to the random error term, and the other assumes it is a parameter that needs to be estimated. The random effects framework is the most efficient if the unobserved effect is not correlated with the explanatory variables, $\text{Cov}(x_{it}, c_i) = 0$, but is inconsistent if significant correlation exists. The fixed effects FE estimator is usually the most practical way to control for time-constant unobservable characteristics, since doing so requires no assumption regarding the correlation between observable determinants, x_{it} , and unobservable heterogeneity, c_i . However, in our case this is problematic since the FE tobit estimator is known to be inconsistent (Wooldridge, 2002).⁴ The FE estimator also has the disadvantage of not permitting estimation of the individual time invariant effects, both observed and unobserved.

We use the more general correlated random effects estimator (Chamberlain, 1984; Mundlak, 1978), which explicitly accounts for unobserved heterogeneity and its correlation with observables, while yielding a fixed-effects like interpretation. The correlated random effects (CRE) estimator, unlike standard random effects, allows for correlation between c_i and x_{it} across all time periods by assuming that the correlation takes the form $c_i = \alpha + \bar{x}_i\gamma + a_i$,⁵ where \bar{x} is a vector of time-averaged data on time-variant elements of x_{it} , $t=1, \dots, T$, α and γ are parameters to be estimated, and a_i is an error term with a normal distribution, $a_i | x_i \sim N(0, \sigma_a^2)$.⁶ In practice a reduced form of the model is estimated where τ is absorbed into the intercept term and \bar{x}_i are added to the set of explanatory variables. A Wald test rejected the hypothesis of zero correlation ($H_0 : \gamma = \mathbf{0}$) between unobserved heterogeneity and explanatory variables indicating that the CRE approach is superior to the pooled or random effects estimators. Pollack and Wales' (1991) likelihood dominance criterion (LDC) was used to identify between the two alternative models (Equation 2 and Equation 3) the one that best fits our data.

The random effects tobit procedure in Stata, which uses an adaptive quadrature approximation to the likelihood integrated over the random effect $a_i | x_i \sim N(0, \sigma_a^2)$, was used to jointly estimate $\theta = \{\alpha, \beta, \gamma\}$, σ_a^2 and σ_ε^2 . A quadrature check using indicated that the approximation was very stable with relative differences as low as 10^{-9} % when the number of quadrature points was varied. As a way to check the robustness of the estimates of the random effects tobit model, a pooled tobit model was also estimated. Heteroskedasticity, found to be significant by the Breusch-Pagan/Cook-Weisberg test ($\chi^2_{(1)} = 13.74$; p - value < 0.001), was corrected by using heteroskedasticity-consistent standard errors.⁷

We used the value of the log-likelihood out of the cross-sectional time series FGLS to do a model selection test with Pollack and Wales' (1991) LDC. In both equations (2) and (3), the validity of the CRE specification was tested by testing the hypothesis that $H_0 : \gamma = \mathbf{0}$ (Wooldridge 2002). Variance inflation factors (VIFs) showed that multicollinearity was not a major problem in our data. With the exception of own and cross externality variables, which had VIFs between 6 and 8, the rest of the variables had VIFs that were less than three, all of which were comfortably below the cutoff point of 10. The mean VIF across all variables was also only equal to about two.

Marginal effects

Because the Tobit model is inherently nonlinear in the coefficients, its estimated parameters do not by themselves represent the marginal effects of the explanatory variables on the dependent variable. Instead, the marginal effects are functions of both the parameters and the data. Skipping the algebraic details, it has been shown that the marginal effect of a variable x_{it} on the dependent variable y_{it} can be computed (McDonald and Moffit, 1980; Shapiro et al., 1990; Wooldridge, 2002; Greene, 2000) as:

$$\frac{\partial E(y_{it})}{\partial x_{it}} = \Phi(z_{it}) \frac{\partial E(y_{it} | y_{it} > 0)}{\partial x_{it}} + E(y_{it} | y_{it} > 0) \frac{\partial \Phi(z_{it})}{\partial x_{it}} \quad (4)$$

where $\Phi(z_{it})$ is the standard normal cumulative distribution function evaluated at $z = \frac{\mathbf{x}\beta}{\sigma}$, $E(Y_{it})$ is the unconditional expected value of y_{it} , and $E(y_{it} | y_{it} > 0)$ is the expected value of y_{it} given that y is above zero. Equation (4) implies that the overall effect of a small change in an explanatory variable can be decomposed into:

- a) the change in the price spread in those markets with positive price spreads, weighted by the probability of the price spread being above zero; and
- b) the change in the probability of the price spread being above zero, weighted by the expected value of the price spread when in fact it is above zero

This ability to unpack the overall effect makes it easier to interpret the marginal effects and has an inherent intuitive appeal.

Data sources and variable construction

This study used a number of data sources to empirically estimate equations (2) and (3). Key among them was a nationally representative two-period panel data set on Zambia's smallholder farmers. The panel dataset consists of 2001 and 2004 supplemental surveys to the 1999/2000 post-harvest survey. The two surveys, conducted by the Zambia Central Statistical Office (CSO) with financial and technical support from Michigan State University's Food Security Research Project (FSRP), were administered to the same ($n=6,922$) households in 2001 and 2004, respectively. The two surveys were based on a sample that was drawn using a multi-stage cluster sampling scheme in which Census Supervisory Areas (CSAs) were selected within districts, and standard enumeration areas (SEAs) were selected within CSAs, both using probability proportional to size (PPS). Households within SEAs were selected using systematic random sampling.⁸ The two surveys collected a wealth of agricultural, economic, and socio-demographic information on the smallholder households and their local markets, including crop production and sales, livestock production and sales, income from vegetable and fruit sales, expenditure on staple food crops, off-farm incomes, and remittances.

Several local market-level variables were constructed from the household data contained in these longitudinal household surveys. Because sufficient observations

were sometimes lacking at the SEA level, the CSA was used to represent the local market.⁹ There were 198 local CSA-level markets in both marketing years of the analysis, 2000/01 and 2003/04. Crop prices in the local markets, p_j , were estimated as the median of the prices received by the individual households in the CSA, where for each commodity the household-level price was taken as the price received at the largest sale.¹⁰ Over 80 % of these transactions occurred within the first 4 months after harvest. As prices were reported in volumetric terms (per 50 kg bag, per 90 kg bag, per 20 litre tin, etc.), standard conversion factors were used to convert them to standard weight units (per kg).¹¹ Because of the fact that we use two time periods, the nominal prices were converted to their real equivalents.¹² Surpluses of the commodity of interest (own externality variable, q_j) and surpluses of all other field crops (cross externality variable, Q_j) were computed as the sum of individual household surpluses divided by the number of producers in the CSA. While q_j was measured in metric tons (per capita) Q_j , was measured in monetary terms as the latter involved aggregating over many different commodities. All monetary variables derived from survey data were normalized in terms of 2004 Kwacha and then converted to 2004 US dollars (US\$) to facilitate interpretation of the estimated marginal effects.

The unit cost of moving commodities from the local market to the nearest destination market was represented in our empirical specification by the vector d_j , which comprised variables such as median wage rates, median land rental cost, and the distance to the nearest district town. In addition to explicitly taking the CSA-level heterogeneity into account through c_i we also account for the fact that districts are unique in their market infrastructure endowment, proximity to major market outlets such as Lusaka, agro-ecological conditions, and several other aspects, by including district dummy variables.

Table 1. Descriptions of variables used in the empirical models

Variable	Variable description
Rpsp	Farm-retail price spread (US\$/metric ton)
Medec	Median expenditure on staple foods ('000 US\$)
Aqci	Per capita maize sales in metric tons (own externality)
Vaqqci	Sales of all other crops in '000 US\$ per capita (cross externality)
Awagec	Average wage rate (US\$/hectare)
Arentc	Average rental charges (US\$/hectare)
Kmtown	Mean distance to the nearest town (kilometre)
Trade	Trade dummy variable, 1=positive price spread

Notes:

All monetary values are in 2004 US\$

To compute the price spreads, the destination markets had to be defined and the consumer price data in those markets had to be collected for the relevant

reference periods (2000/01 and 2003/04). We define the destination market relevant to each local market, or CSA, as the nearest district centre. In most cases, this is the central market for the district in which the CSA is located. The CSO routinely collects retail price data for agricultural commodities in 38 of the country's 72 districts. We used these retail price data in the district market centres to compute p_j^c . This study uses district-CSA combinations as the unit of observation. However, a balanced panel was only possible in 33 districts and 198 CSAs. With two years of data per CSA, our total sample size was 396 CSA-District combinations or observations.¹³

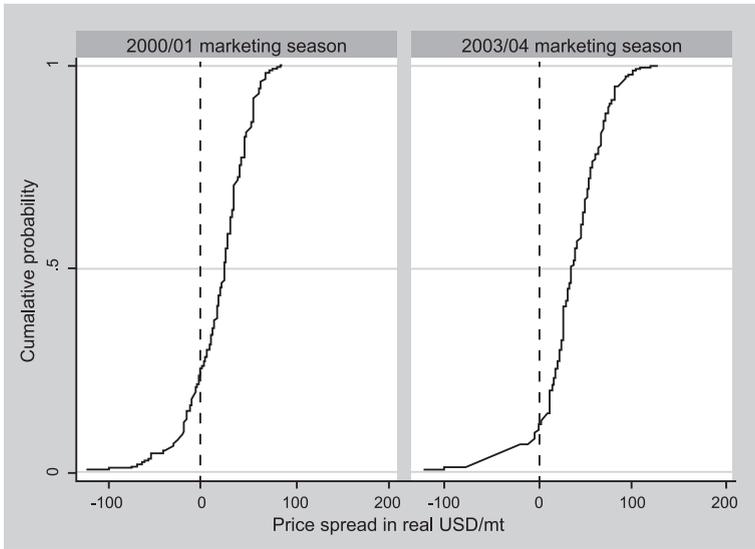
As most of the sales of food crops take place during May through October, the monthly district prices were averaged over this period for both 2000 and 2003. The price spread between the district mean retail price of maize and the median producer price in the relevant *i*th local market or CSA in time period *t* was then computed as $y_{it} = p_{it}^c - p_{it}$.¹⁴ Table 1 summarizes the variables used in the empirical analysis and their descriptions.

4. Results and discussion

Increasing returns in marketing may arise due to high fixed costs that traders face in establishing contacts and transactional relationships necessary for operating in a particular area. Bonaccorsi and Giuri (2001) stress that traders cannot effectively participate in a market without making heavy investments in relational activities. In the presence of these and other initial investments that cause high fixed costs for traders, their per unit costs of marketing are expected to decline as the volumes of trade rise.

Figure 1 presents cumulative distribution functions for the maize real price spread in the two reference marketing seasons (2000/01 and 2003/04). The graphs confirm that the bulk (at least three quarters) of the 198 local markets under study had lower prices than their nearest district centres, a clear indication of the possible existence of incentives to export surplus production. In the 2003/04 marketing season, the proportion of local markets with positive farm-retail price spreads was as high as 90%, compared to 75% in 2000/01. This trend is consistent with the policy thrust towards progressively greater public sector involvement in the maize subsector. Policy instruments such as fertilizer subsidies and output price supports have created artificial incentives even in areas that are not agro-ecologically or economically suitable for maize production (Tembo et al., 2009).

Figure 1. Cumulative distribution function for district-local market maize price spread in Zambia



Descriptive statistics from the survey data indicate a significant reduction in the rural households' reliance on purchases as a means to obtain staple food crops. While on average a household purchased US\$430 worth of staple food crops in the 2000/01 marketing season, in 2003/04 it purchased only US\$170 worth (Table 2). The shrinking numbers of maize deficit local markets seem to discredit empirical estimation strategies that imply bidirectional trade flow of surplus maize, including that from district centres to rural local markets.

Table 2 presents a number of other descriptive characteristics for the markets under study, comparing across trade direction stratum (communities with positive farm-retail marketing margins versus those with negative ones) for each of the two marketing seasons. In general, local markets with positive farm-retail maize price spreads do not differ significantly from those with negative marketing margins. Only land rental charges were significantly higher among positive-margin markets in the 2003/04 season. This could be an indication of increased demand for land triggered by increased public support.

Table 2. Descriptive characteristics of Zambian local maize markets, 2000/01 and 2003/04 marketing seasons

Variable description	2000/01 marketing season		2003/04 marketing season		Market with negative price spread	Markets with positive price spread
	Overall	Markets with negative price spread	Markets with positive price spread	I		
	(1)	(2)	(3)	(4)		
				Mean		
Median expenditure on staples (000 US\$)	0.43	0.33	0.46	0.17	0.18	0.17
Per capita maize sales (mt)	0.61	0.63	0.60	0.59	0.57	0.59
Sales of all other crops (000 US\$ per capita)	0.06	0.07	0.05	0.10	0.12	0.09
Average wage rate (US\$/ha)	44.65	42.04	45.46	26.39	24.63	26.60
Median land rental cost (US\$/ha)	49.68	55.75	48.09	28.78	24.24	29.35**
Mean distance to the nearest town (km)	33.25	34.45	32.88	33.83	29.48	34.37

Notes:

Significance of mean differences (t test): *=10%, **=5%, ***=1%

All monetary values are at constant prices (2004=100)

Table 3 presents the regression results for the correlated random effects linear model with panel- and heteroskedasticity-corrected standard errors (Column 1), and the CRE tobit model (Column 2). Both models represent a very good fit of the data as indicated by goodness-of-fit Wald χ^2 statistics of 822 and 349, respectively (p-values < 0.001). The null hypothesis that the time-averages of time-varying variables are collectively not different from zero (the Mundlak-Chamberlain hypothesis, $H_0: \gamma = \theta$) was strongly rejected with p-values less than 0.01 in both models. This suggests that time-varying unobserved heterogeneity was severe. However, the contribution to the variance by the unobserved market effects, σ_a^2 , was not significant as demonstrated by a failure to reject the null hypothesis that $H_0: a_i = \theta$.

From Model I (Column 1), it is also clear that the relationship between the price spread and the explanatory variables is significantly different between markets with positive spreads and those with negative ones. On average, urban (district)-rural (CSA) price spreads markets are wider by USD 60.2 in markets that have positive margins wider price margins than markets with negative price spreads (p-value < 0.001).

Table 3. Regression Results for the Maize Price Spread (US\$/mt) Between District Markets and Rural Local Markets, 2000/01 and 2003/04 Marketing Seasons

Variable description	CRE tobit marginal effects			
	Correlated random effects (CRE) linear model	CRE tobit-- parameter estimates	$\frac{\partial E(y_{it} y_{it} > 0)}{\partial x_{it}}$	$\frac{\partial \Phi(z_{it})}{\partial x_{it}}$
	(1)	(2)	(3)	(4)
Intercept	1.958 (7.28)	73.58*** (6.58)		
Median expenditure on staple foods ('000 US\$)	-1.058*** (0.31)	-1.275*** (0.42)	-0.767	-0.014
Per capita maize sales in metric tons (own externality)	-4.993** (2.26)	-11.66*** (2.78)	-7.122	-0.125
Sales of all other crops in '000 US\$ per capita (cross externality)	41.12*** (14.0)	31.53 (21.8)	19.039	0.335
Average wage rate in US\$/hectare	-0.213** (0.086)	-0.473*** (0.098)	-0.294	-0.005
Mean distance to the nearest town (km)	0.0684 (0.058)	0.102 (0.067)	0.064	0.0011
Trade dummy variable, 1=positive price spread	60.19*** (3.36)			
<i>Joint tests of significance (Wald Chi-square)</i>				
District dummy variables	133.59***	216.55***		
All time-averaged variables (H0: $\gamma = 0$)	32.56***	36.72***		
Goodness of fit Wald	822.79***	349.39***		
Number of observations	396	396		
Number of local markets (CSAs)	198	198		
Log-likelihood	-1,598a	-1,567		
R-squared	0.67	-		

Heteroskedasticity-corrected standard errors in parentheses; Significance levels: * = at 10%, ** = at 5 %, ***= at 1 %.

Model selection tests based on Pollack and Wales' (1991) likelihood dominance criterion (LDC) indicated that the CRE tobit specification fits the variation in price spreads 30 times better than the linear model.¹⁵ This result strongly suggests that the flow of trade is largely unidirectional from local communities to district central markets and that little trade is observed when the price spread is negative.

Both models indicate that own externality effects are inversely and significantly related to the price spread (p -value < 0.05). That is, the larger the aggregate maize surpluses produced by farmers in the local communities, the lower the gap between p_{ii}^c and p_{ij} . A plausible explanation for this finding is that, other things being equal, the presence of larger crop surpluses in a community reduces traders' per unit transaction costs, thereby providing them with incentives to offer a relatively more attractive price to local farmers. Based on Model I, an increase in maize aggregate supply in the local markets by 1 metric ton would lead to a narrowing of the price spread by US\$ 4.99 per metric ton. The marginal effects of the CRE Tobit model indicate that a one metric ton increase in maize aggregate supply would reduce the probability of the price spread being above zero by 0.125 (or 14.8%) while reducing the expected price spread by US\$ 7.12 per metric ton for those local markets with $p_{ii}^c - p_{ii} > 0$. This margin-reducing effect may help to induce virtuous cycles, in which lower price spreads are likely to translate into farmers supplying more of the crop into their markets, which then has additional margin-reducing effects.

Cross externality effects are significant only in the CRE linear model (p -value < 0.001) but not in the CRE tobit model. Moreover, the positive sign observed in the coefficient of the cross externality effect seems to suggest the existence of scope diseconomies. This could be due to the challenges associated with handling multiple commodities (e.g. quality verification for multiple commodities). That is, there does not seem to be scope for combining maize with other field crops as a way to reduce transaction costs. Rather, the existence of significant margin-reducing own-externality effects and scope diseconomies implies that the market for maize is highly specialized. This is consistent with what Emran and Shilpi (2002) found about the rice market in Bangladesh. It also appears that areas that are big producers of alternative field crops are not really producers of maize surpluses; so much so that in areas where large surpluses of the former are present, maize is insignificant and vice versa.

However, rural areas with active local markets for staples – represented here by the median per capita expenditure on staple crops – have lower margins than do those without significant effective local demand. This makes sense as larger effective demand is expected to raise local prices as well as to stimulate trade with outside markets. According to the CRE linear model (Model I), an increase in the median expenditure on staple food crops of US\$1,000 will narrow the margin by US\$1.06. The CRE tobit model (Model II) shows that a US\$1,000 increase in median expenditure on staple foods would reduce the probability of the price spread being above zero by 0.01 (or 1.2%) while reducing the expected value of the price spread for those markets with positive price spreads by US\$ 0.77.

5. Summary and conclusions

This article was motivated by the need for a better understanding of the existence and effects of increasing returns to marketing in developing country agriculture. Increasing returns in marketing may arise due to high fixed costs that traders face in establishing

contacts and transactional relationships necessary for operating in a particular area. The presence of increasing returns would mean that low production surpluses in rural farming areas may prevent the achievement of scale economies in marketing, and contribute to a reinforcing state of underdevelopment in which traders' costs are increased by low marketed output, and farmers' incentives to expand production for the market are in turn impeded by high marketing costs. The presence of increasing returns to marketing – i.e., marketing margins decline when local marketed surpluses rise – has often been assumed to exist but has rarely been verified or quantified using household survey data from developing countries.

The article used a combination of household panel survey data and market price information to investigate the presence of increasing returns to marketing in an area of Africa characterized generally by weak infrastructure and high fixed costs of trading. It extends the work on this topic by Emran and Shilpi (2002) in two ways. First, using maize price data from rural communities and district markets in Zambia, we were able to directly estimate the impact of increased community-level farm surpluses on the size of farm-retail price spreads while controlling for unobserved market heterogeneity.

Results indicate significant own externality effects and insignificant cross externality effects, implying that the Zambian maize market is substantially specialized. That is, variations in the level of surplus production of other crops have little effect on maize price spreads. Traders do not need - or are not able - to bulk maize with other crops to meet the desired surpluses to reduce the costs of maize trading. Yet the finding that variations in the level of surplus maize production in a particular assembly market is associated with lower price spreads between that market and the nearest urban wholesale market suggests a possible virtuous cycle. Efforts to raise and/or bulk up production surpluses within a market shed could reduce marketing margins and provide further incentives for small farm commercialization. Also, the fact that unobserved market effects exert significant systematic influence on the marketing margins highlights the need to fully identify those sources of market heterogeneity in the design of market interventions.

Despite their mixed record in many parts of the world, farmer cooperatives and other forms of collective action may play an important role in helping to overcome transaction cost-related impediments to the development of rural commodity markets. By bulking up the small surpluses of geographically scattered farmers, these marketing arrangements at least theoretically have the potential to reduce the transaction costs that traders face in serving such areas, which may allow upward pressure on producer prices in competitive markets. However, our results indicate that for the case of rural maize markets in Zambia, such bulking initiatives would be most successful if they are commodity-specific. The extent to which this is the case in other developing areas remains an issue for further investigation.

Notes

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1. Different behaviours and different types of institutions – or rules of the game – emerge in the market with the aim of helping to minimise transaction costs by promoting trust, reputation and social capital (Gabre-Madhin, 2001; Bonaccorsi and Giuri, 2001).
2. These issues are important in countries that are characterised by millions of small farmers producing small surpluses, because the presence of increasing returns in marketing could warrant collective action and other institutional arrangements for aggregating supplies to reduce the transaction costs of coordination between farmers and marketing firms.
3. Suppressing, for clarity's sake, the indices for the crop, j , and for the destination market.
4. This results from what is known as an incidental parameters problem. For a thorough discussion see Wooldridge (2002:483-5).
5. An alternative is to have X_i in place of \bar{X}_i in the linear expectation of the conditional distribution $c_i|X_i$ (Chamberlain, 1982, 1984); we use \bar{X} (Mundlak, 1978) to conserve on parameters. For linear models, such as 3, the CRE estimator of coefficients on time-variant regressors are mathematically identical to the fixed effects estimator, which is why we describe them as "fixed-effects like" in the non-linear case.
6. The CRE estimator is efficient, unbiased, and consistent but only under the assumption of strict exogeneity of regressors. Thus, only the time-averages of all but d_{it-1} are included in \bar{X}_i .
7. A modified Wald test for group-wise heteroskedasticity also confirmed the presence of group-wise (or CSA-wise) heteroskedasticity (p -value < 0.001). Tobit models are inconsistent in the presence of heteroskedasticity.
8. In total, Zambia has 72 districts, 4,400 CSAs and 17,000 SEAs.
9. The CSA, and not the SEA, was the preferred unit as it provided a good sample size from which to estimate local prices and other community variables.
10. Although the government sets prices, not all smallholder farmers actually sell at those prices. This article uses actual prices received by the smallholders as the local market prices and district market prices (collected monthly by the CSO) as retail prices. Preliminary analysis indicates that there is a lot of variation in both these price series
11. Typically, the two surveys collected volumes and prices as much as possible exactly the way the respondent said them. For example, the respondent could say he sold each 20-litre tin of maize at ZMK25,000. That 20-litre tin is just a container and says nothing about the weight of the maize when it is full. To obtain the weight in kilogrammes, we used a table of standard conversion figures developed by the FSRP. The conversion lookup table, which was developed by taking actual weights for different crops and different containers from around the country, relates all the possible containers in which each crop is sold to the average weight in kilogrammes when it is full.
12. The CPI was used as a proxy for the producer price index (PPI) due to data limitations on the latter.
13. There were a little over 11 CSAs sampled per district.
14. Again suppressing the crop index j .
15. With 32 district dummy variables and 12 other variables, the Tobit model had a parametric size (number of parameters) of 44. Because the linear model had an additional parameter to estimate for the trade dummy variable, it had a parametric size of 45. Thus, taking $n_2 = 45$ and $n_1 = 44$ and given the log likelihood values in table 3, it can be shown that $L_2 - L_1 = -30.874$ and that the lower and upper bounds of the LDC are (0.588, 1.075). Thus, the hypothesis with a smaller parametric size (H_1 : Tobit) is preferred and the other (H_2 : Linear) is rejected.

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