Determinants of Post-Harvest practices adopted by smallholder horticulture farmers in Mashonaland West province, Zimbabwe

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Abstract
This study investigates the determinants of post-harvest losses (PHL) and the intensity of post-harvest technology adoption among smallholder vegetable farmers in Zimbabwe's Mashonaland West Province. Utilising a multi-stage sampling technique, primary data were collected from 200 farmers across the Hurungwe and Makonde districts. The research employed a Multinomial Logit (MNL) model to analyse PHL determinants at four value chain stages—farm gate, transportation, storage, and marketing—and a Probit model to identify factors influencing the adoption of mitigation practices. Findings reveal that 70% of losses occur during storage, followed by farm-level and transportation stages. The MNL analysis highlights that farm gate sales and modern technology significantly decrease the likelihood of storage and marketing losses. The Probit model identifies farmer age, production volume, cooperative membership, and access to diverse information sources as significant positive predictors of technology adoption. Notably, radio ownership showed a negative correlation, suggesting a potential deficiency in broadcast technical advice. While limited to cabbage, rape, and tomatoes in two districts, the results advocate for a policy shift toward integrated post-harvest management. Recommendations include establishing decentralised, solar-powered cold storage, strengthening cooperatives for collective investment, and providing specialised technical training via extension services. Additionally, restructuring credit facilities to target post-harvest infrastructure, such as plastic crates and drying tools, is essential to minimise waste and enhance profitability.

Introduction

Smallholder vegetable production constitutes a crucial pillar of household income generation, particularly within the Mashonaland West Province of Zimbabwe, and contributes significantly to the national economy. Smallholder horticulture constitutes a pivotal component of the Zimbabwean agricultural economy, a structural importance magnified across the wider Sub-Saharan Africa (SSA) region where agriculture remains the primary determinant of livelihood and food security for an estimated over 70% of the population (Abass et al., 2023). Smallholder vegetable farmers in developing countries encounter high incidences of post-harvest losses from farm to retail stage. In addition, it has been noted that not much improvement has been attained in trying to reduce percentage losses in post-harvest in most developing countries (Kitinoja et al., 2011). Furthermore, the situation of low agricultural productivity is worsened by high post-harvest losses which are experienced in SSA (World Bank, 2011). The pervasive globalisation of the agribusiness sector has precipitated a fundamental paradigm shift, moving the focus from a traditional production-oriented approach toward market- or consumer-driven vertical value chain coordination. This restructuring has exerted significant strain on smallholder agriculture and rural livelihoods across the globe (Vorley et al., 2023). Recognising the undeniable importance of this sector in bolstering rural livelihoods within the province, this paper addresses a critical challenge: the substantial post-harvest losses experienced by these farmers, which demonstrably diminish their market returns. To address this issue and explore pathways to enhanced profitability, this paper analyses the determinants influencing the post -harvest practices adopted by smallholder horticulture farmers in the study area. Data for this analysis were collected through a survey of 200 horticulture farmers across the Hurungwe and Makonde districts of Mashonaland West Province. This study focuses on four key post-harvest methods as they pertain to the predominant crops – cabbage, rape, and tomatoes – with the number of adopted practices serving as the dependent variable in a Probit model. Adoption of postharvest practices by smallholder vegetable farmers provides adequate opportunities for farmers to increase their profitability through raising local value-added products, increasing bargaining power, enhancing market-access and promoting greater competition among middlemen (Khatana et al., 1997; Mittal, 2007).The main objective of this study was to investigates the determinants governing the intensity of post-harvest technology adoption among smallholder horticulture producers across two districts in Zimbabwe's Mashonaland West Province. The research answers these questions

: What are the primary factors contributing to post-harvest losses at the farm gate, transportation, storage, and marketing stages for smallholder farmers in Mashonaland West?

: To what extent do socio-economic factors (such as age, production volume, and cooperative membership) influence the number of post-harvest technologies a farmer chooses to adopt?

: How effective are current modern post-harvest technologies and specific market channels (like farm gate sales) in reducing losses compared to traditional methods?

The empirical insights derived herein are intended to inform evidence-based policy frameworks aimed at optimising post-harvest management, thereby enhancing the productivity and market profitability of the smallholder sector.

Theoretical Model

This study was anchored on the random utility theory. The theory posits that when a consumer is faced with a set of mutually exclusive choices, s/he will select the alternative that maximises his or her utility (Greene, 2012). For practical purposes when undertaking a study of the market characteristics, a farmer is just like a consumer. Therefore, in the case of this study, a rational farmer will participate in a market outlet that gives him/her the highest utility, based on the post-harvest loss.

Let's consider a farmer choosing between two sources of post-harvest losses to consider before selling: Farm-level(L) and distance to market (H). The farmer's utility for each source of post-harvest loss can be expressed as:

$U_L = V_L + \varepsilon_L$
$U_H = V_H + \varepsilon_H$
Where:

- U_L and U_H are the total utilities of the both farm-level and distance to markets losses, respectively.

- V_L and V_H are the systematic components of utility, representing the observable factors influencing the choice.
- ε_L and ε_H are the random error terms, capturing unobserved factors that affect utility.

The farmer will choose to sell at a distance market considering the post-harvest losses if U_H > U_L. This can be rewritten as:

$V_H - V_L > \varepsilon_L - \varepsilon_H$

Assuming the error terms follow a specific distribution (e.g., Gumbel), we can derive the probability of choosing to sell to a distant market after considering the post-harvest losses associated:

$P(H) = \exp(V_H) / [\exp(V_H) + \exp(V_L)]$

Random Utility Theory provides a valuable framework for analyzing smallholder farmers' market-access decisions. By understanding the factors influencing these decisions, policymakers can develop effective strategies to promote agricultural development and improve farmers' livelihoods.

Methodology

Study Area

The research was conducted in the Mashonaland West Province of Zimbabwe, specifically within the Hurungwe and Makonde districts. These districts were purposively selected due to their high intensity of smallholder horticultural production. This region is characterised by intensive daily vegetable cultivation—primarily tomatoes, onions, cabbages and leafy greens—destined for wholesale markets, including the major urban centres of Karoi, Chinhoyi, and the Mbare Musika terminal market in Harare.

Figure 1: Mashonaland West Province and location of the study areas

Data source and sampling procedures

Primary data were gathered using a structured survey instrument administered to a cross-section of smallholder vegetable farmers. From a targeted sample of N=200 all the 200 observations were successfully captured. To determine the ward sample sizes of smallholder horticulture farmers (SHF) to be interviewed, the probability proportional to size sampling method was employed. This method ensures that the ratio of the ward sample size of SHF(C) to the district sample size of SHF (DSS) is equal to the ratio of the ward population size of SHF (n) to the district population size of SHF (nTOT).

This guarantees proportionate representation of ward sample sizes in the district sample. Mathematically, this is expressed as:

$$\frac{C}{DSS} = \frac{n}{nTOT} (1)$$

Rearranging equation (1), we get:

$$C = (\frac{n}{nTOT}) \times DSS(2)$$

However, the district sample size (DSS) is calculated using the formula:

$$DSS = \frac{N}{1 + N(e)^2} (3)$$

where:

- (N = nTOT) (district population size of SHF)
- (e = 0.05) (level of precision)

Therefore,

$$DSS = \frac{nTOT}{1 + nTOT \times 0.05^2} (4)$$

Substituting equation (4) into equation (2) and simplifying, we get:

$$C = \frac{n}{1 + nTOT \times 0.05^2} (5)$$

where:

- (C) is the ward sample size of SHF
- (n) is the ward population size of SHF (to be obtained from District Agritex Extension Officer and District Agronomist)
- (nTOT) is the district population size of SHF (to be obtained from the latest published figures for the respective districts)

The sample size of SHF for each ward was determined using equation (5). The sample size for each of the two selected districts was calculated before field data collection began, as it relies on secondary or published data. The numerical sample size for each district is given by equation (4). This formula can be used to determine the theoretical and statistically significant sample size for an entire district for administering household questionnaire. This survey required two districts Hurungwe and Makonde districts. Makonde districts have 52486 households (ZimStats, 2022) .Hurungwe have 97726 (ZimStats , 2022) .Using e = 0.05, and inserting figures in the above equation we get theoretical DSS value for Makonde district as 396 and Hurungwe as 398 .Thus theoretically determined sample size of resource adequacy , the sample size would consist of 396 households in Makonde district and 398 households in Hurungwe district , However , the sample size arrived at after factoring in other considerations such as accessibility , the need to have a sample size large enough to obtain statistically significant results and the availability of resources was 200 households using the multi stage sampling . A sample of at least 13 % of the total wards in the district was considered adequate. Therefore, six wards where selected three in each district The fieldwork, executed through face-to-face intervi**ews** between August and October 2024**,** was facilitated by rigorously trained agricultural extension officers who served as field enumerators. Respondent and location selection utilised a systematic multi-stage sampling technique, proceeding hierarchically from the selection of districts to wards, and subsequently to the random selection of villages and individual farm households. This technique was considered the most appropriate for this study because sampling frames were not available at district level. The first stage used purposive selection of two districts (Makonde and Hurungwe) out of the seven districts in the study area. The selection of these districts was based on the intensity of SHFs' vegetable production. These districts are where there is intensive production of vegetables by SHFs for wholesale marketing. The second stage was the random selection of three wards in each district where communities are engaged in Horticulture production to give a total of six wards. The selection of these wards was guided by information obtained from agricultural extension workers and Non-Governmental Organisations (NGOs) that were operating in the districts. Furthermore, accessibility of the area was another criterion which was considered in identifying these wards. The third stage involved use of cluster sampling to select six villages (clusters) in each of the six wards. At the household level cluster sampling and probability proportional to size was applied to select households based on the sampling frame provided by the local village extension officer. Of the total sample of 200 smallholder horticulture farmers all the 200 was ultimately interviewed in all the two districts.

Data Collection

Data was from two districts in Mashonaland West, specifically Hurungwe and Makonde, where horticulture crops are predominantly produced and marketed. A multi stage sampling technique was employed to select a total of 200 smallholder horticulture farmers (SHF).

The survey was conducted using a structured questionnaire, capturing information on the socio-economic characteristics of households, household resource endowment, farm characteristics, access to information, and institutional and market services. A 5 -point Likert scale was added on the columns on the questionnaire numbered 1 to 5. The points on the Likert scale were as follows 1 =strongly disagree, 2= disagree, 3=agree, 4=strongly agree and 5 =very strongly agree.

Data analysis

Following collection, the raw data were systematically coded and transcribed into a digital format. This dataset was then imported into two dedicated statistical software platforms SPSS (version 23) and Stata 15/SE to facilitate rigorous econometric analysis. The initial analytical phase involved the computation of descriptive statistics, a multinomial logit (MNL) model was employed to analyse the determinants of post-harvest loss (PHL) among farmers, specifically focusing on where the most significant losses occurred: at the farm gate, during transportation, in storage, or during marketing. The dependent variable was a multinomial choice representing these four mutually exclusive locations, with losses at the farm gate serving as the reference category. The independent variables were a set of farm-, farmer, and institution-specific characteristics. Probit model was also used to analyse the determinants of post-harvest practices adopted by the smallholder horticulture farmers.

Results and discussion

Sources of Post -harvest losses

Figure 2 shows that most post- harvest losses occurred in storage (70%) while the remaining (30%) losses where accounted at farm levels (20%), long distance to market (5 %) and the aspect of marketing (5%).

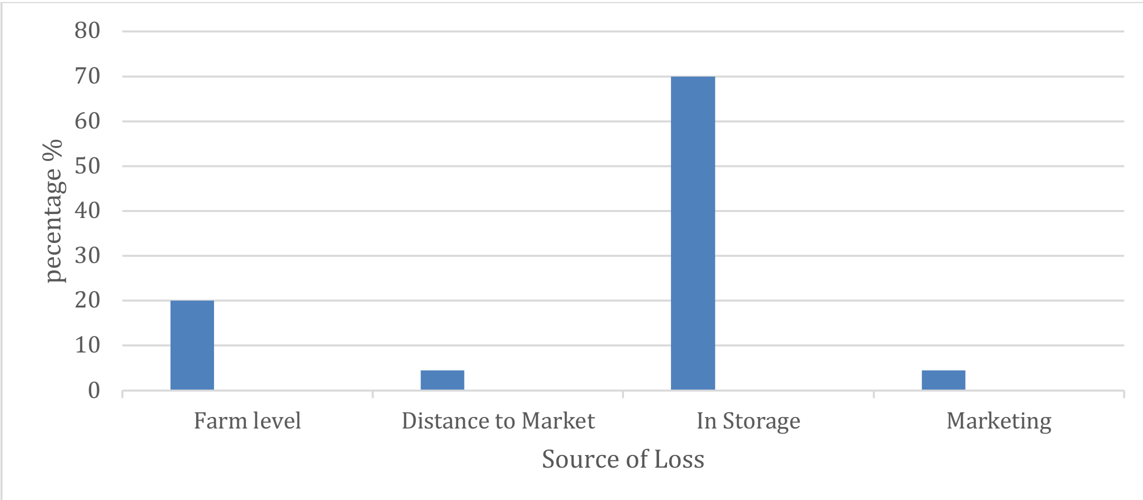

Figure 2: Sources of post-harvest losses by vegetable farmers

Source: Survey Data

Factors influencing Post -Harvest Losses among Small Holder Farmers in Hurungwe and Makonde Districts in Zimbabwe

A multinomial logit (MNL) model was employed to analyse the determinants of post-harvest loss (PHL) among farmers, specifically focusing on where the most significant losses occurred: at the farm gate, during transportation, in storage, or during marketing. The dependent variable was a multinomial choice representing these four mutually exclusive locations, with losses at the farm gate serving as the reference category. The independent variables were a set of farm-, farmer, and institution-specific characteristics.

Model Fit and Overall Significance

The model's overall fit and explanatory power were strong, as evidenced by several key statistics. The log-likelihood ratio statistic ($\chi2=113.28$, df = 57) was highly significant ($p<0.001$), indicating that the independent variables are jointly significant in explaining the determinants of PHL. This suggests that the model is a substantial improvement over a null model with no predictors. Additionally, the goodness-of-fit statistics, including the pseudo-R-squared value of 0.284, provide further confidence in the model's ability to accurately represent the data, aligning with established econometric standards (Hill, 1983).

Specific Factors Influencing Post-Harvest Loss

The results, as detailed in Table1,2 and 3 highlight several significant factors affecting PHL across the different loss categories. The coefficients' signs and significance levels indicate whether a variable accentuates or mitigates losses. A positive coefficient suggests an increased likelihood of losses, while a negative coefficient indicates a mitigating effect.

Analysis of Odds Ratios

The exponential regression coefficient, exp(b), serves as a proxy for the odds ratio. An odds ratio greater than 1 suggests that the odds of experiencing losses in a specific category (e.g., transportation) are higher than in the reference category (farm gate), while an odds ratio less than one indicates lower odds. Transportation Losses: In the transportation category according to table 1, cooperative membership was found to accentuate losses (p =0.10). Conversely, selling produce at the farm gate significantly mitigated losses (p <0.05). The odds of experiencing transportation losses were eight times lower for farmers who sold at the farm gate compared to those in the reference group (p =0.10).

Table 1: Estimated Multinominal logit Model for Factors Influencing PHL among Farmers

		Transport			
Parameter Description	Parameters	Coeff(b)	Std Error	P-Value	Exp (b)
Intercept	Intercept	-0.161	5.31	0.976	_
Years of education(yrs)	educ_yrs	0.064	0.061	0.289	1.067
Farming experience(yrs)	Fmryrs	0.048	0.08	0.544	1.049
Household mbrs above 18 yrs	HHsize _abv18	0.264	0.166	0.112	1.302
Used one or more PHLR Techs (yes =1)	PHLR _use	0.54	0.905	0.55	1.717
Access to credit (yes=1)	Crditacc	1.174	0.834	0.159	3.236
Coop membership (yes =1)	coopmbr	1.343*	0.818	0.100	3.832
Yrs of coop.mmbership (yrs)	Coopyrs	-0.111	0.085	0.191	0.895
Market Distance (km)	Mktdist	-0.004	0.289	0.989	0.996
Sell at farmgate (yes =1)	Salegate	-2.076**	0.812	0.011	0.125
Sell at urban mkt (yes=1)	Saleurbn	0.336	0.832	0.686	1.4
Non-farm income(yes=1)	Nonfminc	0.598	0.584	0.307	1.818
Land area under hort crops(arces)	Landhort	-0.111	0.118	0.345	0.895
Hort crops prd (kg)	Hortprd (log)	0.35	0.484	0.469	1.42
Other crops cultivated (nmber)	multi_cropng	0.148	0.23	0.52	1.16
Extension agts monthly visit (yes =1)	Xgentvst	-0.998	1.153	0.386	0.368
Radio owner (yes=1)	ownradio	-0.229	1.402	0.87	0.795
TV ownership (yes=1)	Owntv	-1.381	1.01	0.172	0.251
own car/transport	Owntrans	-0.259	0.993	0.794	0.772

Source: Survey Data

Storage Losses: Several factors were highly significant in mitigating storage losses according to table 2. The use of one or more modern technologies for PHL reduction, selling at the farm gate, and ownership of a television were all highly significant (p < 0.01). The use of modern PHL-reducing technology reduced the odds of storage losses by approximately 12 times (1/0.084) compared to the reference category. Similarly, selling at the farm gate reduced storage losses by a factor of 6.6 (1/0.15), and TV ownership also had a significant mitigating effect

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Table 2: Estimated Multinominal logit Model for Factors Influencing PHL among Farmers

		Storage			
Parameter Description	Parameters	Coeff (b)	Std Error	P-Value	Exp(b)
Intercept	Intercept	1.524	2.977	0.609	_
Years of education(yrs)	educ_yrs	0.001	0.038	0.996	1.000
Farming experience(yrs)	Fmryrs	0.02	0.045	0.661	1.02
Household mbrs above 18 yrs	HHsize _abv18	0.081	0.099	0.412	1.084
Used one or more PHLR Techs (yes =1)	PHLR _use	-2.48***	0.773	0.001	0.084
Access to credit (yes=1)	Crditacc	0.583	0.568	0.305	1.791
Coop membership (yes =1)	Coopmbr	-0.349	0.495	0.481	0.705
Yrs of coop. mmbership (yrs)	Coopyrs	0.033	0.048	0.497	1.033
Market Distance (km)	Mktdist	0.062	0.179	0.727	1.064
Sell at farmgate (yes =1)	Salegate	-1.895***	0.654	0.004	0.15
Sell at urban mkt (yes=1)	Saleurbn	-0.369	0.49	0.451	0.691
Non-farm income(yes=1)	Nonfminc	0.084	0.355	0.812	1.088
Land area under hort crops(acres)	Landhort	-0.048	0.056	0.386	0.953
Hort crops prd (kg)	Hortprd (log)	0,242	0.269	0.368	1.274
Other crops cultivated (nmber)	multi_cropng	0.182	0.126	0.149	1.2
Extension agts monthly visit (yes =1)	Xgentvst	0.782	0.543	0.15	2.186
Radio owner (yes=1)	Ownradio	-0.184	0.835	0.825	0.832
TV ownership (yes=1)	Owntv	-2.013***	0.542	0.001	0.134
own car/transport	Owntrans	0.245	0.601	0.684	1.278

Source: Survey Data

Marketing Losses: For the marketing category according to table 3, selling at the farm gate ($p < 0.05$) and owning a radio ($p < 0.05$) were both significant factors that mitigated losses.

Table 3: Estimated Multinominal logit Model for Factors Influencing PHL among Farmers

		Marketing			
Parameter Description	Parameters	Coeff (b)	Std Error	P-value	Exp(b)
Intercept	Intercept	6.103	4.374	0.163	-
Years of education(yrs)	educ_yrs	0.056	0.055	0.312	1.057
Farming experience(yrs)	Fmryrs	-0.063	0.069	0.365	0.939
Household mbrs above 18 yrs	HHsize _abv18	0.098	0.151	0.518	1.103
Used one or more PHLRTechs (yes =1)	PHLR _use	-1.694	1.347	0.208	0.184
Access to credit (yes=1)	Crditacc	0.503	0.881	0.568	1.654
Coop membership (yes =1)	Coopmbr	-0.483	0.854	0.572	0.617
Yrs of coop. mmbership (yrs)	Coopyrs	-0.038	0.092	0.679	0.963
Market Distance (km)	Mktdist	-0.074	0.266	0.782	0.929
Sell at farmgate (yes =1)	Salegate	-1.682**	0.846	0.047	0.186
Sell at urban mkt (yes=1)	Saleurbn	-0.78	0.725	0.282	0.458
Non-farm income(yes=1)	Nonfminc	-0.545	0.536	0.31	0.58
Land area under hort crops(acres)	Landhort	0.037	0.09	0.68	1.038
Hort crops prd (kg)	Hortprd (log)	-0.277	0.41	0.499	0.758
Other crops cultivated (nmber)	multi_cropng	0.147	0.186	0.428	1.159
Extension agts monthly visit (yes =1)	Xgentvst	0.088	0.839	0.917	1.092
Radio owner (yes=1)	Ownradio	-2.057**	0.91	0.024	0.128
TV ownership (yes=1)	Owntv	0.013	0.786	0.986	1.013

Own Car /transport (yes=1	Owntrans	0.385	0.866	0.657	1.469

Source: Survey Data

Number of Obs used = 200
LR chi^2 = 113.28
Prob >Ch^2= 0.000
Pseudo R2 =0.284
Goodness of fit: Pearson chi^2(1194) = 1252.30: Value=0.117
*Note : Regression coefficient is significant for coefficients with *=p<0.10,**p<0.05*
****= p<0.01*

Determinants of factors influencing number of post-harvest methods adopted

Table 4 shows the results of assessing factors influencing number of post-harvests methods adopted by smallholder horticulture farmers in Hurungwe and Makonde districts of Mashonaland West province Zimbabwe. Four post-harvest methods were jointly considered as modern technologies and the proportion adopted by each farmer became the dependent variable that was regressed against explanatory variables. Probit model was used with its result summarised in table 4. Based on the log likelihood chi square statistic (Chi ^2 =129.19) and the significance probability level of ($p<0.001$) the model has an overall good fit.

The analysis reveals several statistically significant determinants of post-harvest method adoption among farmers. Farmer age exhibited a highly significant positive correlation ($p<0.01$), suggesting that more senior farmers are considerably more inclined to employ a broader array of post-harvest techniques. Similarly, cooperative membership (coopmbr) demonstrated a positive and significant association ($p<0.10$), indicating that affiliation with a cooperative incrementally increased the probability of utilizing more post-harvest methods by a marginal effect of 5%. Furthermore, the log-transformed volume of horticulture production evinced a positive and significant relationship ($p<0.05$), implying that farmers with higher overall Horticulture crops yields were more prone to adopt additional post-harvest strategies, with a marginal increase of 4%. Lastly, access to multiple sources of information (info_coms) was found to be positively significant ($p<0.05$) in predicting the adoption of numerous post-harvest methods, underscoring the importance of diverse information channels in promoting the uptake of these practices.

Farmers who frequently access urban markets, specifically those in Karoi, Magunje, Chinhoyi, and Harare, demonstrate a notably higher propensity to adopt a wider array of post-harvest management techniques. This positive correlation, statistically significant at the 10% level ($p<0.10$), suggests that the enhanced market opportunities available in urban centres act as a strong incentive. Farmers with such access are approximately 4% more likely to implement a greater number of post-harvest methods, indicating a clear link between market reach and improved post-harvest practices. The ability to directly sell produce in these larger, more demanding markets likely encourages farmers to invest in methods that preserve quality, reduce spoilage, and ultimately fetch better prices.

While radio ownership was found to be highly statistically significant ($p<0.01$), its relationship with the adoption of post-harvest methods presents a perplexing outcome. Despite the common assumption that radio serves as a crucial conduit for information dissemination, the analysis reveals a counterintuitive effect: the predicted probability of a farmer adopting more post-harvest methods actually decreases by a margin of 10% if they own a radio. This suggests that simply owning a radio, despite its potential as an information source, does not directly translate into a greater uptake of post-harvest techniques. Further investigation would be necessary to unravel this unexpected inverse relationship, perhaps exploring the nature of the information being broadcast, the farmers' interpretation of it, or other confounding factors that might be at play. The initial hypothesis that radio ownership would drive adoption was not supported by the evidence.

Table 4: Estimated Probit model to determine factors influencing the number of post-harvest methods adopted among farmers

Parameter Description	Parameters	Coeff(b)	Std Err	Z	P-value	Marginal Effects
Years of Education (years)	Edu years	-0.0210	0.0389	-0.54	0.588	-0.0010
Extension Agent monthly visit (yes 1)	Xagentvst	0.3061	0.5757	0.53	0.595	0.0141
Age of Farmer (yes 1)	Age	0.0560***	0.0211	2.65	0.008	0.0025
Access to Credits (yes 1)	Crditacc	-0.0922	0.52006	-0.18	0.859	-0.0041
Coop membership (yes 1)	Coopmbr	1.0046*	0.52644	1.92	0.055	0.0450
Hort prod (kg)	Hort prod (log)	0.9960**	0.4059	2.43	0.014	0.045
Nonfarm Inc (yes 1)	Nonfarm inc	-0.3281	0.3884	-085	0.398	-0.0445
Multiple sources of info-coms	Info-coms	0.9259***	0.2926	3.16	0.002	0.0414
Radio Ownership (yes1)	Own radio	-2.3382***	0.9097	-2.57	0.010	-0.10477
Sell at urban Market (yes 1)	Sale urb	0.8931*	0.5316	1.68	0.093	0.0400
Intercept	Cons	-14.6125	4.5817	-3.19	0.001	-

Number of Obs= 200

LR Chi^2 =65.75
Prob >Chi^2 = 0.000
Pseudo R2 = 0.4837
Goodness of fit: Pearson Chi^2 (402) =129.19; P-value =0.989
*Note: Regression coefficient is significant for coefficients with * = p<0.10; ** p< 0.05; *** = p< 0.01*

Source: Survey Data

Discussion

This paper provides a comprehensive analysis of post-harvest losses (PHL) among vegetable farmers in the Hurungwe and Makonde districts of Zimbabwe. The results are divided into where losses occur, the factors influencing those specific locations of loss, and what drives farmers to adopt modern mitigation technologies.

Primary Sources of Loss

The descriptive statistics reveal a significant bottleneck in the value chain.

-Storage is the critical pain point: A staggering 70% of all post-harvest losses occur during storage.

-Other stages: Farm-level losses account for 20%, while transportation and marketing contribute a combined 10%.

This suggests that while farmers are relatively efficient at harvesting and moving goods, they lack the infrastructure or climate-controlled environments necessary to keep produce viable once it is harvested.

Determinants of Loss (Multinomial Logit Analysis)

The study uses a Multinomial Logit (MNL) model to identify what factors increase or decrease the likelihood of loss at specific stages compared to the "farm gate" baseline.

Key Mitigating Factors (What reduces loss)

-Farm Gate Sales: Selling directly at the farm gate was the most consistent "protector" against loss. It significantly reduced losses in transportation (8 times lower odds), storage (6.6 times lower), and marketing. This is logical, as it transfers the risk of perishability to the buyer almost immediately.
-Modern Technology: Using at least one PHL-reducing technology reduced storage loss odds by 12 times.
-Information Assets: TV ownership significantly reduced storage losses, and radio ownership reduced marketing losses, likely by providing weather updates or market price information that allows for better timing.
Risk Factors (What increases loss)
Cooperative Membership (Transportation): Surprisingly, being in a coop *accentuated* transportation losses. This might suggest inefficiencies in collective transport logistics or delays caused by waiting for multiple farmers' produce to be pooled.

The data paints a picture of a "survival-based" efficiency. Farmers minimise loss by selling at the farm gate, but this often limits their profit margins compared to urban markets. To move toward higher profitability, the research suggests that targeted investment in storage technology and improved information dissemination is more critical than simply increasing production.

Conclusions

The empirical evidence presented in this study underscores the critical nature of post-harvest losses within the smallholder horticulture sector of Mashonaland West, Zimbabwe, where storage stands out as the most significant point of vulnerability, accounting for 70% of total losses. The multinomial logit and Probit analyses collectively demonstrate that post-harvest loss is not merely a technical failure but a multifaceted issue influenced by institutional, socio-economic, and market-access factors. Key findings indicate that the adoption of modern post-harvest technologies significantly mitigates storage losses, while selling produce at the farm gate serves as a primary strategy for reducing losses across transportation, storage, and marketing categories by minimising handling and transit time. Furthermore, the intensity of adopting post-harvest practices is positively driven by farmer age, scale of production, and membership in cooperatives, highlighting that seasoned farmers with higher output and collective bargaining power are better positioned to safeguard their yields. Interestingly, while diverse information channels promote adoption, the negative correlation between radio ownership and practice adoption suggests a potential disconnect between general media consumption and the delivery of specialised, actionable agricultural technical assistance. Ultimately, the study confirms that improving the profitability of smallholder vegetable production depends heavily on moving beyond production-oriented support toward integrated post-harvest management and structured market participation.

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