Agrekon

Agricultural Economics Research, Policy and Practice in Southern Africa

ISSN: (Print) (Online) Journal homepage: www.tandfonline.com/journals/ragr20

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AGREKON
2024, VOL. 63, NO. 3, 166–180
https://doi.org/10.1080/03031853.2024.2402524

Determinants of crop abandonment by smallholder maize farmers in Zambia

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ABSTRACT
Crop abandonment is when farmers decide not to harvest their previously planted crop. There is limited but emerging literature on crop abandonment or failure predominantly examining weather and crop failure rates. Consistent with these existing scant studies, it is not immediately clear to what extent historical relationships can be extrapolated in the long run under climate change. This paper seeks to improve our understanding of determinants of crop abandonment decisions in Zambia for maize production at subnational level. We find that crop abandonment (harvesting) is positively (negatively) related to fertiliser use, rainfall and temperature and negatively (positively) related to cost of living, price of maize, index-based insurance cover, town and random shocks. Therefore, fertiliser, rainfall and temperature increase the likelihood of crop abandonment in Zambia whereas increasing cost of living, maize price, insurance participation, town specific and random shock reduce it.

ARTICLE HISTORY
Received 27 May 2024
Accepted 3 September 2024

KEYWORDS
Crop abandonment; maize; moral hazard; Zambia

JEL CODES
Q11; Q15; Q18

1. Introduction

Poverty remains one of the main challenges in developing countries. Despite the percentage of people undernourished having drastically decreased in the last fifty years, at least 800 million people are still food insecure (FAO et al., 2021; Sibhatu et al., 2022). Crop production in Africa is manual and labour intensive, with a woman workforce share of 40% (Christiaensen and Demery, 2018). Despite possibly having the least gender gaps, higher female productivity, and empowerment rates as well as higher child health nutritional outcomes (Ahdoot et al., 2015; Cooper et al., 2019; van der Merwe, 2022) in Africa compared to other economics sectors, agriculture is one of the most impacted sectors by climate change. This is most visible through reduced total productivity especially now that our climate is 1°C warmer compared to the preindustrial period (Ortiz-Bobea, 2021, 31; Chekenya, 2023, 142). The climate risks pose disproportionate effect across gender (Farnworth et al., 2016) and nations, with women, rural dwellers and lower income countries bearing the most severe impact regardless of contributing the least to the menace. Reduced total yields, food shortages, rising food prices, hunger and starvation are some of the (un)intended effects of climate change.

In the sub-Saharan Africa (SSA) region in general and Zambia in particular, smallholder famers produce a relatively higher proportion of maize compared to regional counterparts (Lowder et al., 2021). Smallholder agriculture and smallholder farmers are key to the climate change impacts and adaptation in agriculture discourse. The contribution of this study is threefold. First, there is

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dearth of literature on crop abandonment using African countries as laboratories since extant studies focused on developed countries, USA in particular. Second, the scantly available studies focus on soybeans which is not the main staple food crop for Africa, making our selection of maize crop pertinent. Third, agriculture insurance participation by small scale farmers in Africa is still low but gaining momentum while assessment of its potential role on maize abandonment using African case studies is rare. Furthermore, the paucity of studies that capture insurance participation mainly in USA, use government insurance subsidies which are voluntary, market distortionary and inefficient. Thus, the novelty of focusing on the role of African agriculture insurance participation is their unique characterisation of being out of pocket as opposed to being government subsidies. This provides us with the ability to observe if the different agriculture insurance programs have the same incentive or disincentive to be involved in moral hazard action of crop abandonment.

In this paper, we analyze determinants of crop abandonment decisions by smallholder maize farmers in Zambia.[1] We do so by using the Tobit regression approach. Generated harvested-to-planted ratios are also employed and analyzed by Tobit and Amemiya-MacCurdy approaches with Poisson, Fractional Probit and Hausman-Taylor techniques for sensitivity analysis and robustness purposes. We employ annual crop data at town and provincial levels for the period 2009–2015 for 72 towns across 10 provinces over 7 years to give 504 observations.[2] Crop abandonment is our dependent variable with fertiliser use, maize price, average rainfall, mean temperature and crop insurance participation as controls. In terms of participation in an insurance program, we find contradicting moral hazard evidence In line with some existing literature suggesting that different types and/or insurance arrangements between public and private provision have asymmetric incentive and/or disincentives to venture into crop abandonment. That is, public insurance programs incentivize moral hazard incidences which increase the probability of crop abandonment while private provision seems to be more efficient and screening reduces the chances of crop abandonment. But caution must be taken in interpreting these results since more research is needed first that can be generalised to different environments under varying assumptions. Thus, it is argued that understanding crop abandonment is key in ensuring food security (Ma et al., 2024).

Due to observed crop abandonment in Zambia, a reasonable question to ask is why there is significant abandonment of maize each year after cultivation throughout the entire 2009–2015 survey period.[3] The answer may be found after looking at what determines the decision to harvest/abandon a field.

2. Background

2.1 Agriculture and agro-ecological regions in Zambia

The Republic of Zambia is a poor, landlocked country in Southern Africa bordered by eight nations (Sibhatu, Arslan and Zucchini, 2022). Most Zambian farmers and cultivated crops are rainfed and about 60% of the population employed in agriculture. Despite this statistic, the sector contributes only 8% of the nation's GDP (World Bank, 2018).

The country is divided into 28 agro-ecological zones that are further partitioned into three main zones according to received rainfall: (i) region I, (ii) region II and (iii) region III. Region I encompasses the valley areas lying in the far Southern and Western parts. Region II includes the Central regions. Region III covers the Northern the Northern, Luapula, Northwestern, Copperbelt as well as the northern parts of the central province as shown in Table 1.

2.1.1 Crop failure and abandonment

One direct effect of weather variability on the agricultural sector is crop failure and abandonment with resulting effects on food security (Chekenya, 2023).[4] Crop failure, in principle, is a pre-condition for crop abandonment if we consider how the latter is statistically measured. A failed crop is one component in the measurement of crop abandonment ratios (Mulungu and Tembo, 2015, 2859).

Table 1. Zambia's climate and agro-ecological zones.

Agro Ecological Region	Region I	Region II (a & b)	Region III
Average rainfall (mm/year)	<800 mm	800-1,000 mm	>1,000mm
Min. (Dec-Feb)	19–21	17–18	14–16
Elevation (metres)	300–900 900–1,200	900–1,300	1,100–1,700
Growing season (days)	80–129	100–140	120–150
Drought Risk	Medium to High	Low to Medium	Very Low
Dry Season Frost Occurrence	Risk in Plateau areas	Risk in the Central Plateau areas	Mild risk levels in the South-Western regions.
Agricultural Relevance	Suitable for small grains and livestock production	Most productive locations for both cash crops and general agricultural products. Suitable for cassava and rice production and cattle ranching.	Intensive cultivating and consuming region.

Note: This information comes from the Institute of African Studies (1996) and work by Mulungu and Tembo (2015).

On the other hand, crop abandonment does not really imply crop failure because once good rains are received at a particular location in a given period, the unharvested crop is due to crop abandonment and not crop failure. If one wants to argue in terms of causality, the nature of the relationship between the two concepts is unidirectional running from crop failure to crop abandonment (Thurman and Fisher, 1988, 237).

2.2 Index based insurance in Zambia

The history of weather index insurance for agriculture in less developed countries dates to 2003. It transitioned from the pilot scale to more commercial implementation in India and Mexico. Many other countries, such as Thailand; Indonesia; Guatemala; Nicaragua; Honduras; Tanzania; Kenya; Ethiopia and Nepal, are developing or testing this product in feasibility studies and/or pilot programs for agriculture.

Zambia has a small yet robust agricultural insurance scheme. Insurance companies in the country are regulated by the Pensions and Insurance Agency (PIA) equivalent to the Insurance and Pensions Commission (IPEC) in neighbouring Zimbabwe. Insurance in Zambia is regulated by the Insurance Act, 1997, as amended by Act 26 of 2005. Until the last decade, agricultural insurance was only offered by a very few companies. Now, private insurers also provide agricultural insurance products. Index based weather (crop) insurance in Zambia represents a newly developed alternative to the traditional crop insurance programs for smallholder farmers. It aims to mitigate the hardship of the insured farmers against the likelihood of financial loss on account of anticipated crop loss resulting from incidence of adverse conditions of weather parameters like rainfall, temperature, frost and humidity otherwise known as climate-induced shocks.[5]

3. Literature review

At present, our understanding of crop abandonment or crop failure is limited (Chekenya, 2013, 142). In the present paper and future work, it may be instructive to differentiate the two.

3.1. Crop failure vs crop abandonment

Crop failure is different from crop abandonment. Crop failure can be thought of in terms of the total loss of crops on a farm (Mulungu and Tembo, 2015, 2859; Chekenya, 2023, 143). It occurs following catastrophic climate-shocks resulting in the destruction of crops due to flooding, pests or droughts

(Haque and Khan, 2017, 91). Crop failure can be seen as a component of crop abandonment in terms of measurement since a failed crop can still be captured as an unharvested area (Mulungu and Tembo, 2015, 2859). Yet, crop abandonment does not necessarily imply crop failure. In times of good rains, the unharvested area can be because of crop abandonment and not crop failure.[6]

Crop abandonment refers to a scenario in which farmers decide not to harvest previously planted crops (Ortiz-Bobea, 2021, 37). Obembe et al. (2021, 2) contextualise this definition to climate change by describing crop abandonment as happening after adverse weather shocks negatively affect crop yields to such an extent that it no longer makes economic sense to harvest.

Crop abandonment is most likely to happen when harvesting costs outweigh the expected revenue (Ortiz-Bobea, 2021). Expected revenue is determined by both yield quantity and output market price while the cost of harvest depends on input prices like fertiliser and seed. Postharvest and storage costs can also form part of the cost of harvest (Chen and Miranda, 2020).

In the emerging literature, crop abandonment is significantly observed among crops such as cotton (Cui, 2020, 902; Rippey, 2015), corn (Cui, 2020, 902), soybean (Caparas et al., 2021, 10, Cui, 2020, 902), fox tail millet (Bhattarai et al., 2015), maize (Caparas et al., 2021, 10), rice (Caparas et al. 2021, 10), snowpeas (Carletto et al., 2010), vegetables (Key and Runsten, 1999), and wheat (Obembe et al., 2021, 3; Travis and McCurdy, 2015, 12).

Cui (2020, 910) maintains that crop abandonment follows yield loss due to extremely high temperatures such that harvesting can no longer justify the opportunity cost. In this regard, crop abandonment is a decision at the margin made by a farmer not to harvest a field even after committing inputs (Chekenya, 2023, 143).[7]

3.2 Crop failure or crop abandonment: which comes first?

Following these discussions, it emerges that crop failure, strictly speaking, is a pre-condition for crop abandonment if one considers how the latter is statistically measured. A failed crop is one component in computing crop abandonment ratios (Mulungu and Tembo, 2015, 2859). Crop abandonment does not (necessarily) mean crop failure because in a season of good rains, unharvested crops are due to crop abandonment and not crop failure. In terms of causality, the relationship between these two concepts is unidirectional, running from crop failure to crop abandonment (Thurman and Fisher, 1988, 237; Chekenya, 2023, 144). Disentangling differences between these two closely related concepts is key for empirical work.

3.3 Theoretical models

Theoretical models of crop abandonment and crop failure include static model, intra-seasonal dynamic optimisation model and Pareto optimal approach. The static model builds on existing literature on moral hazard in crop insurance (Chekenya, 2023, 45). The key argument in this model is that the analyses build on static models which overlook the fact that crop abandonment decisions naturally occur after variations in harvest-time price and yield expectations in a specific growing season (Chambers and Quiggin, 2022, 320; Chen and Miranda, 2007, 5).

The intra-seasonal dynamic optimisation model borrows from utility theory. It is a theoretical dynamic model of crop abandonment which explicitly accounts for crop abandonment decisions by producers (Chen and Miranda, 2007, 4,5). The key assumption is that a farmer's key objective is to maximise expected net profit after harvest (Chekenya, 2013, 146). The model allows farmers to re-examine their expectations about price at a given intermediate point in time between planting and harvesting and based on their revised expectations, decide whether to abandon the crop or not (Chen, 2007, 27).

In the Pareto optimal model, an average farmer's main objective is to maximise profit under different fields and making decisions on labour allocation to achieve pareto optimality condition with respect to different fields and crops. The decision to abandon one field and allocate labour to the most deserving field is arrived at after considering where the potentially higher returns lie. An average farmer's objective is to maximise profit subject to a labour constraint that needs to be allocated efficiently among competing fields (Mulungu and Tembo, 2015, 2860; Chekenya, 2023, 146).

3.4 Empirical models of crop abandonment

Two popular empirical methods have been used to study crop abandonment at the national and sub-national level. These are ordinary least squares (OLS) and fractional probit. The latter is favoured by most model test statistics. There are some similarities and differences between these models.

The OLS approach is useful in studies making estimations at the national level. As compared to the generalised linear model (GLM), the OLS approach, in general, tends to produce slightly lower estimates in absolute terms (Chekenya, 2023, 146). Precisely, OLS coefficients tend to be lower than those from the fractional probit approach (Papke and Wooldridge, 1996, 619). It is important to note that OLS does not capture the fractional nature of the response variables in many empirical settings because it is measured as the proportion of failed crops. In studies using a fractional dependent variable, OLS is biased and inconsistent. Controlling for this requires the design of a fractional logit model that employs a quasi-maximum likelihood estimation (QMLE) approach to generate estimates that are robust to the conditional mean parameters with satisfactory efficiency properties to control for inefficiencies originating from the use of OLS in the case where we have fractional dependent variables (Papke and Woodridge, 2008, 122; Mulungu and Tembo, 2015, 2864).

The fractional and linear model, also known as the fractional probit or generalised linear model (GLM) is usually estimated in studies on crop abandonment because it is regarded as better option to the OLS model in capturing the fractional nature of crop abandonment at subnational level (Mulungu and Tembo, 2015, 2858). This model is mostly suitable for examining differences in effects across various agroecological regions if one is using disaggregated data. Also, the model allows for time-variant unobserved effects to be correlated with independent variables in panel data (Papke and Wooldridge, 2008, 122; Mulungu and Tembo, 2015, 2861). The model is better than OLS because it has a better fit.[8]

4. Data and methodology

We employ annual data for the period 2009–2015 covering 72 towns. By towns we mean the administrative level at which farm production happens in Zambia. We discuss each variable and data sources below.

4.1 Dependent variable: crop abandonment

Our dependent variable is crop abandonment. We follow Mulungu and Tembo (2015) and Cui (2020) to measure crop abandonment quantitatively using harvested ratios defined as harvested hectares of maize divided by planted hectares.[9]

$$HR = \left(\frac{Hectares^H}{Hectares^P}\right)_{it} \tag{1}$$

This variable has been employed by other scholars like Cui (2020). We construct harvested ratios for maize for each given location i in crop year t. $Hectares^H$ and $Hectares^P$ show, respectively, harvested and planted hectares of maize. The harvested ratio is bound between zero and one. To calculate harvested ratios, we use annual maize crop data for the period 2009–2015 covering 72 towns and 10 provinces collected from the Central Statistical Office of Zambia and the Ministry of Agriculture and Livestock.

4.2. Explanatory variables

4.2.1 Fertiliser use

Fertiliser use is measured as fertiliser consumption as a percentage of fertiliser production. To calculate fertiliser use at town, we take the sum of total quantity of top fertiliser used and the quantity of basal fertiliser used in metric tons. This gives our variable fertiliser use. We include this variable because it is a key input in maize production (Mulungu and Tembo, 2015, 2868). Theoretically, we expect higher fertiliser application rates to be linked to higher levels of harvest, ceteris paribus. Data on fertiliser comes from the World Development Indicators.

4.2.2 Maize price

We also employ secondary data on maize producer price (US$/ton). We employ disaggregated maize price data from the Central Statistical Office's Price Index database. At higher market price rates, a price-taking farmer is likely to harvest a higher proportion of her field, ceteris paribus. This is because the estimated profit exceeds the opportunity cost of harvesting.

4.2.3 Average rainfall

We supplement maize price data with pixel-level rainfall data in the form of average rainfall collected from WorldClim. This is an online database on global climate (Hijmans et al., 2005; Smale et al., 2015). The data covers the periods 2009–2015. Bad weather lowers yield thus reducing expected profits for a price-taking maize farmer. A price-taking farmer is going to harvest her field only if the average rainfall allows for expected profit to justify the opportunity cost of harvesting.

4.2.4 Mean temperature

The mean of temperature is used to capture variations in temperature. Data on mean temperature comes from local weather stations across the country (Mulungu and Tembo, 2015, 2862). Yields respond positively to good temperatures. Extremely hot temperatures can lead to lower expected profits and higher losses (Liu and Lu, 2023).

4.2.5 Crop insurance

The index-based insurance variable is a dummy taking the value of 1 in the presence of the program and 0 otherwise. Zambian smallholder farmers[10] who lack collateral security have the option of a newly developed index-based weather insurance program. The program protects uninsured farmers from the possibility of financial loss owing to crop loss from weather shocks. Participation in a crop insurance program can be a disincentive for a price-taking farmer to practice good farm management or harvest her previously cultivated crop via moral hazard (Chen, 2005; Anna and Schlenker, 2015; Chen and Miranda, 2020).

Table 2 reports descriptive statistics for variables influencing crop abandonment decisions.

4.3 Conceptual framework

A typical maize farmer in a given location in Zambia maximises her profit by choosing harvested hectares at the end of each farming season. In the same spirit as Cui (2020), we assume that the farmer is a price taker. Given output price, p, estimated revenue depends on the level of total output, Q, which is further determined by harvest level h. Production is also determined by the growing season weather variables, W, and yield distribution, α. The marginal cost of harvesting is indexed by c.

According to Cui (2020), production can also be subject to additional planting-related cost, A, which may be a sunk cost at harvesting time.

$$\max_{h} \pi = pQ(h; W, \alpha) - ch - A \tag{2}$$

Table 2. Descriptive statistics for variables affecting crop abandonment.

Variables	Obs	Mean	Std. Dev.	Min	Max	p1	p99	Skew.	Kurt.
Year	504	2012	2.002	2009	2015	2009	2015	0	1.75
Town	504	36.5	20.803	1	72	1	72	0	1.8
Province	504	5.637	2.96	1	10	1	10	−.067	1.609
Country	504	1	0	1	1	1	1		
Yield	504	1.9	1.941	0	11.035	0	8.072	1.418	5.683
Planted	504	15279	18802.282	0	97518.2	0	75923.19	1.902	6.456
Harvested	504	10915.5	14772.192	0	75272.98	0	65570.29	2.168	7.597
H-ratio	504	.618	.367	0	.993	0	.989	−.842	2.066
Fert	504	5536.79	14620.313	0	124000	0	81511.16	5.004	30.48
Cpi	504	102.975	53.931	0	161.465	0	161.465	−1.207	2.879
Mprice	504	191.857	69.938	144	357	144	357	1.763	4.535
Rain	504	1020	0	1020	1020	1020	1020		
Temp	504	150	0	150	150	150	150		
Ibi	504	.286	.452	0	1	0	1	.949	1.9

Note: *H-ratio* is the ratio of maize in a particular location in a given year. *Fert* is the total fertiliser application per hectare, *Cpi* is the annual inflation rate. *Mprice* denotes maize price per tonne in a given year. *Temp* is the mean temperature and *ibi* is a dummy for participation in an index-based insurance program.

We assume that maize production increases with the harvest level at a decreasing rate such that.

$$\frac{\partial Q}{\partial h} > 0; \ \frac{\partial^2 Q}{\partial h^2} < 0 \tag{3}$$

This indicates that the land with the potential to generate higher yield will be harvested first.

Weather variables, W, assumed to be a single dimensional object which affects production positively.

$$\frac{\partial Q}{\partial W} > 0 \tag{4}$$

We also assume that,

$$\frac{\partial^2 Q}{\partial h \partial W} > 0 \tag{5}$$

This implies that favourable weather conditions and higher maize yields are highly correlated. The skewness of yield distribution to the left is measured by . If maize production occurs on more marginal land and/or input use intensity is lower[11], the yield distribution is more left-skewed and α is relatively higher (Cui, 2020).

We further assume that,

$$\frac{\partial Q}{\partial \alpha} < 0; \ \frac{\partial^2 Q}{\partial h \partial \alpha} < 0 \tag{6}$$

The proportion of lower-yield land is supposed to be larger under higher. If we disregard the possibility of corner solutions for a moment, then the farmer maximises her profit if and only if the marginal revenue of harvesting an additional hectare equals the marginal cost of harvesting such that,

$$p\left(\frac{\partial Q}{\partial h}\right) = c \tag{7}$$

The role of weather variables on optimal harvest level can be derived by differentiating the first order conditions on both sides with respect to weather. Theoretically (see Cui, 2020), weather positively affects the level of harvest.

$$\frac{\partial h^*}{\partial W} = -\frac{\frac{\partial^2 Q}{\partial h \partial W}}{\frac{\partial^2 Q}{\partial h^2}} > 0 \tag{8}$$

For any given field, maize is harvested only if expected profit justifies the opportunity cost of harvesting. Bad weather lowers yield thus reducing profits for a price-taking farmer. The decision to harvest becomes complicated due to both maize prices and yield distributions. Following Cui (2020) and by comparative statics,

$$\frac{\partial h^*}{\partial p} = -\frac{\frac{c}{p^2}}{\frac{\partial^2 Q}{\partial h^2}} > 0 \tag{9}$$

$$\frac{\partial h^*}{\partial \alpha} = -\frac{\frac{\partial^2 Q^*}{\partial h \partial \alpha}}{\frac{\partial^2 Q}{\partial h^2}} < 0 \tag{10}$$

Holding all other things constant, the optimal level of maize harvest will be positively impacted by maize price and negatively impacted by the left-skewness of the yield distribution. Higher maize prices technically lead to higher harvests, ceteris paribus. A relatively higher level of skewness to the left indicates that the percentage of low-yield land is high implying a bigger share of land below the level of yield making it a profitable harvest.

This conceptual framework has several empirical implications. Despite weather variables' effect, denoted by W, on harvest being qualitatively like their yield impacts, the quantitative effect can be widely different owing to the economic trade-off in the decision to harvest. Moreso, controlling for location-fixed effects, bad weather is expected to see more hectares of maize abandoned. For farming towns and provinces with lower yield planted hectares, harvest ratios are expected to be lower.

4.4 Estimation

Literature builds on standard panel fixed effects estimation combined with location fixed effects to model the link between weather variables and crop abandonment (Cui, 2020). Mathematically:

$$\left(\frac{Acres^H}{Acres^P}\right) = g(\{T_{it,d}\}_{d=1}^{D}) + \gamma_1 Prec_{it} + \gamma_2 Prec_{it}^2 + h_s(t) + \omega_t + \alpha_i + \varepsilon_{it} \tag{11}$$

Harvested ratio of maize in location i in crop year t is the dependent variable. $Acres^H$ and $Acres^P$ show, respectively, harvested and planted acres. By design, the ratio is bound between zero and one.

Cui (2020, 909) extends this crop abandonment model to include a 3°C bin specification to "flexibly characterise the effects of growing-season temperature on crop abandonment." The resulting equation is expressed as follows:

$$i\left(\frac{Acres^H}{Acres^P}\right) = \sum_j \emptyset_j TBin_{it}^j + \gamma_1 Prec_{it}^2 + h_s(t) + \omega_t + \alpha_i + \varepsilon_{it} \tag{12}$$

$TBin_{it}^j$ controls for temperature distribution in location at time t with each $TBin_{it}^j$ variable counting the days in each growing season and temperature variations falling into the j^{th} bin.

4.5 Tobit regression and Amemiya and MaCurdy (1986) approach

For regression analysis, we employ a panel Tobit regression approach and the Amemiya and MaCurdy (1986) method. The suitability of a Tobit regression is premised on our generated harvested ratios which are censured by being continuous and bound between 0 and 1. The additional benefit of using the Amemiya-MaCurdy instrumental-variable approach is its ability to explicitly account for endogeneity and simultaneity problems by separating variables into time-variant and time-invariant endogenous and exogenous categories (Amemiya and MaCurdy, 1986). Furthermore, compared to the Hausman and Taylor (1981) procedure, it produces more efficient estimators and mostly applicable to situations like ours, where weights are not available (Amemiya and MaCurdy, 1986; Baltagi and Khanti-Akom, 1990). To guarantee consistent and efficient estimates, the pre-condition is to use strong instruments confirmed by high pairwise correlations between endogenous covariates (Baltagi and Khanti-Akom, 1990; Stock, Wright and Yogo, 2002). The results confirming the robustness and validity of endogenous instruments used (CPI, mprice and IBI) are reported in Table 5.

Following Tobin's (1958) methodology, the Tobit model adopted for this study is expressed as:

$$H_{it}^{*} = X_{it}{}'\beta_i + u_i + \varepsilon_{it} \tag{13}$$

where $0 \leq H^{*} \leq 1$ is the interval censored latent variable representing the unobserved true value of the harvested-to-planted ratio, X' is the vector of explanatory variables, β is the vector of estimates, $i = 1, 2, \ldots, 72$, are towns, $t = 1, 2, \ldots, 7$ are years, u_i represents unobservable town effects and ε_{it} are identically distributed random shocks. H^{*} value of 0 indicates total crop abandonment whereas 1 indicates complete harvesting of the total planted area. Thus, an explanatory variable with a negative sign indicates positive association between crop abandonment and the respective covariate and vice versa.

Following the methodology presented in Hausman and Taylor (1981) and Amemiya and MaCurdy (1986)[12], the Amemiya – MaCurdy random effects error-components model adapted is expressed as:

$$H_{it}^{*} = X_{1it}{}'\beta_{1i} + X_{2it}{}'\beta_{2i} + Z_{1i}{}'\sigma_{1i} + Z_{2i}{}'\sigma_{2i} + u_i + \varepsilon_{it} \tag{14}$$

where in addition to already given definitions, X' and Z' are time-variant and time invariant vector of covariates, respectively and both further disentangled into two parts, endogenous ($X_{1it}{}'$ and $Z_{1i}{}'$)[13]

Table 3. Results based on Tobit, Poisson and fractional probit models of crop abandonment.

Dependent Variable: Harvest Ratios (H-ratio)	Tobit Model Model 1	Poisson Model Model 2	Fractional Probit Model Model 3
Lnfert	−0.017***	−0.021**	−0.044***
	(0.005)	(0.009)	(.012)
LnCPI	0.052***	0.051**	0.145***
	(0.015)	(0.021)	(0.039)
Lnmprice	0.385***	0.474***	1.052***
	(0.088)	(0.109)	(0.204)
Lnrain	−0.223***	−0.452***	−0.811***
	(0.073)	(0.089)	(0.165)
IBI	0.224***	0.348***	0.609***
	(0.034)	(0.03)	(0.064)
Lntemp	−0.309***	−0.626***	−1.122***
	(0.101)	(0.123)	(0.228)
/sigma_u	0.153***		
	(0.022)		
sigma_e	0.316***		
	(0.011)		
Lnalpha		−16.557***	
		(1.763)	
Observations	504	504	504

Note: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Robust Standard errors are in parentheses.

Table 4. Results based on Amemiya–MaCurdy and Hausman-Taylor error component models.

Dependent variable: Harvest Ratios (H-ratio)	Amemiya–MaCurdy		Hausman-Taylor	
	Model 1	Model 2	Model 1	Model 2
Time varying exogenous covariates				
Lnfert	−0.083***	−0.083***	−0.084***	−0.084***
	(0.007)	(0.007)	(0.007)	(0.007)
Year	0.263***	0.263***	0.264***	0.264***
	(0.017)	(0.017)	(0.017)	(0.017)
Province	−0.048***	−0.048***	-.048***	−0.048***
	(0.016)	(0.016)	(0.016)	(0.016)
Time varying endogenous covariates				
LnCPI	−0.089***	−0.089***	−0.09***	−0.09***
	(0.018)	(0.018)	(0.018)	(0.018)
Lnmprice	0.405***	0.405***	0.4***	0.4***
	(0.069)	(0.069)	(0.069)	(0.069)
IBI	−0.404***	−0.404***	−0.406***	−0.406***
	(0.034)	(0.034)	(0.034)	(0.034)
Time invariant exogeneous covariates				
Lnrain	−76.365***		−76.593***	
	(4.974)		(5.015)	
Lntemp		−105.579***		−105.895***
		(6.877)		(6.934)
Observations	504	504	504	504

Note: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. Robust Standard errors are in parentheses.

Table 5. Pairwise correlations of endogenous time-variant and invariant variables.

Variables	(1)	(2)	(3)
(1) IBI	1.000		
(2) lncpi	0.254***	1.000	
	(0.000)		
(3) lnmprice	−0.211***	−0.750***	1.000
	(0.000)	(0.000)	

Note: ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$. In parentheses are p-values.

and exogenous (X_{2it}' and Z_{2i}').[14] Following endogeneity and exogenous tests suggested by literature (see Hausman and Taylor, 1981; Amemiya and MaCurdy, 1986; Baltagi and Khanti-Akom, 1990; Stock et al., 2002), time-variant endogenous (exogenous) variables are consumer price index and maize price (amount of fertiliser, year and province) and time invariant exogeneous ones are rainfall and temperature, without any time invariant endogenous variable selected. Model (4) is estimated using the generalised least squares (GLS) estimator given literature showing that micro-panel data is plagued with heteroscedasticity across towns in our case. GLS is also employed to all models estimated using cluster robust standard errors.

For sensitivity and robustness purposes, we also follow Chekenya's (2023) discussion on weakness of OLS and suggestion by employing the Poisson count and Fractional Probit harvesting probability models as well as the Hausman and Taylor (1981) error component modelling technique and their results are reported in Table 3 and Table 4.

5. Results and discussion

We begin by examining the role of fertiliser, maize CPI, maize price, rainfall, temperature, and crop insurance (Tables 2 and 3). In addition to censored Tobit and Amemiya-MaCurdy results, for purposes of sensitivity analysis and ensuring robustness of estimators, we also report results from Poisson, Fractional Probit and Hausman-Taylor models. Results reported in Table 3 show that crop abandonment (harvesting) is positively (negatively) related to fertiliser use, rainfall and temperature and negatively (positively) related to cost of living, price of maize, index-based insurance cover, town and random shocks. Therefore, fertiliser, rainfall and temperature increase the likelihood of crop abandonment in Zambia whereas increasing cost of living, maize price, insurance cover, town specific and random shock reduce it. Surprisingly, and contrary to theoretical expectations from the moral hazard view and empirical evidence (Burke and Emerick, 2016; Annan, and Schlenker, 2015; Cui, 2020) the results suggest that insurance participation increases (reduces) the probability of maize harvesting (maize abandonment). The possible justification for this contradiction is that studies which find evidence of a positive association between participation in an insurance program and crop abandonment are mostly in the United States of America where insurance programs are voluntary and supported by a government subsidy arrangement whereas in Africa, they are out-of-pocket contribution linked to private institutional arrangement. Furthermore, insurance claim payouts in developed countries are guaranteed since they are honoured through government unlike in Africa where the insurance services are offered by private insurers with low probability of honouring claims. Of much interest is the observation that climate change plays a more pronounced role on crop abandonment especially based on instrumental variable error component results presented in Table 4 particularly focusing on the size of the semi elasticities of rainfall and temperature.

Explicitly accounting for simultaneity and endogeneity bias gives some stylised facts. Firstly, the magnitude of the effect of almost all covariates on the likelihood of crop abandonment increases gradually. This indicates that results in Table 3 have downward bias due to the respective models' failure to categorise the covariates into these respective groups, namely time varying and invariant exogenous or endogenous as error component models do. Secondly, signs of some covariates change. For example, CPI changes from positive in Table 3 to negative in Table 4. Robustness and validity of the endogenous instruments (price, CPI and IBI) is guaranteed by strong and significant correlations reported in Table 5 which are in line with literature.[15] Our absolute pairwise correlations are in the ranges 0.21–0.75, which are on the higher side compared to endogenous instrumental variables employed in Baltagi and Khanti-Akom (1990) and Abadie et al. (2024) which range between 0.04 and 0.24.

6. Conclusion

Crop abandonment is a persistent feature in Zambia's agricultural sector especially among smallholder maize farmers. What determines crop abandonment is unclear. As such, examining factors which lead to crop abandonment decisions is crucial to aid our understanding of the subject which is limited at present.

Our findings are as follows. Crop abandonment is positively impacted by fertiliser use, rainfall and temperature and negatively determined by cost of living, maize price, index-based insurance cover, town and random shocks. Collectively, our results contribute some new evidence to the literature on crop abandonment.

Our results have several implications. First, there are missing markets. The government or independent farmers need to establish farmers' cooperatives to bargain on input purchase and sell output in a structured grouping (Porter, 2008). A good example to follow is rice cooperatives in China (Lin et al., 2022). Additional work is needed to establish the impact of the index-based insurance program. Does participation in the IBI program affect yields? What is the role of IBI in input use?

One drawback of our analysis is that we focus on maize only and a relatively short sample period. It is possible to examine heterogeneities in crop abandonment decisions across different crops and over a long period of time. However, this is contingent upon data availability which is a major issue in developing countries like Zambia. In most cases, the data is either unavailable or unreliable in instances where the data is available. We leave this for future research.

Other products such as yield insurance can be designed and implemented in the case of Zambia amidst rising concerns about climate change impacts. Crop insurance is more preferred in times of water shortages as this increases yields. Participation in an insurance program is observed to have a causal effect on revenue. This means that yield insurance and hedging levels are positively correlated. This presents an opportunity for policymakers and business players to help smallholder farmers make a difference in terms of food production and realise a return on investment while doing so. Combining crop insurance, agricultural microfinance products and microinsurance promise to be a key tool to fight poverty in developing economies which are dependent on agriculture (Mookerjee et al., 2014).

Notes

1. The role of risk factors in crop abandonment and how this is impacted by other risk sources (such as maize crop prices) and risk management strategies (like participation in an index-based insurance program) are beyond the scope of this study.
2. This is nationally representative.
3. There is extensive literature linking climate change to agricultural production (See for example, D'Agostino and Schlenker, 2016; Ortiz-Bobea, 2020).
4. Crop abandonment happens after an adverse shock lowers the yield below the point where the value of production equals the cost of harvesting (Obembe, Hendricks and Tack, 2021, 2; Chekenya, 2023).
5. Weather-based index insurance has been offered as an alternative method for increasing uptake of agricultural technology while preventing many of the problems associated with input subsidies (Miranda and Farrin, 2012).
6. We assume ceteris paribus.
7. Cropland abandonment is also gaining popularity in literature. For example, in addition to Sikor et al's. (2009) paper, Deininger et al. (2012) study land fragmentation, cropland abandonment and land markets in Albania. Other papers on the subject include Ortyl and Kasprzyk (2022).
8. Usually shown by the Ramsey's regression specification-error test (RESET).
9. This dataset has been used in literature by scholars such as Smale et al. (2015).
10. These are farmers that who generally cultivate less than two hectares (Muyanga and Jayne, 2019).
11. This case can be true if the Zambian government subsidizes index-based insurance.
12. For more details refer to Hausman and Taylor (1981), Amemiya and MaCurdy (1986), Baltagi and Khanti-Akom (1990), Stock, Wright and Yogo (2002) and Baltagi (2009, 2013).
13. They are correlated with u_i but not with ε_{it}
14. They are uncorrelated with both u_i and ε_{it}
15. For a detailed literature survey refer to Stock, Wright, and Yogo (2002).

Acknowledgements

We thank Chenggang Wang, Anna Josephson, Christopher Hare, Ariel Ortiz-Bobea and participants at the 2024 Agriculture Policy Research Group in New Orleans. The data sets and code generated and/or analyzed during the current study are available upon request from the authors. All errors are ours.

Disclosure statement

No potential conflict of interest was reported by the author(s).

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Appendix

Table A1. List of provinces in our panel.

(1)	(2)
Central	Muchinga
Copperbelt	Northern
Eastern	North Western
Luapala	Southern
Lusaka	Western

Note: There are 10 provinces in our sample which contain 72 towns.

Table A2. 72 Towns included in our sample across 10 Provinces.

(1)	(2)	(3)	(4)
Chadiza	Kalulushi	Mazabuka	Nyimba
Chama	Kaoma	Mbala	Petauke
Chavuma	Kapiri Mposhi	Milenge	Samfya
Chibombo	Kaputa	Mkushi	Senanga
Chienge	Kasama	Mongu	Serenje
Chilubi	Kasempa	Monze	Sesheke
Chingola	Katete	Mpika	Shang'ombo
Chinsali	Kawambwa	Mpongwe	Siavonga
Chipata	Kazungula	Mporokoso	Sinazongwe
Choma	Kitwe	Mpulungu	Solwezi
Chongwe	Livingstone	Mufulira	Zambezi
Gwembe	Luangwa	Mufumbwe	

(*Continued*)

Table A2. Continued.

(1)	(2)	(3)	(4)
Ikelenge	Luanshya	Mumbwa	
Isoka	Lukulu	Mungwi	
Itezhi-tezhi	Lusaka	Mwense	
Kabompo	Luwingu	Mwinilunga	
Kabwe	Mafinga	Nakonde	
Kafue	Mambwe	Namwala	
Kalabo	Mansa	Nchelenge	
Kalomo	Masaiti	Ndola	