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ORIGINAL ARTICLE

Liquidity constraints for variable inputs at planting time and the maize production and marketing decisions of smallholder farmers in Zambia

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Abstract

Increasing smallholders market participation is acknowledged as an important step towards greater rural prosperity in developing countries. While existing literature identifies high transaction costs and market imperfections as challenges faced by smallholders in accessing agricultural markets, less attention has been paid to the role of constraints to the production of a marketable surplus. Specifically, there is a dearth of empirical evidence about how liquidity constraints during the production period that limit smallholders' investments in agricultural inputs can affect agricultural production and subsequently their market participation and choice of marketing channel. We explore this issue in the context of the Zambian maize market during a period when the country's parastatal marketing board – the Food Reserve Agency (FRA) – operated alongside private buyers and purchased large volumes of maize at a pan-territorial price that exceeded average market prices. Although we cannot definitively identify causal effects, we find strong and robust associations indicating that smallholder maize-growing households who were liquidity-constrained during the production period harvested less maize, were less likely to sell maize, and were less likely to sell to the FRA, as compared to those who were unconstrained. Liquidity constraints during the production period likely exacerbate the already disproportionate capture of FRA benefits by wealthier farmers.

KEYWORDS
liquidity, maize, market participation, marketable surplus, staple food grain, sub-Saharan Africa, Zambia

JEL CLASSIFICATION
Q12, Q13, Q18, O13

1 INTRODUCTION

Smallholder farmers in developing countries can potentially improve farm profitability and incomes by participating in agricultural output markets as sellers of low-risk staple food grains that are commonly grown for household consumption (Timmer, 1988; von Braun & Kennedy, 1994). Yet less than 50% of smallholders in several countries across sub-Saharan Africa (SSA) participate in staple food grain output markets as sellers (Alene et al., 2008 – Kenya; Barrett, 2008 – survey of several countries in eastern and southern Africa; and Mather et al., 2013 – Kenya, Mozambique, and Zambia). Uncompetitive markets, high transaction costs, and poor market access have been identified as important reasons for their limited participation (Goetz, 1992; Key et al., 2000). Often overlooked, however, is an additional potential limitation to smallholder participation in agricultural output markets: constraints to producing a marketable surplus. Production constraints, such as a lack of liquidity at planting time, can constrain investment in productivity-enhancing agricultural inputs and the production of a marketable surplus. The seasonal nature of agriculture and the subsequent lag between investments and returns make liquidity a critical production constraint for smallholder farmers (Duflo et al., 2011). These constraints and the resultant effects on marketable surplus can influence the decision to participate in output markets and the choice of marketing channel made by participating smallholders. This has implications for policies aimed at increasing smallholder participation in agricultural markets. In this paper, we explore the link between liquidity constraints for variable inputs at planting time and smallholders' output market participation, using the case of maize in Zambia as an example.

We address three key knowledge gaps in literature. First, while high transaction costs are well understood as major roadblocks to market participation by smallholders in developing countries (de Janvry et al., 1991; Goetz, 1992; Key et al., 2000; Heltberg & Tarp, 2002), relatively little attention has been paid to the potential role of factor market imperfections (Alene et al., 2008; Mather et al., 2013). This is especially relevant for the sale of staple food grains, which is often conditional on the production of a surplus beyond the household's consumption needs. Lower agricultural production can lead to reduced food consumption, reduced sales, or both. If the sale of agricultural output provides an opportunity to meet immediate cash needs and smooth or diversify food consumption (Mulenga et al., 2021; Ntakyo & van den Berg, 2019; Stephens & Barrett, 2011), then the effect of reduced agricultural production due to liquidity constraints during the production period on the sale of agricultural output is ambiguous. Thus, empirical investigation is warranted.

Second, while the literature on smallholder food grain market participation has extensively investigated the influence of liquidity constraints during the *marketing period* (i.e., after the harvest is realized), there is not comparable discussion of the liquidity constraints faced during the *production period*. Per the existing literature, smallholder farmers often sell food grains relatively soon after harvest at low prices due to cash constraints and/or lack of quality storage facilities; many of these same households then purchase grain later at higher prices ("sell low, buy high") (Burke et al., 2019; Dillon, 2020; Stephens & Barrett, 2011). On the other hand, liquidity constraints during the production period have been shown to limit resources spent on crop productivity-enhancing inputs for the next growing season (Dercon & Christiaensen, 2011; Duflo et al., 2011), which in turn can lead to lower agricultural production (Feder et al., 1990; Foltz, 2004; Winter-Nelson & Temu, 2005). The lack of well-functioning credit markets in developing countries can further exacerbate this problem. However, there is a lack of rigorous research linking *liquidity constraints in accessing variable inputs during the production period (LCVIP)* to a household's participation in agricultural output markets as a seller. While LCVIP may be correlated with several other household characteristics such as landholding size, household assets, and household labor that have been explored in previous studies, no attempt was made at a causal analysis in these studies (Boughton et al., 2007; Cadot et al., 2006; Mather et al., 2013; Renkow et al., 2004). More importantly, LCVIP differ from these household characteristics because the former can vary significantly over short periods of time due to a sudden loss in income and/or poor crop harvest, while the latter are relatively fixed in the short run.

Another less explored aspect of smallholder market participation is the choice of marketing channel that households make when faced with several buyer types. The existing literature in this field focuses mainly on (i) commercial crops or largely commercialized markets, and (ii) the choice to sell at the farmgate versus at a distant market (Fafchamps & Hill, 2005; Negi et al., 2018; Shilpi & Umali-Deininger, 2008; Zanello et al., 2014). Very few papers emphasize the non-separability of production, consumption, and marketing decisions that is essential when discussing semi-commercialized markets such as food grain markets (Muamba, 2011; Takeshima & Winter-Nelson, 2012). Further, the binary choice between selling at the farmgate versus at a distant market is not the only marketing choice that farmers make; they also choose to which marketing channel(s) to sell, including, *inter alia*, traders of various sizes, other households, and, in some countries, government crop purchase programs. Production constraints such as LCVIP may limit farmers from participating in and benefitting from more remunerative

AGRICULTURAL ECONOMICS
The Journal of the International Association of Agricultural Economists

marketing opportunities, but this has not been explored in the existing literature.

The article makes four main contributions to literature. First, it generates empirical evidence about whether and to what extent LCVIP are associated with food grain market participation and sellers' choice of marketing channel. Second, it adds to the thin literature on farmers' marketing channel choice when production and consumption (and thus marketing) decisions are non-separable. Third, it provides a rigorous theoretical framework that helps illustrate the mechanisms through which LCVIP may affect farmers' choices regarding market participation and marketing channel. Finally, the paper provides empirical evidence on the relatively less researched link between constraints faced in agricultural production and smallholder access to remunerative output markets.

We address these knowledge gaps using Zambian smallholder maize-growing households as a case study. Zambia has a considerably large agricultural sector that employs 49% of the country's population (World Bank, 2019a). Maize is the main staple food grain in Zambia, is grown by almost all smallholder households, and is an important source of income for them (Chapoto et al., 2015). However, maize market participation as a seller is far from universal.[1] Further, credit markets in rural Zambia are poorly developed. For example, in the 2013/14 agricultural season only 19% of rural households in our sample reported acquiring credit for agriculture from any formal or informal source. Fink et al. (2020) find almost universal uptake of lean season informal loans at high interest rates in rural Zambia, indicating severe cash needs among agricultural households.

Smallholders' choice of marketing channel is of particular interest for Zambia given the important role played by the country's maize marketing board, the Food Reserve Agency (FRA).[2] During the study period, the FRA bought maize from farmers at its depots throughout the country at a pan-territorial price that was higher than the average market price. Previous studies have shown that the FRA's activities have raised the mean level and reduced the variability of maize market prices (Mason & Myers, 2013), which has induced farmers to bring more land under maize cultivation (Mason et al., 2015). The FRA has been shown to benefit smallholders who sell to it, while having very limited spillover effects on the remaining population and likely negative effects on maize net-buyers (Mason & Myers, 2013; Fung et al., 2020). The activities of grain marketing boards like the FRA are often justified by governments as responses to the presence of uncompetitive grain markets and high transaction costs in remote areas. However, recent evidence shows that the argument of widespread uncompetitive food markets in rural SSA may be unsubstantiated, and that market access has improved significantly (Chamberlin & Jayne, 2013; Dillon & Dambro, 2017; Jayne et al., 2011; Sitko & Jayne, 2014). On the other hand, payment delays by the FRA to farmers is a perennial problem, as is the significant uncertainty each year regarding the timing and scale of FRA's maize purchases. These and other factors likely make the FRA a less viable marketing channel for LCVIP households – something we explore empirically in this paper, and a dimension that has not been explored in previous studies on the FRA.

2 | CONCEPTUAL FRAMEWORK AND TESTABLE HYPOTHESES

We use the framework of a non-separable agricultural household model and assume that production, consumption, and initial marketing decisions are made simultaneously at the time of planting (Key et al., 2000; Singh et al., 1986). The full theoretical model is available in Appendix A in the Supplemental Online Appendices; in this section, we highlight its key points.[3] For simplicity and tractability in the theoretical model, we assume maize is the only agricultural good produced by the household.[4] Following de Janvry et al. (1992), LCVIP and unconstrained (UC) households maximize their expected utility under different sets of constraints and have different input demand and output supply functions. An important implication is that LCVIP households are expected to use fewer inputs and produce less output than unconstrained (UC) households, *ceteris paribus*. Once agricultural output has been realized and harvest-time prices revealed, the household is assumed to update its marketing decisions. The household's marketing position is determined by comparing the prevailing post-harvest maize price with the household-specific maize shadow price, which is itself

[1] For the period covered in the analysis for this paper (the 2011/12 and 2014/15 marketing years), the percentage of maize growers who sold more maize than they purchased (maize net-sellers) was 52% and 42%, respectively.

[2] During the period of analysis for this study (2010–2015), the FRA played a major role in maize marketing in Zambia and purchased an average of 75% of the total volume of maize sold by smallholders each year (Fung et al., 2020).

[3] All references to appendices in the remainder of the paper refer to items in the Supplemental Online Appendices. Key points from these items are described in the main paper when referenced, with the details available in the appendices for interested readers.

[4] Smallholder farmers in Zambia, including those in the analytical sample used in this study, grow a wide variety of crops including, among many others, groundnuts, mixed beans, seed cotton, and sweet potato. Maize is the most commonly grown crop among Zambian smallholders, with 90% of such households producing the crop per the nationally-representative survey data used in this study. We focus on maize to simplify the conceptual framework and because of its importance as a staple crop and for public policy in Zambia.

a function strictly decreasing in maize output. Households with lower (higher) maize output thus have higher (lower) shadow prices and are less (more) likely to sell maize.

Some marketing channels, like the FRA, have high fixed costs to access. (The reasons for this are discussed in detail in the "Important Definitions – Maize Marketing Channels" section below.) A household's capacity to overcome these high fixed costs depends on its marketable surplus. LCVIP households that *do* sell maize have a relatively lower marketable surplus than UC households that sell maize, making them less likely to overcome these high fixed costs and thus less likely to sell to the FRA.

Three testable hypotheses flow from the theoretical model:

- Hypothesis 1: LCVIP households are less likely than UC households to become maize sellers.
- Hypothesis 2: Compared to UC households, LCVIP households' probability of selling maize is less responsive to changes in expected maize prices because the liquidity constraint limits the households' capacity to increase production in response to an increase in expected maize prices.
- Hypothesis 3: Compared to UC households that sell maize, LCVIP households that sell maize are less likely to sell to the FRA.

3 | DATA

The main data source used in this analysis is the Rural Agricultural Livelihoods Survey (RALS), a three-wave nationally representative panel survey dataset of smallholder farm households in Zambia. We utilize the first and second waves of the RALS data.[5] These waves were implemented in June–July of 2012 and 2015, respectively, by the Indaba Agricultural Policy Research Institute (IAPRI) in collaboration with the Zambian Central Statistical Office (CSO) and the Ministry of Agriculture (MoA). (See CSO (2012) for details on the RALS sample design.) The dataset contains detailed information on household demographics, agricultural input use, crop and livestock production and marketing, off-farm employment and own business activities, and distances to roads, markets, and public services. The 2012 survey covered the 2010/11 agricultural year (October 2010–September 2011) and the associated crop marketing year (May 2011–April 2012). The 2015 survey covered the 2013/14 agricultural year and the 2014/15 crop marketing year. See Figure 1 for a calendar showing Zambia's maize growing and marketing seasons.

A total of 8839 households were interviewed in the 2012 RALS. Of these, 7254 (82%) were successfully re-interviewed in 2015. Our analytical sample consists of the balanced panel of 6063 RALS households that grew maize in both 2012 and 2015, leading to a total of 12,126 household-year observations. This is 84% of the total household-year observations in the full balanced panel. Tests for attrition bias based on a procedure recommended by Wooldridge (2010) – described in detail in Appendix B – fail to reject the null hypothesis of no attrition bias for all outcome variables except one (maize market position). We suspect this exception is due to our inability to control for time-constant unobserved heterogeneity in the attrition bias tests – something we do control for in the main analysis. We therefore do not consider attrition bias to be a major cause for concern in our analysis.

The maize output price data used in the analysis are from CSO. We refrain from using household level prices from RALS to avoid bias due to incidental truncation.[6] Maize market prices in Zambia are significantly affected by the FRA's intervention (Mason & Myers, 2013). We do not explicitly model the interdependence of market and FRA prices; rather we include separate variables for the FRA and market prices. For each of these, we compute estimates of each household's expected and realized post-harvest farmgate maize price. (See Appendix C for details on construction of these farmgate maize prices.)

Rainfall is an important factor for agriculture in Zambia because smallholder production is almost exclusively rainfed. Thus, in the analysis of maize output we include total rainfall during the current growing season as well as long-term average rainfall (a 16-year moving average). These rainfall variables are based on geospatial rainfall data compiled by Snyder et al. (2019) from Tropical Applications of Meteorology using Satellite data and ground-based observations (TAMSAT) and have a spatial resolution of approximately 4 km (Maidment et al., 2014, 2017; Tarnavsky et al., 2014).

An excess rainfall shock in the *previous* growing season is used as the instrumental variable (IV) for production period LCVIP. Here we describe the data source for the IV, with arguments for the validity of the IV reserved for the

[5] Data from the third wave, which was conducted in June–July 2019, were not publicly available at the time of this study.

[6] Since the price information in RALS was only recorded for households that sold maize, these prices may not accurately reflect the prices faced by all households. Any resulting measurement errors may in turn be systematically correlated with unobservables that determine market participation.

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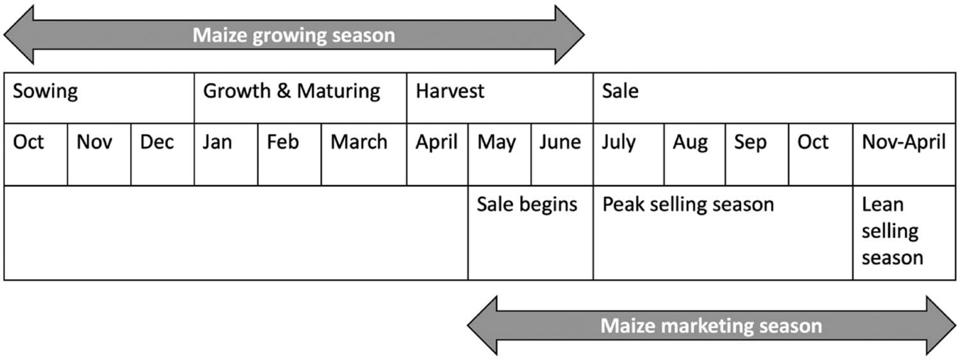

FIGURE 1 Zambia's maize growing and marketing seasons.

identification strategy section later in the paper. The excess rainfall shock variable was constructed using the Standardized Precipitation Evapotranspiration Index (SPEI) (Vicente-Serrano et al., 2010) obtained from Peng et al. (2020) at a resolution of 5 km. The SPEI is a widely used index of anomalous rainfall that incorporates information on temperature and precipitation. Positive (negative) SPEI values denote precipitation in excess (deficit) to meet the loss of water through evapotranspiration. Values near zero denote near normal precipitation. Thus, it is a better measure of water availability for agricultural production than simply using rainfall as demonstrated by a growing body of research (McKee et al., 1993; Nam et al., 2015; Wang et al., 2014). The SPEI is also multi-scalar, that is, it can be computed over several time scales depending upon the purpose of the study. For our analysis, we need a short-term weather shock as an IV for LCVIP. The 3-month SPEI is known to be suitable to examine the short-term effect of weather on agricultural production (Adisa et al., 2019; Peng et al., 2020). In this paper the 3-month SPEI that covers December, January, and February is used. This period marks the reproductive stage of the maize crop (known as tasseling and silking) in Eastern and Southern Africa and is most susceptible to yield loss (personal communication with Brian Chisanga, Research Associate, IAPRI, Zambia, April 27, 2024; Meskelu et al., 2014; Liu et al., 2022).[7]

Both the TAMSAT and SPEI data were matched to RALS households based on their GPS locations. In practical terms, these rainfall-related variables are approximately village-level measures.

Finally, the consumer price index from the World Bank (2019b) was used to convert all prices from nominal to real terms (base year 2017 = 100). This implicitly controls for variation in the prices of consumer goods. See Table D1 in Appendix D for descriptive statistics for all outcome and explanatory variables used in the analysis.

[7] We conduct robustness checks based on SPEI for the months October to December and November to January; associated results are discussed later in the paper.

4 | IMPORTANT DEFINITIONS

In this section we describe three variables that are integral to the analysis: the household's liquidity status (LCVIP), their maize market position, and the choice of maize marketing channel.

4.1 | Liquidity status

Liquidity is a difficult concept to measure because it is not easily observable. Further, different types of liquidity constraints can affect different household decisions such as production of farm and non-farm goods, and consumption of market and home-produced goods (Sadoulet & de Janvry, 1995). In this article, we focus on liquidity constraints during the production period that hinder households from investing in productivity-enhancing variable agricultural inputs. We use an approach like Winter-Nelson and Temu (2005) and exploit unique data in the RALS to define a household as LCVIP if one or both of the following criteria are met:

- Criterion 1: The household claims to have not acquired fertilizer from the market due to lack of cash.
- Criterion 2: The household claims to have not obtained fertilizer from the Farmer Input Support Program (FISP) due to (a) not being able to afford the farmer's down payment for obtaining fertilizer through FISP, and/or (b) not being able to afford membership in a cooperative or other farmers' group, as required for participation in the program.[8,9]

[8] FISP is a large-scale government program designed to enable eligible farmers to obtain farm inputs at subsidized prices. Eligibility is primarily determined by landholding, membership in a farmer cooperative, and payment for part of the cost for inputs received (Mason et al., 2013). During the study period, the program focused on maize inputs (inorganic fertilizer and improved seed).

[9] Cash outlays to obtain FISP inputs cost up to 20% of annual gross income for 60% of smallholders in Zambia, thus precluding many from participating in FISP (Burke et al., 2012).

TABLE 1 Percentage of sample households categorized as LCVIP, by RALS wave and criterion.

RALS wave	Criterion 1 or 2 A	Criterion 1 B	Criterion 2 C	Criteria 1 and 2 D
2012	62%	57%	26%	23%
2015	52%	47%	18%	15%

Notes: Sample consists of maize growing households in the balanced panel in each wave (N = 6063).
Three hundred and sixty-eight households that claimed to be LCVIP according to our criteria purchased > 100 kg of fertilizer from the market. We re-defined these households as UC.

Approximately 62% (52%) of households were LCVIP in RALS 2012 (2015) using this approach (Table 1, column A). 13% of households were UC in RALS 2012 and became LCVIP in 2015, whereas 23% of households were LCVIP in 2012 and became UC in RALS 2015; the remaining households were LCVIP in both survey rounds (39%) or UC in both rounds (25%) (Table D2, Appendix D). Most households were defined as LCVIP because they met criterion 1; relatively fewer met criterion 2 (Table 1, column C). Only 23% and 15% of sample households met both criteria in RALS 2012 and 2015, respectively (Table 1, column D).

There are some concerns with our measure of LCVIP. Farmers may misreport other reasons for not purchasing fertilizer as 'lack of cash' – for example, soil quality that has poor response to inorganic fertilizers (Marenya & Barrett, 2009), lack of improved seeds that respond well to such fertilizers, or limited fertilizer access for other reasons. The use of panel data econometric methods (described below) alleviates concerns of time-invariant soil and other characteristics that could be associated with LCVIP, fertilizer uptake, and maize outcomes. Further, the RALS survey respondents could choose from a rich set of options for not buying fertilizers including those mentioned above (Tables D3 and D4, Appendix D), increasing the probability that respondents accurately stated their reasons for not buying fertilizers. It may also be the case that some households overstated their liquidity constraints (hypothetical bias) and may have had access to fertilizer despite their claims. We found 368 such cases and redefined them as UC (Table 1, notes). Moreover, between criteria 1 and 2, households that fulfill criterion 2 are likely to be more severely constrained and less likely to be overstating their constraints. Our results (discussed later) are robust to using only criterion 2 to identify LCVIP households. Finally, credit is fungible, and households may allocate available credit to areas other than agriculture (Feder, 1982; Elahi et al., 2018). This choice does not, however, undermine the fact that they may need more credit than is currently available to relax their agriculture-specific liquidity constraints.

4.2 | Maize market position

Following Bellemare and Barrett (2006) and Burke et al. (2015), we define three mutually exclusive maize market positions.[10] A household is a maize *net-seller* if the quantity of maize sold is greater than the quantity of maize grain and maize meal purchased; *autarkic* if the household has no maize sales and purchases; and a *net-buyer* if the quantity of maize sold is less than the quantity of maize grain and maize meal purchased.[11,12] During the 2014/15 (2011/12) marketing year only 38% (42%) of LCVIP households are classified as maize net-sellers compared to 67% (67%) of UC households (Table D5, Appendix D). An alternative definition of maize market position was computed using value (instead of quantity) of maize and maize meal sold and bought (Table D6, Appendix D). This value-based maize market position was used for conducting a robustness check.

4.3 | Maize marketing channels

Smallholders in Zambia sell maize to a wide variety of buyers. Although some sell to more than one type of buyer, most maize net-sellers (87% in 2011/12 and 88% in 2014/15) had only one maize sale transaction per marketing year. Additionally, the largest sale accounts for approximately 90% of a household's total maize sold on average. For tractability, we focus on the largest maize sale made by each household (in quantity terms), and group maize marketing channels into four categories: the FRA, small-

[10] The mutually exclusive positions help us in conducting the empirical analysis (discussed later) as well as in identifying the beneficiaries of access to agricultural markets. Further, in our sample, only 7% of net buying households sold any maize (600kg on average). Only 5% of these households sold to the FRA.

[11] Maize meal is a type of maize flour that is used to prepare *nshima*, a thick porridge that is the most common way maize is consumed in Zambia.

[12] Maize meal was converted to maize grain equivalents using conversion factors from Mwiinga et al. (2002).

AGRICULTURAL ECONOMICS
The Journal of the International Association of Agricultural Economists

scale private traders, large-scale private traders, and other households.

Using this definition, in the 2014/15 (2011/12) marketing year, 48% (64%) of net-seller households sold maize to the FRA, 26% (17%) sold to a small-scale trader, 16% (10%) sold to a large-scale trader, and 11% (9%) sold to another household (Table D7, Appendix D). A smaller percentage of LCVIP households than UC households sold to the FRA in both years. The median farmgate price received from the FRA was 42% (24%) higher than the price received from small-scale traders in 2011/12 (2014/15). The median price received from sales to other households was also slightly higher (1% and 8% for 2011/12 and 2014/15, respectively) than that for small-scale traders (Tables D8 and D9, Appendix D). This is probably because maize sales to other households were spread more evenly over the maize marketing season than sales to small-scale traders, and thus the prices received from other households would reflect, in part, the higher maize prices that prevail later in the marketing season.[13]

Even though the price offered by the FRA during our period of analysis was higher than average market prices, there was considerable uncertainty each season about when the FRA would start buying maize and when it would pay farmers. For example, almost 50% of farmers who sold to the FRA had to wait at least 2 months to be paid. In contrast, more than 90% of those who sold to private traders or another household received payment immediately (Figure 2). Furthermore, even though maize harvesting begins in May, farmers typically had to wait until July or August for the FRA to start buying maize. Almost 90% of the households selling to the FRA had to travel more than 1 km to make the maize sale. In contrast, 74% (64%), 33% (30%), and 87% (85%) of the transactions made to small-scale traders, large-scale traders, and other households, respectively, in 2011/12 (2014/15) were made at the farmgate (Tables D8 and D9, Appendix D). Another potential constraint faced by smallholders in selling to the FRA is the official minimum limit of 500 kg that must be met by an individual selling to FRA (Mason, 2011), while the median quantity of maize sold by LCVIP households in our sample was only 50 kg. The FRA also has quality requirements related to moisture content, aflatoxin content, and so forth, of the maize grain, which smallholders are typically not equipped to measure. Farmers may need to be members of a cooperative/farmer group to take advantage of collection and transport of maize in bulk from the village to an FRA depot. The combination of these factors can pose high fixed costs for accessing the FRA marketing channel and discount the FRA prices effectively received by households that sell to it, especially for those that may be in urgent need of cash.[14]

5 | ESTIMATION

Guided by our theoretical framework (Appendix A), we estimate the impact of LCVIP on maize marketing outcomes in four steps. First, we estimate the effect of LCVIP on maize output (1). Then, we estimate the effects of maize output on maize market position (2) and choice of maize marketing channel for maize net sellers (3). Finally, we combine the results from (1), (2), and (3) to test the paper's hypotheses (4). Each of these steps is discussed in detail below.

5.1 | Step 1

We first estimate the effects of LCVIP and expected farmgate FRA and market maize prices on maize output using a linear switching regression. This approach allows the parameter estimates to differ between LCVIP and UC households, in line with the theoretical model where LCVIP and UC households were found to solve different optimization problems (Appendix A). The availability of panel data enables us to control for unobserved time-invariant household-level heterogeneity. Given the non-linear-in-parameters nature of our estimators in the second step regression (discussed below), we use a correlated random effects (CRE) approach (Chamberlain, 1984; Mundlak, 1978) rather than a fixed effects approach to control for time-invariant unobserved heterogeneity throughout the paper.

However, time-varying unobservables (such as unreported access to productive resources from family or friends) that are correlated with both a household's LCVIP status and their maize output can potentially result in omitted variable bias. To test for such endogeneity (and correct for it, if present), we use the two-step control function (CF) endogenous switching CRE-pooled ordinary least squares (CRE-POLS) procedure suggested by Wooldridge (2015) and Murtazashvili and Wooldridge

[13] Figure D1, Appendix D shows that > 50% of the largest maize transactions to other households occur in months *other than* July, August, and September (the peak maize marketing months). This is in comparison to < 10% for FRA and < 40% for small- and large-scale traders.

[14] While LCVIP households may sell to UC households who then sell to FRA, a spillover of benefits via this route is unlikely. Less than 6% of LCVIP farmers sold maize to other households. In the few cases that such a transaction occurs, LCVIP farmers are likely to accept lower prices from the other households to whom they sell (the median prices received by selling to other households were approximately 20% lower than prices received from FRA).

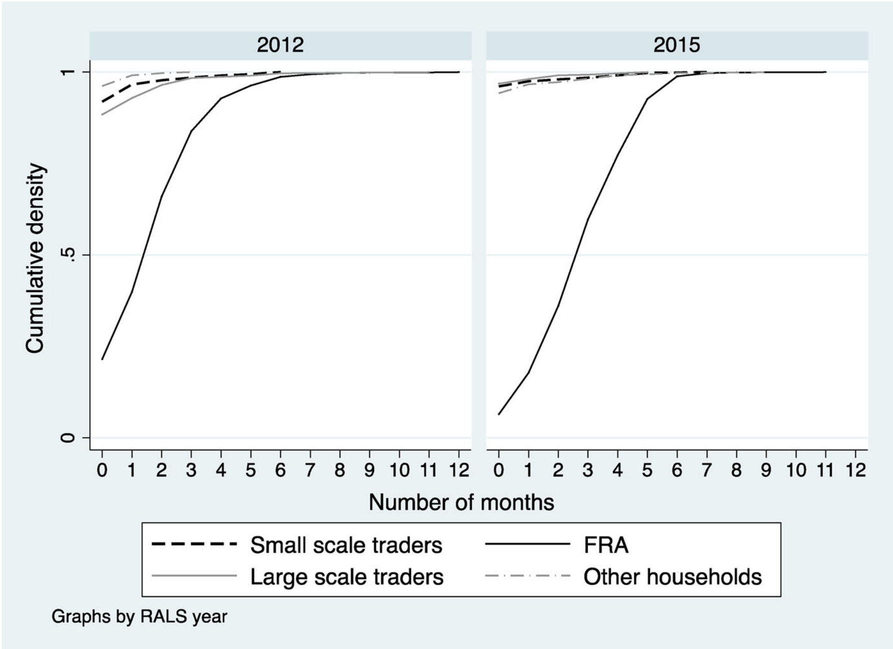

FIGURE 2 Number of months between sales transaction and payment to farmer for the largest maize transaction.

(2016) (particularly, Section 3.1 pages 45–46). This two-step approach entails estimating a first stage POLS regression in which liquidity status is the dependent variable and the regressors include all explanatory variables from the main equation, a valid IV, and time averages of all exogenous variables. Residuals from this equation are computed. The second step entails a POLS regression of maize output on the full set of exogenous variables, their time-averages, first stage residuals, and their interaction with the endogenous switching variable of liquidity status.[15]

Equation (1) represents the main equation to be estimated:

$$q_{mz,it} = LC_{it} \times \boldsymbol{X}_{1it}\boldsymbol{\beta}_1 + \boldsymbol{X}_{1it}\boldsymbol{\beta}_0 + LC_{it} \times c_i + c_i + LC_{it} \times \upsilon_t + \upsilon_t + \tau_1 LC_{it} \times \widehat{u_{it}} + \tau_0 \widehat{u_{it}} + \epsilon_{it} \quad (1)$$

Here, $q_{mz,it}$ is the maize output of household i in agricultural year t, LC_{it} is an indicator variable that equals 1 if the household was LCVIP, and 0 if not. $\boldsymbol{X}_{1it}$ is the vector of explanatory variables which includes, per the theoretical model, expected farmgate FRA and market prices for maize ($\boldsymbol{p_e}$), prices of agricultural inputs and the agricultural wage ($\boldsymbol{p_x}$ and w), household characteristics ($\boldsymbol{z^h}$), and quasi-fixed factors ($\boldsymbol{z^q}$) such as current and long-run average growing season rainfall. c_i represents household-specific time-invariant unobserved heterogeneity, υ_t is the year fixed effect, $\widehat{u_{it}}$ are the residuals from the first stage regression of the LCVIP status, and ϵ_{it} is the idiosyncratic error term. $\boldsymbol{\beta}_1$, $\boldsymbol{\beta}_0$, τ_1, and τ_0 are parameters to be estimated. Failure to reject $\tau_0 = 0$ and $\tau_1 = 0$ indicates failure to reject the null hypothesis that LCVIP status is exogenous to maize output. In that case, we can use an exogenous version for the main analysis (i.e., a CRE-exogenous switching regression). Alternatively, rejecting that at least one of τ is equal to zero implies that liquidity status is endogenous. The inclusion of the first stage residuals corrects for this endogeneity (conditional on the validity of the exclusion restriction). We refer to this as the CRE-endogenous switching regression.

The estimates of interest are the difference in expected maize output between LCVIP and UC households and the marginal effects of increases in the expected FRA and market maize prices on maize output for LCVIP and UC households.

5.2 | Identification strategy

The first stage liquidity status regression is estimated using a CRE-linear probability model that involves regressing the LCVIP status (LC_{it}) on the full set of exogenous variables ($\boldsymbol{X}_{1it}$) and an IV (z_{it}):

$$LC_{it} = \boldsymbol{X}_{1it}\,\boldsymbol{\alpha}_1 + \alpha_2 z_{it} + c_i + \upsilon_t + u_{it} \quad (2)$$

Identification hinges on the IV having a strong statistically significant effect on the household's selection into one of the two LCVIP status regimes, yet which we can confidently assume is not correlated with the household's

[15] All analysis was conducted using Stata/SE 17.0.

AGRICULTURAL ECONOMICS
The Journal of the International Association of Agricultural Economists

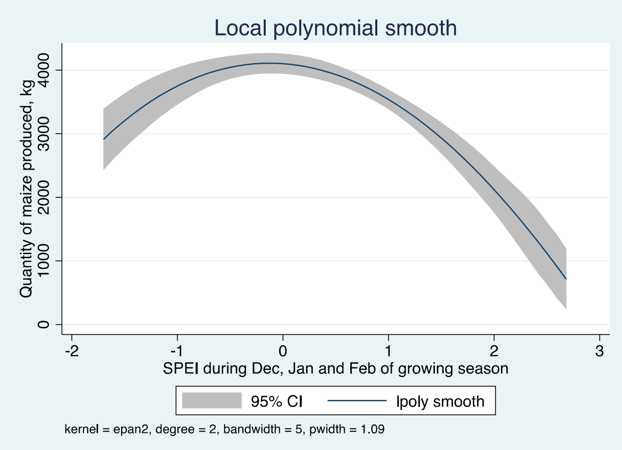

FIGURE 3 Local polynomial plot of maize output as a function of SPEI.

maize output through any channel other than its effect on LCVIP status.

An excess rainfall shock in the *previous* growing season, constructed using the SPEI index, is used as the IV for LCVIP. While droughts are the more commonly known extreme weather events that affect agricultural production and incomes, we rely on an excess rainfall shock because several incidences of excess rainfall were observed during the growing seasons of interest for our sample (agricultural seasons 2009/10 and 2012/13) (Appendix D, Figure D2). As noted in the World Bank's Climate Knowledge Portal, these periods were marked by severe floods in Zambia (World Bank, n.d.). On the other hand, no households in our sample faced droughts in either period per the standard SPEI classification.

We construct the IV as an indicator variable that equals 1 if the household experienced SPEI > .99 (i.e., an excess rainfall shock) during the key growing period of December-February of the previous agricultural year, and 0 otherwise. This classification is based on the standard categorization followed in the agronomy literature (Mc Kee et al., 1993) and is also supported by our data. As shown in Figure 3, maize output increases with increasing SPEI up to roughly .5 SPEI, beyond which maize output declines with increasing SPEI.

Next, we discuss the relevance of the IV and the exclusion restriction. See Figure 4 for an illustration of the identification strategy and hypothesized mechanism of impact of LCVIP on maize output and maize marketing decisions.

Relevance: An excess rainfall shock in growing season $t-1$ is expected to lead to poor crop output as well as potential loss of assets and thus a higher chance of being LCVIP in year t (Kim et al., 2023; Svetlana et al., 2015). The first-stage results suggest that the IV is strongly partially correlated with being LCVIP in year t (F-stat = 19.93; $P < .01$; Table E1 Model 1, Appendix E).

Exclusion restriction: If an excess rainfall shock in the $t-1$ season affects maize output in the current year through any channel other than via LCVIP, this would violate the exclusion restriction assumption. For example, potential serial correlation in the excess rainfall shock may invalidate our instrument – that is, a rainfall shock in $t-1$ that is correlated with similar weather in period t, and thus with maize output. The use of panel data econometric methods (CRE) and inclusion of the current and long-run average growing season rainfall should alleviate some of these concerns. That leaves time-varying unobservables that might be correlated with changing rainfall conditions and maize output. For example, the impact of a rainfall shock in one season may linger to the next season through effects on nutrient balances, pest and weed infestation, or recycled seed quality.[16] Major shifts in rainfall or irrigation-induced soil productivity and pest incidence can also influence maize output. For example, Urama and Hodge (2004) find changes in pest incidence in irrigated fields after several years of continuous irrigation. The development and adoption of new agricultural technologies, changes in cropping patterns, and land use can also be correlated with both changing weather and crop outcomes. However, such changes are unlikely within the short period that is covered in our study.[17] Overall, lingering effects of an excess rainfall shock in $t-1$ on crop growth in season t – if there are any – are likely to be very small in comparison to the effects of the shock on crop growth in season $t-1$ (personal communication with Dr. Lisa Tiemann, May 14, 2024).

Finally, we run a falsification test by including a lead of the IV (i.e., excess rainfall measure in period $t+1$) in the first stage CRE-POLS for LCVIP status and the CRE-exogenous switching regression for maize output in year t. We test the null hypotheses that maize output and LCVIP status are not correlated with rainfall shocks in the next period through any serial correlation in the rainfall shock variable. We fail to reject this null for both liquidity status and maize output (Table E2, Appendix E), providing evidence against the presence of serial correlation. Despite

[16] For example, as per Qin et al. (2015), soybean pod borer's overwintering behavior can change due to past droughts and excess rainfall. This could be relevant for 10% of households in our sample that grew soybeans. Dang and Chen (2011), cited by Qin et al. (2015), provide further insights on how rainfall conditions and soil moisture can affect insects including agricultural pests.

[17] For example, thirty years is the accepted reference period in the climatology and agronomy literature (Lindsey & Dahlman, 2020; Schlenker & Roberts, 2009).

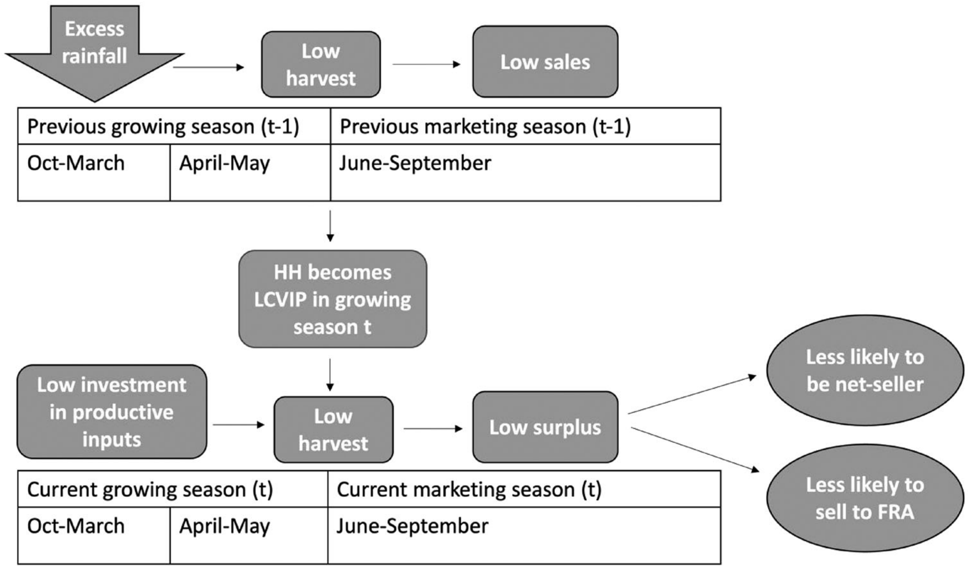

FIGURE 4 Illustration of identification strategy and mechanism of impact.

these tests and the arguments above, we acknowledge the limitations of the IV used in this study and interpret our results with caution.

Use of alternative instruments: We formulated alternative instruments, including those based on water scarcity instead of excess rainfall and different critical growing periods, and tested for robustness. SPEI-based excess rainfall indicators for October–December and November–January were used as alternative instruments and results were found to be robust (Table E1 Models 2–3, Appendix E). We also computed the monthly deviation of rainfall from the long term mean and used it to create indicators of *rainfall shortfalls in specific months* and *excess rainfall in specific months.* Rainfall shortfall in month m is an indicator variable that equals 1 if the absolute value of the negative deviation of rainfall from long-term mean rainfall in month m is greater than .5 times the long-term standard deviation of rainfall in m; 0 otherwise. Similarly, excess rainfall in month m is an indicator variable that equals 1 if the positive deviation of rainfall from long-term mean rainfall in month m is greater than .5 times the long-term standard deviation of rainfall in m; 0 otherwise. Less than 2% of households were found to experience *rainfall shortfalls*, leaving us with inadequate spatial variation. More importantly, neither the *rainfall shortfalls* nor *excess rainfall in specific months* variable was strongly partially correlated with liquidity constraints and thus neither could be used as an alternative (or additional) IV (Table E1 Models 4–9, Appendix E).

5.3 | Step 2

We next estimate the effect of changes in maize output on the household's maize market position using a CRE-ordered probit approach. The respective probabilities of being a net-buyer and net-seller of maize are given as follows:

$$Pr\left(M_{it}=1\,|\,q_{mz,it},\,\boldsymbol{X}_{2it},\,c_i,\,\upsilon_t\right)=\Phi\left(0-\left(\delta q_{mz,it}+\boldsymbol{X}_{2it}\,\boldsymbol{\gamma}+c_i+\upsilon_t\right)\right) \tag{3}$$

$$Pr\left(M_{it}=3\,|\,q_{mz,it},\,\boldsymbol{X}_{2it},c_i,\,\upsilon_t\right)=\Phi\delta q_{mz,it}+\boldsymbol{X}_{2it}\,\boldsymbol{\gamma}+c_i+\upsilon_t \tag{4}$$

where M_{it} is the household's maize market position (= 1 if net-buyer, = 2 if autarkic, and = 3 if net-seller); $\boldsymbol{X}_{2it}$ is a vector of explanatory variables suggested by the theoretical model and consisting of the post-harvest (realized) farmgate FRA and market prices of maize, proxies for transaction costs and access to markets, and household characteristics; and δ and $\boldsymbol{\gamma}$ are parameters to be estimated. The estimate of interest is the marginal effect of an increase in maize output on maize market position . We make the simplifying assumption that maize output is pre-determined at the time of maize market position and marketing channel decisions (and thus a weakly exogenous variable). However, if there are any time-varying unobservables that affect both maize output and these outcome variables, then endogeneity is an issue, and the parameter estimates may be biased.

AGRICULTURAL ECONOMICS The Journal of the International Association of Agricultural Economists IAAE

5.4 | Step 3

The effect of an increase in maize output on a maize net-selling household's choice of maize marketing channel for their largest maize sale transaction is estimated using a CRE-Multinomial Logit (MNL) regression. The choice of marketing channel can be represented as:

$$Pr\left(V_{jit} - V_{kit} > 0 \mid q_{mz,it}, \boldsymbol{W}_{it}, c_i, \upsilon_t\right) = exp\left(\lambda_j\, q_{mz,it} + \boldsymbol{W}_{it}\, \boldsymbol{\pi_j} + c_i + \upsilon_t\right)/1 + \sum_{j=1}^{4} \exp\left(\lambda_j\, q_{mz,it} + \boldsymbol{W}_{it}\, \boldsymbol{\pi_j} + c_i + \upsilon_t\right) \tag{5}$$

Here V_{jit}- V_{kit} is the difference in utilities obtained by a maize net-seller from choosing channel *j* versus channel *k*. $q_{mz,it}$ is as defined above and $\boldsymbol{W}_{it}$ is a vector of control variables consisting of $\boldsymbol{X}_{2it}$ (the same as in Step 2) and residuals from a selection equation described below. λ_j and $\boldsymbol{\pi_j}$ are parameters associated with marketing channel *j*. The estimate of interest is the marginal effect of an increase in maize output on the maize net-selling household's choice of maize marketing channel.

The CRE-MNL is estimated for maize net-sellers only to ensure that we follow a mutually exclusive group of households that are most likely to benefit from selling maize. However, this could introduce selection bias if this subset of maize growers is a non-random sub-sample of all maize-growing households with respect to unobservable, time-varying characteristics. To address this potential problem, we first estimate a CRE-Tobit selection equation for a maize grower's net maize quantity sold using the full sample, where net maize sales are zero for both autarkic and net-buying households. The residuals from this Tobit regression are then used as an additional regressor in the CRE-MNL to test and control for sample selection bias. The use of Tobit instead of probit as the selection equation allows us to solve the selection problem without need for an exclusion restriction (See Wooldridge (2010) – Procedure 19.3 – for details.)

5.5 | Step 4

Table 2 summarizes the estimates to be computed to test the focal hypotheses by combining the relevant estimates from Steps 1, 2, and/or 3. Standard errors are computed by bootstrapping over 500 replications.

6 | RESULTS

Table 3 reports the average partial effects (APEs) from the CRE-POLS switching regressions for maize output by liquidity status for key variables of interest. The residuals in the endogenous switching regression are not statistically significant (at the 10% level of significance). This suggests that, controlling for the observables and time-invariant unobserved heterogeneity via CRE, LCVIP is exogenous to maize output. Although these results suggest that we can focus on the results from the exogenous switching regression in the remainder of the paper, given the potential limitations of the IV for LCVIP, we interpret our results as associations, not causal effects.

We find that LCVIP are associated with a 1246 kg reduction in maize output ($P < .01$), on average. This is both a statistically significant and economically significant result. It is equivalent to roughly 1700 Zambian Kwacha (ZMW) at the 2014/15 marketing year price (280 USD at the exchange rate during that period), and 33% of the annual average maize production of a Zambian smallholder. We find no statistically significant relationship between expected FRA and market maize prices and household maize output for LCVIP and UC households. This may in fact be the case, or there may be measurement error in our expected maize price variables, which would likely bias the estimated effects toward zero. The lack of a statistically significant effect may also be due to multicollinearity, as the variance inflation factor (VIF) for the expected FRA price and the year dummy is greater than 10.[18] This is expected because there is relatively little variation in FRA farmgate prices within a given year as the FRA depot-level price is pan-territorial. The correlation coefficient between the two maize price variables is also very high (.90). We therefore interpret with caution the estimated effects of the expected maize prices on maize output.

We further use the CRE-POLS switching approach to investigate the premise that the difference in maize output between LCVIP and UC households is at least partly due to LCVIP households' relatively lower capacity to invest in maize productivity-enhancing inputs such as inorganic fertilizer and improved seed (i.e., hybrid and improved open pollinated varieties). The results of these regressions (Table E5, Appendix E) suggest that LCVIP households use 117 kg less fertilizer per hectare on their maize fields and are 19-percentage points less likely to grow an improved maize variety, on average ($P < .01$). These estimates represent 55% and 25% reductions in the fertilizer application rate and the probability of using improved seed, respectively, relative to the sample averages. This further emphasizes how LCVIP is associated with a foregone opportunity for households to improve their land productivity through investment in inorganic fertilizer and improved seed.

The CF approach adopted here to control for time-varying endogeneity imposes more functional form assumptions than the more commonly used two-stage least squares (2SLS). Yet, we prefer the CF approach in

[18] The VIF for all other variables was within the acceptable range (≤ 10).

TABLE 2 Values to be estimated/calculated and hypotheses to be tested.

Hypothesis	Statement (all refer to maize-growing households)	Values to be estimated/calculated	Derived from
1	LCVIP households are less likely to become maize net-sellers, relative to UC households	$E[(q_{mz}\|LCVIP=1)-(q_{mz}\|LCVIP=0)] * E[\frac{\partial \Pr(M=3))}{\partial q_{mz}}] < 0$	Step 1
2	An LCVIP household's probability of being a maize net-seller will be less responsive to changes in expected maize prices (market and FRA), relative to a UC household's	$E[\frac{\partial q_{mz}}{\partial p_e}\| LCVIP=1] * E[\frac{\partial \Pr(M=3))}{\partial q_{mz}}] < E[\frac{\partial q_{mz}}{\partial p_e}\| LCVIP=0] * E[\frac{\partial \Pr(M=3))}{\partial q_{mz}}]$	Steps 1 and 2
3	Net-seller LCVIP households are less likely than net-seller UC households to sell to the FRA	$E[(q_{mz}\| LCVIP=1)-(q_{mz}\| LCVIP=0)] * E[\frac{\partial \Pr(V_{FRA}-V_k>0)}{\partial q_{mz}}] < 0$	Steps 1 and 3

Note: Hypothesis 3 here refers to the marketing channel for the net-selling household's largest maize sale transaction.

TABLE 3 APEs of key variables on maize output.

Variables	Exogenous switching CRE-POLS		Endogenous switching CRE-POLS	
	UC	LCVIP	UC	LCVIP
Household is liquidity-constrained (= 1)		−1246.3***		−4225.9
		(66.15)		(3545.30)
Expected farmgate FRA maize price (ZMW/kg, 2017 = 100)	368.0	86.6	464.4	141.00
	(768.1)	(247.5)	(1765.22)	(483.61)
Expected farmgate maize market price (ZMW/kg, 2017 = 100)	7.53	−66.5	−102.9	−99.8
	(217.9)	(64.99)	(384.29)	(120.45)
Residuals			4076.9	1529.7
			(5874.32)	(1887.50)
Other controls	Yes		Yes	
Time fixed effects	Yes		Yes	
Province fixed effects	Yes		Yes	
CRE time averages	Yes		Yes	
Observations	12,126		12,126	

Notes: *** $P < .01$, ** $P < .05$, * $P < .1$; standard errors in parentheses have been clustered at household level and bootstrapped with 500 replications to account for the generated regressor (residuals from the first-stage regression of liquidity constraints on all explanatory variables and an IV).
Abbreviations: FRA, Food Reserve Agency; LCVIP, liquidity constraints in accessing variable inputs during the production period; UC, unconstrained; ZMW, Zambian Kwacha. See Tables E3 and E4, Appendix E for full results.

our case because our estimation model is non-linear in the endogenous variable due to the several interaction terms. The CF is known to be a relatively more parsimonious and efficient approach to deal with such cases than 2SLS (Wooldridge, 2015). Nevertheless, to test the robustness of our results, we re-analyze Equation (1) using a CRE-2SLS approach. Unfortunately, in these models we are unable to estimate the effects of expected maize prices for LCVIP and UC households separately due to lack of sufficiently strong IVs for the interaction terms of liquidity status and expected prices. The results (Table E6, Appendix E) show that LCVIP households produce 4355 kg less maize, on average, than UC households, although the effect is only weakly significant ($P < .1$). The test of endogeneity of liquidity status in the 2SLS estimation fails to reject the null of exogeneity. Both results are consistent with our main results.

The key results from the CRE-ordered probit of maize market position are reported in Table 4.[19] Consistent with

[19] The CRE-ordered probit failed to converge even though the estimates remain stable after the 15th iteration. We report estimates from 2,000 iterations here. To ensure that results are robust, we repeated the analysis with the value-based definition of maize market position. The model using this definition attains convergence and its results were very similar to the main specification (Table E8, Appendix E).

TABLE 4 APEs of key variables on the maize market position (CRE-ordered probit).

Variables	Net-buyer	Autarkic	Net-seller
Maize output (kg)	−.00012***	−.000020***	.00014***
	(.000016)	(.0000015)	(.000016)
Farmgate maize price (ZMW/kg, 2017 = 100)	−.0021	−.00036	.0025
	(.012)	(.0020)	(.014)
Farmgate FRA maize price (ZMW/kg, 2017 = 100)	−.061	−.010	.071
	(.106)	(.018)	(.124)
Other controls	Yes		
Time fixed effects	Yes		
Province fixed effects	Yes		
CRE time averages	Yes		
Observations	12,126		

Notes: *** $P < .01$, ** $P < .05$, * $P < .1$; standard errors clustered at household level in parentheses.
Abbreviations: FRA, Food Reserve Agency; ZMW, Zambian Kwacha. Full results in Table E7, Appendix E.

TABLE 5 APEs of maize output on choice of maize marketing channel for the largest transaction by net-seller households (CRE-multinomial logit).

	APEs			
Variables	Small-scale traders	FRA	Large-scale traders	Other households
Maize output (kg)	.0000030	.000039***	.000012***	−.000054***
	(.0000081)	(.0000089)	(.0000036)	(.000013)
Residuals from CRE-Tobit selection equation[a]	Yes			
Time fixed effects	Yes			
Province fixed effects	Yes			
CRE time averages	Yes			
Observations	7108			

Notes: *** $P < .01$, ** $P < .05$, * $P < .1$; standard errors are clustered at household level and bootstrapped with 500 replications to account for the generated regressor (CRE-Tobit residuals).
[a]The CRE-Tobit residuals are significant at 1% level of significance, implying that the sample of net-sellers is non-random, and our estimates would have been biased if we had not corrected them through inclusion of the residuals (see Tables E10 and E11 in Appendix E for the first-stage CRE-Tobit results for the quantity of maize sold and the full CRE-MNL results, respectively.).

the hypothesis derived from our theoretical framework, a one metric ton (1000 kg) increase in maize output is associated with a 12-percentage point decrease in the probability of being a maize net-buyer, and a 14-percentage point increase in the probability of being a net-seller ($P < .01$). However, maize market and FRA prices are not statistically significantly related to household maize market position, likely for reasons similar to those discussed above for maize output. Repeating this analysis with a household's maize net sales as the outcome variable (and using a CRE-POLS approach, Table E9, Appendix E), we find that a 1 kg increase in maize output is associated with an average .86 kg increase in net maize sales ($P < .01$).

Table 5 summarizes key results from the CRE-MNL for maize net selling households' choice of maize marketing channel. A one metric ton increase in maize produced is associated with a 3.9-percentage point increase in the probability of selling to the FRA, a 1.2-percentage point increase in the probability of selling to a large-scale trader, and a 5.4-percentage point decrease in the probability of selling to another household ($P < .01$). However, increased maize production does not have a statistically significant association with choosing to sell to small-scale traders. These results support our proposition that households that produce a larger maize surplus are more likely to sell to marketing channels that entail larger fixed costs (such as uncertainty and payment delays associated with selling to the FRA, negotiation and search costs for large-scale sellers, and transportation costs for both).

TABLE 6 Hypothesis test results.

Hypothesis	Effect of interest	APE
1	LCVIP on the probability of being a net-buyer	.15*** (.024)
	LCVIP on the probability of being a net-seller	−.17*** (.026)
2	Expected FRA price on the probability of being a net-seller for LCVIP HH	.01 (.053)
	Expected FRA price on the probability of being a net-seller for UC HH	.05 (.222)
	Expected market price on the probability of being a net-seller for LCVIP HH	−.01 (.014)
	Expected market price on the probability of being a net-seller for UC HH	.001 (.049)
3	LVCIP on the probability of a net-selling household selling to:	
	- A small-scale trader	−.009 (.011)
	- The FRA	−.06*** (.013)
	- A large-scale trader	−.02*** (.005)
	- Another household	.09*** (.022)

Notes: *** $P < .01$, ** $P < .05$, * $P < .1$; Standard errors clustered at the household level are computed by bootstrapping over 500 replications.
Abbreviations: APE, average partial effect; FRA, Food Reserve Agency; HH, household; LCVIP, liquidity constraints in accessing variable inputs during the production period; UC, unconstrained. Hypothesis 3 refers to the marketing channel for the household's largest maize sale transaction.

The estimates computed above are used to test the hypotheses stated in Table 2, and the results are summarized in Table 6. In support of hypothesis 1, LCVIP households are found to be 17-percentage points less likely to be net-sellers of maize ($P < .01$). We do not find any evidence in support of hypothesis 2 (which was that compared to UC households, LCVIP households' probability of being maize net-sellers would be less responsive to changes in expected maize prices). However, as discussed earlier, due to multicollinearity and potential measurement error, we are unable to draw a firm conclusion regarding hypothesis 2. Lastly, consistent with hypothesis 3, compared to net-selling households that are UC, net-selling households that are LCVIP are estimated to be 6-percentage points less likely to sell to the FRA. They are also 2-percentage points less likely to sell to a large-scale trader but 9-percentage points more likely to sell to another household ($P < .01$). There is no statistically significant relationship between LCVIP status and a net-seller's probability of selling to a small-scale trader. Previous studies (Fafchamps & Hill, 2005; Zanello et al., 2014) have hinted at the potential links between farmers' wealth and their ability to access markets that offer remunerative prices. Our stepwise analysis that closely follows our theoretical framework provides empirical evidence related to this relationship. Specifically, LCVIP farmers (who are likely to also be less wealthy) are found to produce less maize and to thus be less likely to overcome the high fixed costs associated with accessing a market like the FRA.

7 | ADDITIONAL ROBUSTNESS CHECKS AND LIMITATIONS

In this section we probe the validity of our results through several additional robustness checks and discuss the paper's limitations. As mentioned earlier, our measure of LCVIP may suffer from hypothetical bias and thus we defined an alternative measure based on a potentially more severe constraint on liquidity during the production period (i.e., based on criterion 2 only). Our results are robust to the use of this alternate measure (Table F1, Appendix F). However, despite our best efforts, measuring liquidity using observational data has its drawbacks and we acknowledge the limits of our work. The gold standard measure of liquidity is often only possible in randomized control trials (Duflo et al., 2011; Fink et al., 2020). Yet, the evidence generated through an observational study like ours, using nationally representative survey data, is an important complement to experimental studies that can suffer from external validity and site selection issues (Ahlin, 2023).

AGRICULTURAL ECONOMICS
The Journal of the International Association of Agricultural Economists

A major challenge for this study was to find a sufficiently strong IV that also satisfies the exclusion restriction. While we do our best to justify the IV that was ultimately used, we recognize its limitations and interpret all results as associations. Additionally, the assumption of maize output being pre-determined at the time of market decision making (and thus a weakly exogenous variable in Equations 3–5) might not always be true. While this is unlikely in our sample, developing the conceptual framework and empirical strategy to test the effect of LCVIP on market outcomes under such circumstances could be a potential area for future research.[20]

Another limitation is that the assumption of a single crop production system made in the theoretical model for tractability is far from realistic. Some farmers may change cropping patterns to cope with LCVIP or poor access to markets. Extending the conceptual and empirical models to incorporate multiple crops could be areas for further research.

Guided by our theoretical framework, we did not include production period variables (e.g., farm size, input prices, etc.) in the market period regressions and instead estimated the association of LCVIP with market outcomes via a multi-step procedure. As robustness checks, we re-estimated the maize market position and maize marketing channel regressions with the LCVIP variable and the full set of marketing and production period explanatory variables directly included as regressors. Our main findings are robust to this specification (Tables F2 and F3, Appendix F).

We also check if our results are sensitive to the use of alternate market prices for maize (which in the main model are computed using August prices). The first alternative measure is the average of monthly maize retail prices over the entire peak maize marketing season (May-October). The second is a similar measure computed for the months of July, August, and September only. Our results are robust to these alternate measures (Tables F4 and F5, Appendix F).

8 | CONCLUSIONS AND POLICY IMPLICATIONS

In this article, we study the effects of liquidity constraints in accessing variable inputs during the production period (LCVIP) on the maize output and marketing behavior of maize-growing smallholder households in Zambia. While there is a large literature on the effects of high transaction costs (de Janvry et al., 1991; Goetz, 1992; Heltberg & Tarp, 2002; Key et al., 2000) and liquidity constraints during the *marketing* period (Burke et al., 2019; Stephens & Barrett, 2011) on participation in agricultural output markets, there is a dearth of empirical evidence on the effects of *production* period liquidity constraints on crop marketing behavior. We find that LCVIP are prevalent in Zambia, with 57% of smallholders in our sample categorized as LCVIP due to cash constraints that prevented them from accessing inorganic fertilizer through the market and/or the government subsidy program. In fact, 22% of sample households were so resource-constrained that they could not afford the farmer downpayment or cooperative membership required for participation in the subsidy program. Further, our econometric results suggest that LCVIP households, compared to unconstrained households, invest much less in productivity-enhancing inputs (e.g., inorganic fertilizer and improved maize seed), produce less maize output, and are less likely to be maize net-sellers.

Since LCVIP households produce less maize (and likely have a smaller marketable surplus), we hypothesized that they would be less likely to sell to marketing channels that have high fixed costs to access. We find evidence in support of this hypothesis. Specifically, LCVIP net-seller households were found to be less likely than unconstrained net-sellers to sell to the Zambian parastatal marketing board, the FRA, hindering their ability to benefit from the FRA's maize purchase program and the typically above-market prices it offers. For LCVIP households, their smaller expected returns due to a smaller marketable surplus are not able to offset the fixed costs incurred in accessing the FRA marketing channel, such as transportation costs and uncertainty over when the FRA would start buying, how much it would buy, and how long it would take to pay farmers, *inter alia*. Like the "sell low, buy high" phenomenon (Albuquerque et al., 2024; Burke et al., 2019; Dillon, 2020; Stephens & Barrett, 2011), this keeps cash-constrained farmers from taking advantage of remunerative market opportunities.

This paper builds upon previous work that demonstrates that liquidity constraints can lead to low input use (Kusunose et al., 2020) and thus low crop output (Feder et al., 1990; Foltz, 2004; Winter-Nelson & Temu, 2005), and extends this literature to consider the effects of LCVIP on farmers' marketing behavior. Our results complement those of Alene et al. (2008), Boughton et al. (2007), and Mather et al. (2013), who found that poor access to public and private assets can prevent smallholders from producing a marketable surplus and thus reduce their participation in output markets. Moreover, the current study's findings are consistent with previous work that highlights

[20] This is unlikely in our sample because households are free to update their marketing decision post-harvest unless tied by contractual agreements. While we could not rule out the possibility of informal contracts, in our sample, less than 1% of households had formal maize marketing contracts.

poor access to credit for agricultural inputs as a severe constraint faced by smallholders in SSA (Adjognon et al., 2017; Fink et al., 2020; Sheahan & Barrett, 2017).

A key policy take-away from this article is that production bottlenecks, such as LCVIP, can limit smallholders' capacity to benefit from remunerative market and price policies by adversely affecting their access to the inputs needed to expand production. Indeed, LCVIP likely exacerbate the already disproportionate capture of benefits from agricultural market policies like the FRA by wealthier farmers that has been documented in the literature (Fung et al., 2020; Mason & Myers, 2013). Future work could delve more deeply into the effects of the FRA on smallholder maize marketing decisions as well as the effects of the FRA on other aspects of smallholder behavior and welfare that have not yet been studied in the literature.

While we do not directly explore solutions to address liquidity constraints among smallholders, our results highlight that LCVIP are a major challenge in Zambia. Future studies could work to identify cost-effective strategies to relax these constraints, such as potentially cash transfers or other social protection programs (Asfaw et al., 2017; Harman and Chapoto, 2017; Lawlor et al., 2019). Weather insurance or disaster relief are additional alternatives to investigate, given this study's finding that excess rainfall shocks in the previous period are associated with a higher probability of being LCVIP in the current period. Working through agro-dealers or other small and medium enterprises that interface with smallholder farmers to improve farmers' access to credit and inputs could also be explored (Liverpool-Tasie et al., 2020). Overall, our results suggest that relaxing production period liquidity constraints would likely improve Zambian smallholders' ability to invest in productivity-enhancing inputs, increase their maize output, and help them be in a better position to take advantage of lucrative marketing opportunities.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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