Incomplete Credit Markets and Commodity Marketing Behavior*

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Abstract

Seasonal market participation patterns for smallholder farmers in western Kenya indicate that a significant proportion follow a 'sell low, buy high' marketing strategy, in which these households forego opportunities for intertemporal price arbitrage through storage and are observed to sell output post-harvest at prices lower than observed prices for purchases in the subsequent lean season. We use data from the region to examine whether this behavior can be partly explained by the presence of a binding liquidity constraint for these farmers. We estimate a multi-period market participation model in the presence of liquidity constraints and transactions costs using maximum likelihood. Access to credit and off-farm income indeed seem to influence crop sales and purchase behaviors in a manner consistent with the hypothesized patterns. JEL Codes: O13, O12, Q12, D91

Regular, sharp seasonal price fluctuations are a common characteristic of staple grains markets in many developing countries. Yet many farmers appear not to take advantage of the apparent intertemporal arbitrage opportunities created by predictable seasonal price variation in storable commodities. Instead, they often sell their output at low prices post-harvest and buy back identical commodities several months later for prices far higher than they received post-harvest.[1]

Several candidate reasons exist that might explain this 'sell low, buy high' puzzle, which is clearly at odds with unconstrained, intertemporal profit-maximizing behavior (on which, see Williams and Wright (1991)). First, impatience could lead to very low storage rates of staple commodities. However, seasonal price increases often so far exceed prevailing local interest rates that this explanation frequently seems implausible. For example, in Kenya in the 2002-2003 crop year the mean annual change in maize prices across three large market centers (Bungoma, Kisumu and Nairobi) was 44%, while the mean bank deposit rate was only 5% (IGAD, Central Bank of Kenya). Given such patterns and continuous household demand for basic grains for survival, it seems implausible that discount rates could be high enough to broadly explain the sell low-buy high puzzle.

Second, appropriate storage technologies might not be available, raising intertemporal storage costs to the point that storing output for future sale becomes unprofitable. But even at high inter-seasonal storage loss rates of 10-30%,[2] the preceding argument still applies; one would need an implausibly high discount rate to make 'sell low, buy high' an attractive strategy. Moreover, given the predictability of sharp seasonal price increases and the availability of inexpensive grains storage technologies that reliably exhibit annual loss rates of only 1-2% (Barrett 1997), there would seem to be high returns to investment in better household-level storage technologies that would obviate such explanations. Furthermore, we routinely observe households investing in retaining calves or other not-yet-productive livestock, in children's education that will pay off only with a long lag, and in other ventures; thus there is plainly a general willingness to invest, just not necessarily in holding grains stocks interseasonally. The low storage quality explanation of 'sell low, buy high' marketing patterns therefore also seems implausible.[3]

A third possible explanation for low storage demand could be longer term concerns about price risk over several growing seasons. However, Saha and Stroud (1994), Barrett and Dorosh (1996) and Park (2006) have all explored the role of grain storage as a price hedge *ex ante* and find analytical and empirical support for storage patterns that run contrary to the 'sell low, buy high' puzzle; they show that price risk aversion should generate excessive, rather than insufficient, stockholding post-harvest.

An alternative class of explanations unexplored to date in the literature is that the 'sell low, buy high' phenomenon represents a 'displaced distortion' (Barrett 2007) arising due to financial markets failures that people implicitly resolve through seemingly-irrational resource allocation patterns. If people have no other means of addressing temporary liquidity constraints, they might find it optimal to convert non-cash wealth in the form of grains into cash, even knowing that they will need to buy back grain later at a higher price, with the associated losses representing the de facto interest rate on a quasi-loan for several months. In this paper, we examine this hypothesis with recently collected seasonal marketing data from a sample of 1682 maize farmers in western Kenya. By modifying a multivariate market participation model to examine the correlates of both purchases and sales, we find that access to credit does affect market participation as hypothesized, while controlling for other possible alternative explanations.

Household Seasonal Market Participation

We assume that households in our sample optimize their consumption and production decisions using the basic agricultural household framework (Singh, Squire, and Strauss 1986), but allow for time-varying market prices, transactions costs and a possible liquidity constraint.[4] The household's solution to their intertemporal optimization problem results in consumption smoothing over time for both goods and in a system of output supply and consumption demand equations that are functions of current and expected future prices, as well as current and future realizations of income and fixed factors of production. Current consumption is decreasing in all own prices as well as in the ratio of current to expected future own prices, and increasing in current and future incomes, and supply is increasing in current and future prices.

In the presence of transactions costs, the household's demand and supply functions for agricultural output described above define its time-varying shadow price for grain, which forms the base-case for the market participation decision (Key, Sadoulet, and de Janvry 2000). If shadow prices fall below current market prices, net of transactions costs, it is worthwhile for the household to enter the market as a seller, while upward spikes in shadow prices induce the household to buy grain in the market, rather than remain in autarky. Under unconstrained conditions and predictable seasonal grain price patterns, household grain demand should increase during harvest periods, due to the current relative abundance of grain and the expectation of higher future prices, while during lean periods, household grain demand should fall. Assuming constant transactions costs, under these conditions, if the household participates in the market at all, it should engage in canonical intertemporal arbitrage, buying during the low-price harvest season, selling during the higher-price pre-harvest season, or both.

However, under a binding liquidity constraint, household grain demand will fall in the harvest season. This is due to the fact that, with the constraint, it is no longer possible to perfectly smooth consumption across time periods. Thus, the current marginal utility of grain consumption rises, but the household has insufficient resources to satisfy demand. The resultant 'stockout' behavior (Deaton 1991) reduces the household's internal shadow price for grain. If this effect is significant enough, a household may optimally sell grain during the harvest period, even knowing that future prices may rise. Then, after a household stocks out of its own grain stores, it will be forced to purchase grain in the market to satisfy basic consumption demands. This will likely occur at higher prices, given the overall seasonal patterns at play. The key point to note about the effect of liquidity constraints on household demand is that when the constraint binds, future prices and future income no longer affect consumption choice because optimal stock-out breaks the linkage. The household consumes all of its available resources, irrespective of expected change in prices over time. Because the liquidity constraint disrupts equilibration of marginal utility across periods, it likewise obviates the standard intertemporal arbitrage conditions that guide household behavior. Hence the basic intuition behind our model of the 'sell low, buy high' phenomenon: that liquidity constrained households may optimally sell when prices are low not because they do not recognize predictable seasonal appreciation in the value of storable grain stocks but, rather, because their current income and expenditure needs force liquidation of their entire asset stock, rendering intertemporal arbitrage opportunities moot.

The presence of physical grain storage in the model does not change this fundamental point. When there exist both physical and financial assets, the household can choose the form in which to hold its wealth: either as cash savings or as stored grain. The optimal asset allocation then depends on the relative returns to different assets, on risk preferences, etc (Park 2006). This does not change the fundamental, qualitative result of the preceding analysis: a binding liquidity constraint makes storage–whether in cash or in kind–less likely. The value of stored grain is proportional to the marginal value of cash over time. As consumption falls when the liquidity constraint binds, the current marginal utility of consumption increases, making storage so as to increase expected future cash returns less likely.[5]

It is important to note that 'sell low' behavior is surely not a ubiquitous condition but may occur with some frequency due to some combination of a poor harvest, highly inelastic demand for non-grain items such as school fees, medical or ceremonial (e.g., funeral, wedding or religious festival) expenses, or debt repayment obligations, each of which effectively reduces discretionary income. Higher income households would thus be less likely to sell at post-harvest lows and those with extraordinarily high non-discretionary expenses or debt repayment burdens would be most likely. The 'buy high' phenomenon, in contrast, depends upon reduced latent grain supplies coupled with high lean season prices. This is especially likely if households stop holding grain stores and stock out due to a binding credit constraint. In the case of individual households, the liquidation of household stores to satisfy consumption requirements can lead to extreme spikes in the household shadow price for grain. If this occurs in the lean season, which seems likely due to primary income realization in the harvest period, then it can be enough to push credit constrained households to become grain purchasers, despite prevailing high prices. Thus the effect of the credit constraint is transferred to market participation behavior throughout the time between harvest realizations and can lead to rational sales at low prices and subsequent purchases of the same commodity at higher prices. The scenario presented above brings into stark relief the quite distinct expected grain marketing choices of liquidity constrained and unconstrained households.

Estimation Strategy

The hypothesized relationship between liquidity and market participation suggests clear, testable hypotheses. By reducing latent household demand in the harvest period, liquidity constraints should decrease the likelihood of (low price) harvest season purchases and increase the likelihood of (low price) harvest season sales. Further, households that experience harvest period liquidity constraints should also be more likely to undertake (relatively expensive) lean season purchases and less likely to undertake (high price) lean season sales. We can thus empirically explore the liquidity constraints explanation of the 'sell low, buy high' puzzle by testing those hypotheses.

The econometric challenge is that transactions costs create unobserved market participation thresholds, shadow prices are unobservable, market participation behaviors are surely correlated within (i.e., between autarky, buyer and seller status) and across seasons for a given household, and transaction volume decisions are not independent of households' self-selection into the market. One needs to employ an estimation strategy that will address these thorny issues. Yen's (2005) multivariate sample selection model (MSSM) is a switching estimator that allows for simultaneous estimation of separate parameters across multiple market participation equations with potentially correlated error structures.[6] In our case, we apply the MSSM to the market entry and quantity decisions for maize grain sales and purchases in both a harvest and a lean season, i.e., to a system of four market entry decision equations and four censored market quantity equations per household i that can be summarized as follows:

$$
\begin{aligned}
&Entry\ Decision\ Vector = K_{sn,i} = \{k_{HP,i}, k_{HS,i}, k_{LP,i}, k_{LS,i}\} \\
&Marketed\ Quantity\ Decisions = Q_{sn,i} = \{q_{HP,i}, q_{HS,i}, q_{LP,i}, q_{LS,i}\} \\
&k_{sn,i} = \{0, 1\}, s = \{harvest\ season(H), lean\ season(L)\}, \\
&n = \{purchase(P), sale(S)\}
\end{aligned}
\tag{1}
$$

The entry decision is assumed to depend upon the (time-invariant) covariates that influence the shadow price through latent demand or latent supply as well as factors influencing the household specific fixed transactions costs that impact the size of the price band around the market price (Key, Sadoulet, and de Janvry 2000). The marketed quantity decisions (conditional upon entry) are also functions of the factors that influence household latent demand and supply, as well as the (time-varying) market prices net of any proportional transactions costs for the particular type of market participation it chooses as optimal.[7] The full specification for the joint entry and quantity equations is therefore:[8]

$$
log(q_{sn,i}) = \begin{cases} x'_{sn,i}\beta_{sn} + \nu_{sn,i} & if\ z'_i\alpha_{sn} + u_{sn,i} > 0 \\ 0 & if\ z'_i\alpha_{sn} + u_{sn,i} \leq 0 \end{cases}
\tag{2}
$$

Both market entry and marketed quantities are random variables. Market entry is observed if the entry equation (shown as $z_i'\alpha_{sn} + u_{sn,i}$ in (2)) is greater than zero. If market entry is observed, then the quantity transacted in the market is given by $x_{sn,i}'\beta_{sn}+v_{sn,i}$. Both $u_{sn,i}$ and $v_{sn,i}$ are assumed to be mean zero, normally distributed random variables. If we let the concatenated vector of the entry and level equation error terms be represented by e, then the full variance-covariance matrix for the specification is an 8x8 matrix, composed of the variance-covariance matrices of the error terms in the market entry and level equations, both within as well as between these equations:

$$(3) \quad \sum_{8x8} = E(e'e) = \begin{bmatrix} \sum_{u'u} & \sum_{u'v} \\ \sum_{v'u} & \sum_{v'v} \end{bmatrix}, \quad e \equiv [u_{sn}, v_{sn}]$$

The full likelihood function is identical to that of Yen (2005).

The MSSM estimator was initially developed to identify significant covariates of household decisions to purchase consumer goods as well as the quantity purchased in censored demand systems. One identifies the market entry equation by incorporating covariates thought to affect the discrete market participation decision but not the conditional quantity choice. We use the MSSM estimator in a similar way in order to investigate the significance of household cash liquidity constraints on sales and purchases entry and quantity decisions in the harvest and lean seasons. We operationalize (the absence of) liquidity constraints using the ability to borrow (i.e., access to credit) and access to steady, significant cash flow associated with off-farm income from salaried or skilled employment (or self-employment). Off-farm income is included in our tests for the effect of liquidity since, in the absence of more formal borrowing, households with consistent cash flow from a salary may nonetheless also be able to avoid the ‘sell low, buy high’ marketing pattern as this income is likely readily available for non-market purchases (for example through holding cash savings). In terms of our model, households with a better ability to cover all consumption expenses adequately, either through readily available cash or borrowing, have incomes consistently above the threshold and therefore avoid such mis-timed marketing of their agricultural output. Finally, because access to credit is likely endogenous, we need to instrument for it before testing our core hypotheses. We identify the instrumenting regression for credit access using covariates likely to reflect lenders' costs of extending credit to a given household and other transactions cost measures associated with credit access but not with maize market participation. To separately identify the entry equation, theory implies that fixed transactions costs are associated with market entry, and should be irrelevant to the marketed quantity decision conditional on participation. We now explain the data and these variables.

Data

The data, collected by the Tegemeo Institute of Agricultural Policy and Development, come from a 2005 survey of 1682 households in 4 Districts across 137 villages in western Kenya and report on many aspects of household production, consumption and marketing behavior, including monthly purchases and sales (and associated prices) over the course of the past year (i.e. from July 2004 to June 2005).[9] The survey data also contain information on local commodity markets as well as market-based interventions like cereal banks, market information initiatives and a program designed to increase agricultural credit by extending credit to agricultural input retailers. So as to increase the observation of rare events (e.g., cereal bank membership), the survey design was choice-based rather than a strictly random sample. Therefore, all statistical analysis has been appropriately reweighted to account for the sampling design. Summary statistics appear in table 1.

Most farmers in the sample engage in rainfed agriculture, on farms of three acres or less. Households grow maize, the staple crop, and either sell or store it on the farm until it is either consumed or sold in the period between harvests. Typical storage facilities for maize are open bins constructed of wood or bamboo that are raised off the ground to protect the output from pests, or simply in bags inside the family home. In rare cases, a household will have a concrete storage area for grains. Households that belong to cereal banks store some of their output as a share contribution held at the cereal bank, which typically occupies a concrete structure in the local market place. However, the combination of these storage technologies appear to be sufficient to protect households from high storage losses, as over 87% of the maize growing households in the sample report zero losses of harvested maize due to spoilage and the average rate for those experiencing any losses was less than 8%.

Seasonal market participation

The data collected summarizes monthly marketing patterns for the households. However, to make the estimation more tractable and to limit the number of zero observations, we aggregated household market participation into a single, average harvest period and lean period. Kenya's western region has bimodal rainfall, with a 'long rains' season that runs from April to June (with long rains harvests beginning in July) and a 'short rains' season from October to November (with harvests from November to January). For this analysis, we divided the data into a broadly defined 'harvest period' (running from July to January) and a 'lean period' from February to June, although it technically encompasses two distinct growing seasons. We did this because survey data indicates that over 80% of the households had no stored maize grain at the time of the survey (which occurred at the end of the short rains season) and that most had run out during the month of February. Thus, the stock-out behavior we wish to study did not occur with great frequency in the period between the long and short rains season.[10] We then calculated an average sale and purchase quantity for each period for households that participated and used these averages in the market participation estimation. We also divided the off-farm income into seasonal averages, so that the estimation represents household average behavior for harvest and lean period transactions.

Lean season prices were higher than harvest period prices and the purchase price — sales price margin was greater in the harvest season as well (table 1 and figure 1); these seasonal differences are statistically significant. Given mean purchase-sales price differences, there was no money to be made by farmers who bought maize at harvest, stored it for a few months, and resold it in the lean season. But those who sold in the harvest season and bought maize back in the lean season faced an average loss of 29.3% (KSh17.393/KSh13.462) on the interseasonal terms of trade, far greater than prevailing local interest rates for those with access to credit. Hence the 'sell low, buy high' puzzle.

Yet many indeed follow that practice. Table 2 summarizes households' net maize marketing position per season. Most households were either net buyers of maize in both the harvest and lean seasons, or net buyers only in the lean season. But these pure net buyers aside, the most common pattern was 'sell low, buy high,' precisely the puzzling pattern we seek to explain. Nearly one in five households was a net seller in the low-price harvest season and a net buyer in the high-price lean season. Ten percent of the sample was autarkic in both periods, neither buying nor selling maize. Other combinations of seasonal purchase and sales behaviors were practiced by less than ten percent of the sample. Of the nearly 30% of the sample that were net sellers in the harvest period, an astonishing 62% were net buyers a few months later, raising the obvious question of why they would choose a nearly 30% loss on the maize they sold immediately post-harvest and then bought back in the lean season.

Household credit access

Households were asked about credit received (in cash or in kind) for agricultural inputs as well as any credit obtained for non-agricultural purposes. For non-agricultural credit, households were asked whether or not they tried to apply for a loan to cover any non-agricultural expense (like school fees or another similar item), whether or not they were successful in their application and how much they received. Due to the fungibility of credit, we created a single dummy variable indicating reported credit use, whether for agricultural or non-agricultural purposes. We use credit use as a proxy for credit access.

It is important to note that we cannot precisely distinguish the credit constrained from the non-constrained given the data available. More informal sources of credit, such as extended family or local community groups, are not covered by the data and we do not know if people who received credit were nonetheless quantity rationed in the volume received or if those who did not receive credit had no need for it. Our credit use variable is thus an imperfect proxy for the true variable of interest–(the absence of) liquidity constraints by virtue of credit access but is the best available, given the data.

To account for the possible endogeneity of the credit use dummy variable, we predict credit use probabilities for each household in the sample using a probit model instrumenting regression, and then use these predicted values in the second-stage MSSM model of market participation decisions. We follow Kochar (1997) and characterize this first stage equation as representing the difference between a household's marginal return from using credit and the marginal cost to a lender of providing it. We therefore include several household demographic variables and distance measures[11] to control for household credit demand as well as variables that are associated with potential household collateral (income and land owned) and monitoring (experience) that might reduce the costs of credit for lenders as identifying variables.

Table 3 shows the results of the first stage probit on credit usage. As one would expect, credit use is strongly and statistically significantly increasing in household income, in household labor endowments, longevity in the village, in the educational attainment of the household head. The identifying vector of distance variables is jointly statistically significant and generally exhibits the expected, negative point estimates, indicating proximity to places where one commonly finds (typically micro-) financial institutions in rural western Kenya fosters greater credit access. The one curious exception is distance to a health center, which is positively and significantly correlated with credit use, which likely reflects the low density of health centers in the region.

Econometric Results

As indicated previously, the core hypotheses of interest concern the coefficient estimates on our two variables reflecting household liquidity: predicted probability of credit use and household off-farm income.[12] With respect to the four market entry equations, we expect that household liquidity should reduce the probability of harvest period sales and lean season purchases, and increase the probability of harvest season purchases and lean season sales. The literature on market participation indicates parallel predictions with respect to the volume equations, although without detailed income data to fully control for income effects, we are less confident about those point estimates than about the market entry decision estimates. Tables 4-8 display the MSSM estimation results.[13]

The coefficient estimates on our two measures of liquidity, predicted credit access and off-farm income, jointly seem to confirm our hypothesis that households with sufficient access to liquidity successfully avoid selling low and buying high in the maize market. Credit use is associated with reducing the likelihood of market entry as sellers in the harvest period and off-farm income is associated with reduced likelihood of purchases in the lean period. Further, predicted credit use is significantly associated with an increased likelihood of harvest season purchases. The lack of significance for either liquidity measure on lean period sales is likely due to the fact that sample households are overwhelmingly net maize buyers and thus sales of any sort are not expected. The different forms of household liquidity have similar estimated effects on marketed quantities. Households using credit and with larger off-farm incomes transact more in the market than those without. This may well pick up omitted income effects. Overall, while the results are not entirely clear cut, the balance of the evidence clearly supports the hypothesis that liquidity constraints drive households to practice the seemingly irrational 'sell low, buy high' maize marketing strategy in rural Kenya.

Other point estimates are likewise consistent with expectations. For example, the entry coefficients for total acres owned show that households with more land holdings are more likely to sell and less likely to buy maize in either season, and once part of the market, these same households tend to transact in larger quantities than those with smaller land sizes with the exception of harvest period purchases. This makes intuitive sense if these households are simply producing more on their land and therefore enjoy larger marketable surpluses. This surplus allows larger sales quantities in both periods, as well as greater ability to consume out of own production at harvest time. For lean period purchases, these households may also benefit from greater income earned during the year, which may boost lean period purchases.

Prices influence marketed quantities in the manner expected except for lean period sales, but again, this is likely due to the fact that lean period sales are not frequently observed. The signs of the estimates on greater storage capacity suggest that households with better storage facilities tend to participate less in the market overall, although this relationship is not statistically significant. This fact aligns with previous work on the role of grain storage already cited above (Barrett and Dorosh 1996; Park 2006).

The cross-equation correlations provide additional evidence on the relationships between harvest and lean period market participation decisions. Although the covariances between entry equations are not well identified, the diagonal elements in the matrix of covariances from Entry-to-Level equations are analogous to the inverted Mills ratios that are often calculated as part of typical univariate Heckman models of sample selection. We can therefore see from these estimates that households in the market in general transact more than a randomly selected household, as all of the entry-to-level covariances on the diagonal are positive. We can also see this by looking at the Level-to-Level covariances, which are all positive, indicating that both sales and purchase quantities are positively correlated for market participants. Overall, the statistical significance of many of the cross-equation covariance estimates underscores the importance of estimating these behavioral equations using a systems approach such as MSSM.

A few of the parameter estimates run counter to intuition. The mostly positive point estimates on transactions costs seem to indicate that households farther from markets are more likely to make transactions in markets. However, Renkow, Hallstrom and Karanja (2004) found little relationship between distance to market and transactions costs for villages in Kenya without access to motorized transport. It is possible therefore that our parameter estimates are capturing some other features of our sample villages such as those that lie behind the results in Renkow et al, and our distance variable is thus only an imperfect proxy for fixed transactions costs. However, we are not able to include specific transport types in our estimates, and are limited in our ability to further explore this issue.

A final point on the presented estimates concerns the validity of the standard errors. Given that we have used predicted credit as a regressor in the final estimation of the MSSM, the distribution of the estimated parameters is non-standard. In such a case, an appropriate solution is typically the use of bootstrapping techniques (Horowitz 2001) to produce consistent standard errors. However, given the fact that the dependent variable in the first stage is binary, bootstrapping in our case produced a high number of samples that could not be used to estimate the model, as there were no observations of individuals with access to credit in the replication sample produced by the bootstrap procedure. Therefore, the standard errors have not been corrected to account for the presence of the generated regressor, due to the infeasibility of the standard corrective with our particular model, and the absence of other acceptable alternatives.

Conclusions

This paper empirically explores the oft-observed 'sell low, buy high' puzzle of smallholder food marketing behavior based on the hypothesis that liquidity constraints drive poor households to use commodity markets as a substitute for financial markets to which they have limited or no access. Although considerable, predictable seasonal increases in grain prices should, in a world absent liquidity constraints, dissuade households from selling staples at low prices post-harvest and buying them back again a few months later, we find that 18% of a recent sample of smallholder households in rural western Kenya in fact practice the 'sell low, buy high' strategy. As noted by Park (2006, pg. 1088), grain stores maintained from harvest to harvest are typically used as a price hedge to ensure adequate consumption. By contrast, a 'sell low, buy high' behavior between harvests would seem to reflect not only an inability to hedge, but liquidity constraints that compel households to quasi-borrow by liquidating physical grain inventories in an interseasonally unprofitable fashion.

Using an adaptation of a recently developed censored demand systems estimator, we reject the hypothesis that liquidity has no effect on household marketing patterns in favor of the alternate hypothesis that it indeed reduces the likelihood of selling low or buying high. While the quantity parameter estimates vary depending on the kind of liquidity to which the household may have access, the market entry parameter estimates that are more reliable in these data are broadly consistent with the model we lay out. Other parameter estimates largely make sense as well.

The practical concern, of course, is that households who engage in 'sell low, buy high' behavior use up scarce resources in costly grain market transactions, making it more difficult for them to accumulate resources necessary to invest in productive assets or improved technologies so as to sustainably increase incomes. Thus not only do these seasonal flow reversals reflect lower welfare just as they do at more aggregate levels (Barrett and Dorosh 1996, pg. 636) they also reflect displaced financial market failures that can trap households in long-term poverty through distorted grain marketing patterns.

Notes

[1]See Barrett (2007). However, this is not a universally widespread phenomenon, as Alderman and Shively (1996) show for Ghana.

[2]These losses could be due either to biophysical deterioration or loss of commodities or to claims made on stored grains by family and friends, i.e., implicit social taxation of storage.

[3]In principle, if farmers expect future prices to fall, this should also limit intertemporal storage. However, given the regular seasonality of maize prices in the region, under a rational expectations perspective, lean season price increases likely already incorporate farmer expectations about future prices. It is thus unlikely that farmers would rationally expect lean season prices to fall below a level necessary to justify intertemporal arbitrage.

[4]For a more detailed exposition of the theoretical model, please see Stephens and Barrett (2009).

[5]This holds true even when considering a situation of storage under output price risk aversion, and seasonal price *decreases*, as in Saha and Stroud (1994). The partial effect of the credit constraint is to encourage households to transfer resources to current consumption as much as possible, thereby reducing the demand for storage. Whether this effect dominates over other motives that influence storage demand will vary by household.

[6]Goetz (1992) also estimates a switching model of market participation, but considers only one time period.

[7]The households in our sample are conducting market transactions at very small quantities. Therefore, in practice, we are only considering fixed transactions costs in the entry decision in our estimation.

[8]The logarithmic transform of the marketed quantity variable, $q_{sn,i}$ is used to avoid having to compute the multivariate likelihood function using a truncated normal distribution for strictly positive marketed quantities. This is a common simplification used in other studies of multivariate censored demand systems (Jones 2000; Yen 2005).

[9]Further information about the institute can be found on their website: www.tegemeo.org

[10]Defining seasons in this manner also increased the total number of observations of each of the four types of market participation.

[11]Distances from financial institutions have been shown in previous work to affect borrowing behavior (Behrman, Foster, and Rosenzweig 1997) and thus we are using distances to markets, piped water, etc. as proxies for possible distances to other kinds of infrastructure and institutions,

like banks.

[12]Off-farm income could be endogenous to market participation and volume decisions as well. But since we use exclusively salaried and skilled, year-round employment, we appeal to a reduced form argument that this is likely predetermined when households made their 2005 marketing decisions. Moreover, the data have no suitable instruments to identify this variable separately from the market entry and credit use variables, so we have no viable options for resolving any prospective endogeneity in the off-farm income variable.

[13]The estimation procedure was performed using GAUSS 9.0. The necessary multivariate cumulative distribution functions were evaluated with the GHK simulator (Hajivassiliou 1997).

Table 1. Summary Statistics

Variable Name	Mean	Linearized s.e.
Latent Demand		
Age Household Head (years)[a]	51.380	0.427
Gender Household Head (1=Male)	0.798	0.011
Dependency Ratio[b]	1.011	0.023
Education[c]		
Head has High School Education (1=yes)	0.751	0.012
Head has more than High School Education (1=yes)	0.082	0.007
Liquidity Measures		
Predicted Prob. of Non-Agricultural Credit Usage	0.285	0.004
Total Off-Farm Income (x100000 Ksh)[d]	0.032	0.002
Latent Supply		
Total acres owned	2.310	0.074
Weather shock (1=yes)[e]	0.167	0.010
Value of grain storage unit (x1000 Ksh)	0.859	0.319
Transactions Costs		
Distance to nearest shopping center (km)	1.727	0.035
Other Infrastructure		
Distance to nearest fertilizer seller (km)	3.642	1.222
Distance to nearest seller of hybrid maize seed (km)	2.251	0.049
Distance to a tarmac road (km)	4.368	0.119
Distance to the health center (km)	2.496	0.052
Distance to electricity (km)	3.411	0.110

Table 1. (*continued*)

Variable Name	**Mean**	**Linearized s.e.**
Distance to public telephone (km)	2.432	0.054
Distance to obtain extension advice (km)	4.211	0.091
Distance to piped water (km)	3.667	0.11
Market Variables		
Prices[f]		
Harvest Season Maize Grain Purchases (Ksh/kg)	16.331	0.093
Harvest Season Maize Grain Sales (Ksh/kg)	13.462	0.115
Lean Season Maize Grain Purchases (Ksh/kg)	17.393	0.046
Lean Season Maize Grain Sales (Ksh/kg)	15.702	0.179
Market Quantity		
Harvest Season Maize Grain Purchases (kg)	58.130	2.202
Harvest Season Maize Grain Sales (kg)	319.227	22.261
Lean Season Maize Grain Purchases (kg)	55.892	1.415
Lean Season Maize Grain Sales (kg)	598.869	62.839
District Fixed Effects	*Freq.*	*% of Sample*
Number of Households in Bungoma District	591	35.1
Number of Households in Butere-Mumias District	210	12.5
Number of Households in Siaya District	388	23.1

Table 1. (*continued*)

Variable Name	**Mean**	**Linearized s.e.**
Number of Households in Vihiga District	493	29.3

[a]Linearized s.e.s reported to account for sample design on calculation of sample means.

[b]Dependency ratio is defined as ratio of children less than 15 plus adults over 65 to all other adults in the household.

[c]Comparison case is household heads without any formal education.

[d]Off-farm income is measured over the entire year for all members of the household who had any kind of off-farm employment

[e]This is a zero-one variable indicating whether or not a household performed any crop planting tasks late because of bad weather.

[f]Prices and quantities are averaged only over market participants.

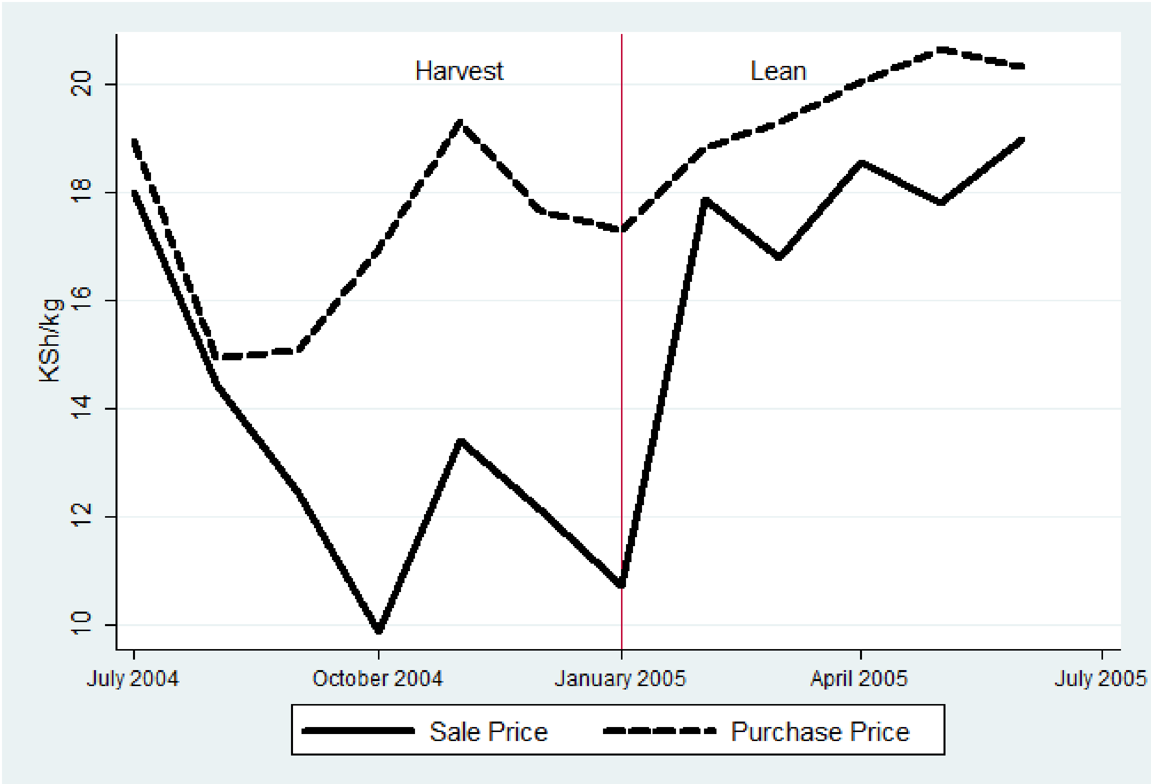

Figure 1. Average maize sale and purchase prices for the overall sample (N=1682)

Table 2. Frequency of maize marketing regimes

Marketing Regime (harvest-lean)	Frequency	Percentage of Sample
Net Buyer-Net Buyer	550	33
Net Seller-Net Buyer	300	18
Autarkic-Net Buyer	327	19
Net Buyer-Net Seller	38	2
Net Seller-Net Seller	73	4
Autarkic-Net Seller	79	5
Net Buyer-Autarkic	36	2
Net Seller-Autarkic	114	7
Autarkic-Autarkic	165	10
	N=1682	*100%*

Table 3. **Results of Probit Regression for Probability of Use of Credit**

Dependent variable=1 if household obtained credit for either agricultural of non-agricultural purposes	
Variable Name	**Estimate**[a]
Total yearly earnings from HH members	0.002
who earn salaried wages (x1000 Ksh)	(0.001)***
Total acres owned	0.024
	(0.016)
Years household has been farming in the village	0.008
	(0.004)***
Household size (number of members)	0.036
	(0.013)***
Age of household head (yrs)	-0.007
	(0.004)*
Gender of household head (1=male)	-0.092
	(0.109)
Head has no formal education (1=yes)	-0.242
	(0.129)*
Head has obtained more than high school education (1=yes)	0.348
	(0.144)**
Distance to a tarmac road (km)	-0.014
	(0.012)
Distance to a health center (km)	0.057
	(0.021)***
Distance to electricity (km)	0.008

Table 3. (*continued*)

Variable Name	**Estimate**
	(0.011)
Distance to public telephone (km)	-0.059
	(0.030)*
Distance to obtain extension advice (km)	0.007
	(0.014)
Distance to piped water (km)	-0.014
	(0.014)
Distance to nearest fertilizer seller (km)	-0.002
	(0.000)***
Distance to nearest certified maize seller (km)	-0.038
	(0.028)

[a]Note: Robust standard errors in parentheses. *,**,*** indicates significant at 10%, 5% and 1% level, respectively. Division fixed effects included but not reported. N=1682, pseudo R^2=0.1124

Table 4. **MSSM Estimates of Market Entry by Season**

	Entry Decision Equations[a]			
	(HP)	(HS)	(LP)	(LS)
	Liquidity Measures			
Predicted Probability	2.918	-3.277	-0.7142	-3.351
of Credit Use	(1.200)**	(1.194)***	(1.209)	(2.075)
Off-Farm	-8.899	-2.839	-7.579	5.308
Income (1xE6 Ksh)	(2.832)***	(2.751)	(2.654)***	(3.395)
	Supply Shifters			
Total Acres	-11.766	8.301	-7.413	7.279
Owned	(2.323)***	(1.882)***	(1.864)***	(2.567)***
Weather Shock (1=planted	-0.439	0.410	-0.329	0.948
late due to bad weather)	(0.355)	(0.352)	(0.332)	(0.603)
Storage Container	-2.614	-8.088	-15.753	27.431
Value (x1000 Ksh)	(31.061)	(22.509)	(26.262)	(38.962)
	Demand Shifters			
Age Household	-0.141	-1.480	-0.691	-1.089
Head (Yrs)	(0.765)	(0.735)**	(0.684)	(1.247)
Gender Household	-0.082	-0.054	-0.772	0.851
Head (1=Male)	(0.371)	(0.386)	(0.364)**	(0.730)
Dependency	1.581	0.717	-0.120	0.547
Ratio	(1.224)	(1.255)	(1.273)	(2.218)
Head completed High	0.268	0.484	0.489	0.199
School Education (1=yes)	(0.424)	(0.458)	(0.389)	(0.958)

Table 4. (*continued*)

	Entry Decision Equations			
Head has more than High	0.154	1.199	0.099	-0.035
School Education (1=yes)	(0.755)	(0.760)	(0.708)	(1.382)
	Transactions Costs			
Distance to	2.497	0.379	0.948	-0.297
Market Shops (km)	(0.986)**	(1.017)	(0.982)	(1.465)

[a]Note: $N = 1682$. Standard errors in parentheses. We omit coefficient estimates associated with District dummy variables and the constant. Data has been scaled to remain within the range {0,1} as follows: $x_{scaled} = \frac{x - x_{min}}{x_{max} - x_{min}}$. *,**,*** indicates significant at 10%, 5% and 1% level, respectively. The entry equation variances have been normalized to 4 to allow for numerical evaluation of the likelihood function. HP=Harvest Season Purchase Equation, HS=Harvest Season Sales Equation, LP=Lean Season Purchase Equation, LS=Lean Season Sales Equation

Table 5. MSSM Estimates of Market Quantity by Season

	Quantity Decision Equations			
	(HP)	(HS)	(LP)	(LS)
	Liquidity Measures			
Predicted Probability	1.255	0.143	1.035	-0.116
of Credit Use	(0.196)***	(0.606)	(0.160)***	(0.755)
Off-Farm	1.326	1.192	1.258	1.731
Income (1xE6 Ksh)	(0.568)**	(1.286)	(0.382)***	(1.536)
	Supply Shifters			
Total Acres	-0.047	2.864	0.327	2.793
Owned	(0.470)	(1.195)**	(0.277)	(1.230)**
Weather Shock (1=planted	0.100	0.041	0.126	0.321
late due to bad weather)	(0.065)	(0.146)	(0.051)**	(0.292)
Storage Container	-1.185	0.601	4.075	-3.365
Value (x1000 Ksh)	(6.752)	(8.722)	(5.148)	(3.158)
	Demand Shifters			
Age Household	0.203	0.518	0.242	0.028
Head (Yrs)	(0.134)	(0.338)	(0.103)**	(0.491)
Gender Household	0.304	0.339	0.239	0.056
Head (1=Male)	(0.061)***	(0.154)**	(0.052)***	(0.339)
Dependency	0.299	-0.454	0.171	-1.251
Ratio	(0.231)	(0.480)	(0.171)	(0.851)
Head completed High	0.030	0.615	0.120	0.991
School Education (1=yes)	(0.073)	(0.209)***	(0.055)**	(0.337)***

Table 5. (***continued***)

	Quantity Decision Equations			
Head has more than High School Education (1=yes)	-0.331 (0.131)**	1.024 (0.336)***	-0.190 (0.106)*	1.432 (0.502)***
	Market Prices			
Market Prices (Ksh/kg)	-1.163 (0.173)***	1.773 (0.445)***	-1.084 (0.200)***	0.162 (0.697)

Table 6. Estimated Error Correlations: Entry-to-Entry

	Entry-to-Entry $(E(u_i, u_j), i, j = \{HP, HS, LP, LS\})$			
	u_{HP}	u_{HS}	u_{LP}	u_{LS}
Harvest Purchase	—-	-0.999	0.892	-0.999
Entry (u_{HP})	—-	(0.928)	(0.896)	(1.532)
Harvest Sales	—-	—-	-0.888	0.994
Entry (u_{HS})	—-	—-	(1.104)	(1.779)
Lean Purchase	—-	—-	—-	-0.999
Entry (u_{LP})	—-	—-	—-	(1.080)
Lean Sales	—-	—-	—-	—-
Entry (u_{LS})	—-	—-	—-	—-

Table 7. Estimated Error Correlations: Entry-to-Level

	Entry-to-Level $(E(u_i, v_j), i, j = \{HP, HS, LP, LS\})$			
	u_{HP}	u_{HS}	u_{LP}	u_{LS}
Harvest Purchase	0.999	-0.833	-0.999	-0.999
Level (v_{HP})	(0.485)**	(0.143)***	(0.136)***	(0.323)***
Harvest Sales	—-	0.999	-0.576	-0.105
Level (v_{HS})	—-	(2.597)	(0.133)***	(0.347)
Lean Purchase	—-	—-	0.999	-0.999
Level (v_{LP})	—-	—-	(0.384)***	(0.203)***
Lean Sales	—-	—-	—-	0.999
Level (v_{LS})	—-	—-	—-	(1.644)

Table 8. Estimated Error Correlations: Level-to-Level

	Level-to-Level $(E(v_i, v_j), i, j = \{HP, HS, LP, LS\})$			
	v_{HP}	v_{HS}	v_{LP}	v_{LS}
Harvest Purchase	0.495	0.019	0.627	0.127
Level (v_{HP})	(0.030)***	(0.118)	(0.052)***	(0.177)
Harvest Sales	—-	1.168	0.136	0.521
Level (v_{HS})	—-	(0.285)***	(0.097)	(0.124)***
Lean Purchase	—-	—-	0.421	0.077
Level (v_{LP})	—-	—-	(0.018)***	(0.139)
Lean Sales	—-	—-	—-	1.105
Level (v_{LS})	—-	—-	—-	(0.216)***

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