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Postharvest losses and the impact of reusable plastic container technology on profitability

Evidence from tomato traders in Nigeria

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ABSTRACT

Postharvest loss is a major challenge in food production and supply chains in developing countries. Using primary data from fresh tomato traders in Lagos, Nigeria, and endogenous switching econometric modelling, this study investigates the effects of reusable plastic containers (RPC) technology on traders' net profits and the factors determining the adoption of the technology. Results indicate that the trader's position along the supply chain, income level, seasonality, sales frequency, and technology affordability positively influence their adoption decision. We found that the use of RPC technology significantly increases traders' net profits. The counterfactual impact analysis indicates that traders who adopted RPC would have earned 7 percent lower net profits had they not used RPC. Conversely, non-adopters would have increased their net profit by 5 percent had they adopted the technology. However, heterogenous treatment effects were observed due to heterogeneities among the adopters. Based on the results, we suggest policy interventions to enhance access to postharvest technology for reducing losses and creating job opportunities for actors along the value chain. The cost of the technology is found to be the major barrier to adoption. Thus, policy interventions, such as access to affordable financing options, subsidies, incentives for low-cost local producers, or duty-free importation, should be considered to make RPC technology affordable to fresh tomato traders and to increase wider adoption.

Keywords: adoption, endogenous switching regression, postharvest loss, profit, reusable plastic container, small traders

1. INTRODUCTION

The problem of food losses has been a notable challenge in food production and supply chains in different countries of the world. The total food lost globally every year is estimated to be able to feed about 1.5 billion people (Gustavsson et al. 2013). Several national and multinational level policy measures have acknowledged the need for tackling the problem of post-harvest food losses. These are reflected in the Sustainable Development Goal (SDG) and the Malabo Declaration. SDG 12.3 states that by 2030 there should be a reduction of food losses along the production and supply chain, including postharvest losses (United Nations 2016). Similarly, the Malabo Declaration of 2014 commits to reducing postharvest losses by at least half in 2025 (NEPAD 2016).[1] Multi-national institutions, like the Postharvest Loss Alliance for Nutrition (PLAN) and Postharvest Education Foundation, among others, were also established with the common goal of reducing postharvest losses. The Agricultural Promotion Policy (APP) of Nigeria has a component that focuses on reducing food losses along the production and supply chain to curb the spread of hunger and food security.

One of the effects of postharvest losses is that it reduces the food that is available for human consumption, which is worsened by rising demand for food (Sheane et al. 2008; Rutten 2013; Natsa 2015; Kikulwe et al. 2018). Food losses also cause negative externalities to society by increasing the emission of greenhouse gases and subsequently aggravating the risk of climate change (Chaboud and Daviron 2017). This leads to an added cost in waste management and resource wastage (Chaboud and Daviron 2017; Sheane et al. 2008). High levels of postharvest losses also lead to declines in the welfare of farmers and traders (Natsa 2015), adversely affecting desired global trend towards ending poverty and hunger, as highlighted in the SDG 1 and 2 (United Nations 2016). Countries like Nigeria are far from reaching these global goals partly due to high levels of losses in food value chains, especially those for fresh fruits and vegetables.

Tomato is the most widely consumed vegetable in Nigeria after onion and pepper (Oke et al., 2020). Nigeria is the largest producer of fresh tomato in Africa south of the Sahara (FAO, 2016). However, the country experiences the highest level of tomato postharvest losses in Africa and is unable to satisfy its local demand for tomato (Ugonna et al. 2015). Postharvest losses along the tomato value chain in Nigeria are estimated to be at about 40 percent (Ugonna et al. 2015). As a result, the country has to import tomato paste worth about USD 60 million annually to make up the demand gap (FAO 2018a). Perishable commodities, such as tomato, require delicate handling, packaging, and stringent conditions to maintain quality along the supply chain. The primary cause of tomato postharvest damage in Nigeria is primarily attributed to the kind of container used in the packaging, storage, transporting, and sale of fresh tomatoes (Arah et al. 2015; Sinha et al. 2019). Findings at the continental level also reveal that a high share of postharvest losses in fresh tomato in Sub-Saharan Africa (SSA) occur in the handling, packaging, distribution, and processing of the vegetable (Idah et al. 2007; Gustavsson et al. 2013).

The capacity of the packaging container to give protection to fruits and vegetables and preserve their quality are vital in the reduction of postharvest losses (Akter and Khan, 2012; Gautier et al. 2008). The right packaging container protects the produce from physical damage and compression and permits adequate airflow during distribution and sale (Idah et al. 2007). The traditional woven baskets commonly used in to package fresh tomatoes for distribution and sale in Nigeria do not, however, provide protection from physical damage, compression, and excessive heat (Hurst 2010);

[1] The Malabo Declaration on Accelerated Agricultural Growth and Transformation for Shared Prosperity and Improved Livelihoods is a set of goals adopted by Heads of State and Government of the African Union in 2014 in Malabo, Equatorial Guinea, showing a targeted approach to achieve the agricultural vision for the Africa, which is shared prosperity and improved livelihoods. https://www.resakss.org/sites/default/files/Malabo%20Declaration%20on%20Agriculture_2014_11%2026-.pdf.

Kitinoja et al. 2019). These baskets are also not strong enough to stack well during transportation and do not allow sufficient airflow. This causes an accumulation of excessive heat, compression, and quick deterioration of the fresh tomatoes during transportation and storage (Hurst, 2010; Arah et al. 2015; Ugonna et al. 2015; Macheka et al. 2017; Kitinoja et al. 2019). Moreover, these baskets can only be used once due to their fragile nature. Despite their low cost, traditional baskets are not considered cost-effective in the long run (Kitinoja 2013; Macheka et al. 2017).

In response to this problem, in 2017 the Global Alliance for Improved Nutrition (GAIN) through the Postharvest Loss Alliance for Nutrition (PLAN) program formally introduced the use of reusable plastic containers (RPC hereafter) in the fresh tomato market in Nigeria (GAIN 2017). The PLAN program aimed to reduce the level of tomato postharvest losses by making RPC more available, accessible, and affordable for tomato traders as a replacement for woven baskets (GAIN 2017). Unlike woven baskets, RPCs possess smooth edges and reduced depth, which greatly reduces compression or mechanical damage to the fresh produce. RPCs also are easily stackable due to their firmness and afford sufficient airflow to the produce (Babarinsa et al. 2018). RPCs can be re-used many times. Each container carries about 25 kg of produce, which is a standard quantity for vegetable marketing (Naika et al. 2005). According to Adegbola et al. (2011), PRCs are more efficient and effective than traditional baskets for handling and packaging fruits and vegetables through all the stages in the supply chain. Babarinsa et al. (2018) showed that the use of RPCs reduced in-transit tomato losses by up to 80 percent. In terms of economic returns, a study in Afghanistan demonstrated that the use of these plastic crates in packaging fresh fruits and vegetables augments the proceeds obtained by the farmers and traders who adopted them (Lipinski et al. 2013). Although adoption of RPCs has been increasing since the PLAN project, recent studies show that the majority of the tomato traders in Nigeria still make use of traditional woven baskets (Babarinsa et al. 2018; Kitinoja et al. 2019; Olumuyiwa et al. 2017).

Several studies have analyzed postharvest losses and their effects on welfare among tomato farmers in Nigeria (Olayemi et al. 2010; Akangbe et al. 2014). However, there remains a knowledge gap on postharvest loss and technological options to manage such losses in the context of tomato traders. Previous studies (Kitinoja 2013; Rapusas and Rolle 2009) have analyzed the relative profitability of RPC users versus non-users using cost-benefit analysis, simple comparison tests on the profits of adopters and non-adopters, or ordinary least squares regression in estimating the financial benefits of this technology. However, such analytical approaches do not take into account the problem of endogeneity and selection bias, which could lead to inconsistent and inefficient estimates and unreliable conclusions and policy recommendations (Cerulli 2014). Using empirical data collected from tomato traders in Nigeria and an endogenous switching regression (ESR) modeling approach, the objectives of this study are to analyze: (1) the factors influencing the adoption of RPC, (2) the impact of the adoption of RPC technology on the profits of tomato traders, and (3) the heterogeneous effects of RPC technology on trader's profits.

As discussed in section 3, the use of the ESR modeling approach takes care of the endogeneity and selection bias that may exist in the data. To the best of our knowledge, no empirical studies have assessed the impacts of technologies for tackling postharvest tomato losses using an ESR modeling approach. Thus, we believe that the findings and policy recommendations developed through this study will provide more reliable evidence for addressing problems related to the packaging technologies used in the distribution and sale of fresh tomato and reduce postharvest losses in the tomato value chain in Nigeria.

The remainder of this paper is as follows. A review of the research literature is presented in the next section. The context of the study, data collection techniques, and estimation approaches are presented in section 3. Descriptive results and analysis of econometric results are presented in sections 4 and 5, respectively. The last section concludes the study with key policy recommendations.

2. LITERATURE REVIEW

2.1 Overview of postharvest losses in Africa

FAO (2018) reports that over 250 million people in Africa (20 percent of the African population) suffer from chronic hunger and undernourishment. Many African countries have become major food importers in a bid to meet the high level of unmet food demand in the country. Meanwhile, large quantities of food products are being wasted along food value chains in these countries (Kitinoja and Kader, 2015). The World Bank estimates the annual value of postharvest grain losses in Africa at US$ 4 billion, which exceeds the total value of food aid that was received over the last decade and is equal to the yearly caloric requirements of 48 million people (Zorya et al. 2011). Reducing the level of postharvest food losses is a quick impact intervention to enhance food security and nutrition in African countries (Kitinoja et al. 2019).

Food losses are particularly higher in SSA countries like Nigeria because of the low quality of storage and food-handling technologies used in food value chains (Kitinoja et al. 2019). According to Gustavsson et al. (2013), higher levels of food wastage are realized along the value chain than at the consumer level. Fruits and vegetables are the food groups with the highest levels of postharvest losses in SSA. This is due to their perishability and high moisture content (Jaspreet and Anita, 2013). Fresh fruits and vegetables, therefore, requires delicate handling and appropriate technologies to reduce the level of losses encountered during packaging and distribution.

In Nigeria, there are high levels of food losses despite food shortages, undernourishment, and prevailing hunger in the country. Up to 12.1 million people in the country are severely food insecure (FAO 2019). Although Nigeria is a major food producer, agricultural output has not kept pace with domestic food demand for the growing population. This has resulted in increased imports of food items (FMARD 2011). Regardless of the high level of food insecurity, the country still experiences postharvest losses estimated at 20 percent for grains, 20 percent for fish, and about 40 percent for fresh fruits and vegetables (Natsa 2015). The country's ability to effectively minimize postharvest losses in food, therefore, is a critical component in ensuring food security. However, the reduction of food losses is an area that has not been given much attention in the formulation of agricultural policies (Aulakh et al. 2013; Mothibatsela, 2015; Rutten, 2013). Sharply reducing such losses could contribute significantly to ensuring food security in Nigeria, complementing increased agricultural production (Kitinoja and Kader 2015b).

According to Jaspreet and Anita (2013), postharvest losses include both food losses along the supply chain and food wastage at the consumer level. However, food wastage at the consumer level is less predominant in Sub-Saharan African countries than food losses along the postharvest value chain (Gustavsson et al. 2013). Food losses in developing countries mostly occur before reaching the consumer due to technical, financial, and managerial drawbacks during harvesting, storage, transportation, and sale of the food produce (Gustavsson et al. 2013; Kitinoja et al. 2019; Olumuyiwa et al, 2017). About 47 percent of the total funds needed to get rid of hunger in SSA countries should be directed towards the reduction of postharvest losses in order to make available more food for human consumption (FAO-World Bank 2010). Postharvest losses, therefore, pose a serious challenge to overcome in efforts to eradicate hunger in SSA.

2.2 Effects of postharvest loss management on livelihood outcomes

Research and interventions on postharvest losses in SSA countries could help achieve four key developmental objectives in low-income countries – improve food security, enhance food safety, increase resource use efficiency, and improve livelihoods among value chain actors:

Reducing food losses offers an important pathway for improving food security and nutrition by increasing the amount of food available for consumption. A large proportion of people in developing countries spend a large share of their income on food items (FAO 2018b). Increased food supply, therefore, will translate into reduced food prices, increased food access, and augment the real income of consumers (Sheahan and Barrett 2017).

Reducing post-harvest losses would also reduce food contamination and spoilage, as these are major factors associated with high postharvest losses (Arah et al. 2015). The World Health Organization reported that there are up to 91 million cases of illness and 137,000 deaths in Africa per year due to the consumption of contaminated food (WHO 2015). Spoilage and deterioration of agricultural products post-harvest produces toxins and substances that are harmful to the human body (Sheahan and Barrett, 2017).

The reduction of postharvest losses can also result in more effective and efficient use of farm inputs like fertilizer, water, labor, and land. Farmers have to use more of these scarce resources to meet market demand if they anticipate high levels of losses postharvest (Sheahan and Barrett, 2017). Reducing these losses would, therefore, translate into reduced input consumption, lower production costs, and higher profit margins for farmers and other value chain actors (Akangbe et al. 2014; Obayelu et al. 2014).

Studies have documented the positive effects on livelihoods of postharvest loss management through increased profitability and incomes, improved welfare, greater food availability, and poverty reduction. Babarinsa et al. (2018) found that the use of RPC in packaging fresh tomato during transportation reduced the level of postharvest losses by up to 80 percent in comparison to the use of woven baskets. Similar findings were documented by Bokusheva et al. (2012) and Obayelu et al. (2016). Thus, reductions in postharvest losses would lead subsequently to an increase in profits, income, food security, and welfare for farmers and traders.

3. METHODOLOGY

3.1 Context and the study area

This study is based on primary data obtained from a sample of fresh tomato traders in Lagos State, located in the southwestern part of Nigeria. Lagos state has the second largest population in the country, but is the smallest in terms of the land area covering an area of only 3,671 km^2 (NBS 2011). The population density of the state is estimated at 6,871 persons per km^2 as compared to the national average population density of about 226 persons per km^2 (Avis, 2019). The state experiences two rainy seasons annually with average annual rainfall of about 1300 mm (NBS 2011). Temperatures range from 24 to 33°C, and the mean relative humidity annually is 70 percent (Iwugo et al. 2003; NBS, 2013).

Lagos is the country's largest urban center. The largest tomato markets in Nigeria are found there. Most of the fresh tomatoes from local farms go straight to the markets in Lagos (Babarinsa, et al. 2018). Five of the largest tomato processing factories in Nigeria are also located in Lagos (Ugonna, et al. 2015). Therefore, farmers find it advantageous to deliver their fresh tomato directly to Lagos due to the presence of large fresh tomato markets and the processing factories. Tomato retailers from different parts of the country prefer to buy from Lagos due to the abundance of tomatoes and lower prices. The use of RPC technology was introduced in Lagos in part due to the sizeable fresh tomato markets there and substantial postharvest losses associated with them (Babarinsa et al. 2018).

3.2 Data

The data used in this study were collected through a questionnaire-based survey of fresh tomato traders in Lagos state. Before developing and administering the survey instrument, focus group discussions and key informant interviews were conducted with tomato market association leaders and representatives from different actors along the tomato value chain – farmers, wholesalers, retailers, handlers, carriers, distributors, and consumers – to acquire insights on the fresh tomato trade and the use of RPC. The information from these discussions and interviews provided a clearer understanding of the context of tomato trading and the problems associated with postharvest losses in Lagos. The focus group discussions and key informant interviews also provided inputs for developing the quantitative survey instrument.

For the quantitative data, a multi-stage sampling procedure was used in the selection of respondents. Lagos state was purposively selected because it is the largest fresh tomato trading hub in southwestern Nigeria through which about 70 percent of the tomato produced in the state is distributed (Babarinsa et al. 2018). In the second stage, a purposive sampling technique was used to select fourteen large tomato markets in different Local Government Areas (LGAs) of Lagos state. These markets were selected through the help of key informants and tomato market association leaders. After determining the necessary sample size for the survey following Cochran's (1963) formula, a sample of 267 fresh tomato traders, including both adopters and non-adopters of the RPC technology, were randomly selected using a simple random sampling technique.[2] However, 12 traders were dropped due to their inability to complete the survey, thus data from 245 observations were used in the analysis.

Pre-testing of the questionnaire was carried out to ensure consistency, relevance, and its validity in the local context. The survey questionnaires were administered using trained enumerators recruited from the local area who have prior field experience in conducting surveys in the area. Fieldwork was supervised daily by the first author of the paper.

3.3 Modelling approach

This study uses an endogenous switching regression (ESR) model (Croppenstedt et al. 2003; Lokshin & Sajaia 2004), which accounts for selection bias, to examine the adoption of RPC technology and its impacts on the profitability of fresh tomato traders in the tomato value chain in Lagos state, Nigeria. Endogenous switching regression models are widely used to investigate the joint determination of technology adoption and the effects of technologies in the agricultural economics literature (Alene and Manyong 2007; Amare et al. 2012; Abdulai and Huffman 2014; Acheampong et al. 2018; Kassie et al. 2018; Kumar et al., 2020). In the present study, we model the choice of fresh tomato trader to adopt RPC technology as a selection process, where traders choose to adopt RPC if the expected net return from switching to the technology is higher than the status quo, i.e., use of traditional woven baskets. But the observed samples of adopters and non-adopters were not randomly assigned or experimentally controlled groups. The adopters and non-adopters are likely to be heterogeneous due to unobserved factors, such as their entrepreneurial capacity, risk behavior or preferences, and business aspirations. This could lead to a sample selection bias in the estimation of parameters related to the impacts of technology adoption on outcome variables. Similarly, these unobserved factors could affect both the decision

[2] Cochran's formula is used to obtain a representative sample for proportions within an unknown population (Singh and Masuku 2014).

to adopt the RPC technology and the outcome variable (profitability). Hence, these factors could lead to endogeneity bias in the parameter estimates.

In the absence of a randomized trial, by estimating the selection and outcome equations simultaneously, the endogenous switching regression model addresses the endogeneity problem arising from the use of non-experimental survey data. The switching or selection equation sorts individuals into adopters and non-adopters of RPC, which in turn determines the net returns for fresh tomato traders.

Let π_{1i} be the net profit for the i^{th} tomato trader who adopted RPC technology and π_{2i} be the profit for the i^{th} tomato trader who did not adopt RPC. The selection equation can be expressed as:

$$I_i^* = (\pi_{1i} - \pi_{2i})\,\Upsilon + \psi\, Z_i + u_i, with\, I_i = \begin{cases} 1\; if\; I_i^* > 0 \\ 0\; otherwise \end{cases} \quad (1)$$

where I_i^* is the latent variable that determines whether an individual chooses to use RPC technology ($I_i = 1$) or not ($I_i = 0$), i.e., I_i is the actual value we observe as to whether an individual uses RPC or not. The latent variable I_i^* is not observable to the researcher, but its value perceived by a trader leads to the dichotomous realization of the adoption decision. I_i^* can be interpreted as a measure of the expected profit differences between adopters and non-adopters. $\Upsilon\; and\; \psi$ are the parameters to be estimated and Z_i is a vector of observed characteristics that influence an individual's adoption decision. Z_i may include some or all of the X_i variables (see Equations 2 and 3) and one or more instrumental variables (exclusion restrictions) to improve identification. The instruments do not have a direct effect on the dependent variable (profit) other than through the selection equation. u_i is an error term normally distributed with 0 mean and constant variance σ_u^2 which is assumed to be one, since the parameters of the selection equation are estimable only up to the scalar factor (Lokshin and Sajaia 2004).

The profit functions for the two groups can be represented in two regime equations.

$$\text{Regime 1: } \pi_{1i} = \beta_1 X_{1i} + \varepsilon_{i1}\; (If\; I_i = 1) \quad (2)$$

$$\text{Regime 2: } \pi_{2i} = \beta_2 X_{2i} + \varepsilon_{i2}\; (If\; I_i = 0) \quad (3)$$

where X_{ji} is a vector of individual characteristics and other attributes that influence profit levels, β_i are coefficient parameters; $\pi_{1i}\; and\; \pi_{2i}$ are indicators of profit levels for RPC users and non-users, respectively; and $\varepsilon_{i1}\; and\; \varepsilon_{i2}$ are disturbance terms for the regime 1 and regime 2 equations, respectively. The error terms in the selection and regime equations are assumed to have a tri-variate normal distribution with zero mean and with σ_1^2 and σ_2^2 as variances of the error terms in the regime equations; $\sigma_{1u}$and σ_{2u} are covariances between the error terms ε_{i1} and u_i and $\varepsilon_{i2}\; and\; u_i$, respectively. Since π_{1i} and π_{2i} cannot be observed simultaneously, the covariance between ε_{i1} and ε_{i2} is not defined.

The conditional expectations, i.e., the impacts of RPC adoption on adopters' profit and the counterfactual outcomes, can be computed using the following equations (Abdulai and Huffman 2014; Lokshin and Sajaia 2004; Kumar et al. 2020). The results to be generated and variables used from these equations can be summarized as in Table 1 and Table 2, respectively.

$$E(\pi_{1i} / I_i = 1,\; X_{1i}) = \beta_1 X_{1i} + \sigma_1\, \rho_1\, [f(\psi Z_i)/F(\psi Z_i)] \quad (4a)$$

$$E(\pi_{1i} / I_i = 0, X_{1i}) = \beta_1\, X_{1i} - \sigma_1\, \rho_1\, [f(\psi Z_i)/F(1 - \psi Z_i)] \quad (4b)$$

$$E(\pi_{2i} / I_i = 1, X_{2i}) = \beta_2 X_{2i} + \sigma_2\, \rho_2\, [f(\psi Z_i)/F(\psi Z_i)] \quad (4c)$$

$$E(\pi_{2i} / I_i = 0,\; X_{2i}) = \beta_2 X_{2i} - \sigma_2\, \rho_2\, [f(\psi Z_i)/F(1 - \psi Z_i)] \quad (4d)$$

where ρ_1 is the correlation coefficient between the error terms ε_{i1} and u_i and ρ_2 is the correlation coefficient between ε_{i2} *and* u_i, $f(\psi Z_i)$ is a density function, $F(\psi Z_i)$ is a cumulative distribution function, and $f(\psi Z_i)/F(\psi Z_i)$ is the Inverse Mill's Ratio.

Table 1. Treatment and heterogeneity effects

	Adopters of RPC	Non-Adopters of RPC	Treatment effects
Adopters (RPC)	(5a) $E(\pi_{1i}/I_i = 1, X_{1i})$	(5c) $E(\pi_{2i}/I_i = 1, X_{2i})$	TT
Non-adopters (RPC)	(5b) $E(\pi_{1i}/I_i = 0, X_{1i})$	(5d) $E(\pi_{2i}/I_i = 0, X_{2i})$	TU
Heterogeneity effects	BH1	BH2	TH

Source: Authors' presentation of treatment and heterogeneity effects
Note: (5a) and (5d) are observed profits for adopters and non-adopters on RPC technology. 5(c) represents the counterfactual expected profit for adopters. 5(b) is the counterfactual expected profit for non-adopters.
TT= treatment effects on the treated (5(a)-5(c)).
TU= Treatment effects on the untreated (5(b)-5(d)), i.e., the effect of RPC on profits of non-adopters had they adopted the technology.
BH1 and BH2 are the effects of base heterogeneity between adopters and non-adopters.
TH is transitional heterogeneity, i.e., TH=TT-TU.

The parameters of the models in equations 1, 2, and 3 are estimated simultaneously using the Full Information Maximum Likelihood (FIML) method.[3] This approach relies on joint normality of the error terms in the binary and continuous equations.

3.4 Identification strategy

Three instrumental variables that affect the first stage (selection) equation but do not have a direct effect on the trader's profit were identified. These are the intensity of radio-use, traders' perception of the affordability of RPC, and their knowledge of the supply chain for RPC, i.e., knows of local sellers and distributors.

- The intensity of radio use by the trader was hypothesized to have a significant effect on the adoption decision of the technology. This is because the use of radio has been highlighted in previous studies as a powerful tool for obtaining information and creating awareness of agricultural technologies (Obidike 2011; Elemasho et al. 2017a). Masuki et al. (2006) emphasized the importance of an agricultural information pathway in increasing the adoption of agricultural technologies. Radio was the major means of creating awareness and disseminating information on the use of RPCs in the study area (GAIN 2017). The use of radio, however, would not directly influence the trader's profit, as it has not been observed to reduce costs or increase the sale of agricultural products.
- The perception of traders towards the affordability of the RPC technology is expected to significantly affect the trader's decision to use RPCs. Studies have shown that a positive perception towards a particular agricultural technology would significantly increase the likelihood of its adoption (Asfaw et al. 2011; Elemasho et al. 2017b). Adegbola et al. (2011) also enlisted the perceived high cost of RPCs among tomato farmers in Nigeria as a major barrier hindering its use. Therefore, if the trader perceives RPCs to be affordable, they are more likely to adopt it. This factor, however, has not been observed to have any direct influence on their profit level.
- The trader's knowledge of RPC sellers or distributors was also expected to affect their adoption decision significantly and directly, but not their profit margin. This is because a trader who has better information on the supply chain for the technology, such as knowing of local sellers or distributors, are more open to adopting RPCs. However, this knowledge has no direct influence on the profitability of the trader's use of the technology.

[3] FIML was shown the most efficient estimator to estimate models with endogenous switching (Ali et al. 2014; Lokshin & Sajaia, 2004) to yield consistent standard errors. We used the *movestay* STATA command to simultaneously fit the binary selection equation and regime equations and generate consistent standard errors.

Table 2 describes the variables used in the analysis.

Table 2. Descriptions of variables used in the study

Variable name	Description and measurement
ln_net profit (Naira)	Natural log (ln) of total annual profit from tomato business (in Naira)
Trader uses RPC	Trader currently makes use of RPC in tomato business. (1=yes, 0 = no)
Retailer_trader (=1)	Trader's position in the value chain; (1 = retailer, 0 = wholesaler)
Female_trader (=1)	Sex of trader (1 = female, 0 = male)
Age_trader (yrs)	Natural log (ln) of age of the trader, in completed years
ln_education (years)	Years of formal schooling (in completed years)
ln_income (Naira)	Natural log (ln) of total estimated monthly income (in Naira)
ln_experience (years)	Natural log (ln) of experience in tomato trading (number of years)
Married (=1)	Marital status of a trader (1 = married, 0 = otherwise)
Hh_size (#)	Number of household members (head count)
Oth_perish_sale (yes=1)	Trader sells other perishable products in addition to tomato (1 = yes; 0 = no)
Percent_spoilt (%)	Percentage of tomato trader handles that typically are damaged (%)
Tom_mkt_asso (yes=1)	Trader is member of tomato market association. (1 = yes, 0 = no)
ln_peak_purc (kg)	Natural log (ln) of quantity of tomato purchases for sale in peak season (kg)
ln_lean_purc (kg)	Natural log (ln) of quantity of tomato purchased for sale in lean season (kg)
Sale_freq_week (#)	How many days in a week typically sells tomatoes? (#)
Radio use intensity (#)	Intensity of radio usage – number of times listens to radio per week
Know_RPC_seller	Trader knows any distributor or seller of RPC? (1 = yes, 0 = no)
Perception_RPC_affordable	Trader perceives that RPC are affordable to tomato traders (1 = yes, 0 = no)
RPC_awareness	Trader is aware of reusable plastic containers (RPC)? (1 = yes, 0 = no)

Source: Authors' presentation of model variables

4. DESCRIPTIVE RESULTS

Table 3 reports the descriptive results of the variables used in the model. The dependent variable is the net profit from tomato trading, measured in Naira. The average profit made from tomato trading was significantly higher among adopters than non-adopters. About 33 percent of the traders adopted RPC. Retailers constituted up to 66 percent of the traders in the study.

As the t-tests comparing the means for adopters and non-adopters indicate, significant differences are observed in most of the explanatory variables. For instance, a significant difference is observed between the retailers and wholesalers in terms of the rate of RPC adoption. The pooled-mean age of traders was approximately 38 years, suggesting engaging in fresh tomato trading may require some level of physical capability to endure the labor-intensive nature of the business. Other studies have also shown that a larger percentage of tomato traders in Nigeria were aged between 31 and 40 years (Haruna et al. 2012). Results also indicate that RPC adopters had a lower mean age than non-adopters, which could point to the fact that the younger traders are more likely to adopt new technologies than older ones, as other studies have similarly revealed (Elemasho et al. 2017a; Obuobisa-darko 2015). The mean schooling of the traders was 8 years, which reveals that a greater proportion of the traders in the sample attained either primary or some secondary level schooling. This finding is consistent with that of Osuji et al. (2016) where the highest percentage of tomato traders had attained at least primary school education. However, there is a significant difference between adopters and non-adopters in terms of average schooling.

Table 3. Summary descriptive statistics of model variables, with comparison of means for reusable plastic container adopters and non-adopters

Variables	Pooled Mean	Pooled Standard deviation	RPC adopters Mean	RPC adopters Standard deviation	RPC non-adopters Mean	RPC non-adopters Standard deviation	Means comparison (t-test)
In_net profit (Naira)	13.272	1.765	14.014	1.356	12.905	1.831	-1.109***
Trader uses RPC	0.331	0.471	1.0	0.0	-	-	-
Retailer_trader (=1)	0.665	0.473	0.296	0.459	0.848	0.361	0.551***
Female_trader (=1)	0.494	0.501	0.222	0.418	0.628	0.485	0.406***
Age_trader (yrs)	38.37	9.355	36.14	9.643	39.48	9.036	3.340***
In_education (years)	8.17	4.639	6.15	5.230	9.17	3.969	3.023***
In_income (Naira)	10.32	0.964	10.91	1.060	10.03	0.760	0.976***
In_experience (years)	13.2	8.975	12.556	7.697	13.518	9.549	0.963
Married (=1)	0.837	0.370	0.852	0.357	0.829	0.377	-0.023
Hh_size (#)	5.55	3.245	5.48	3.340	5.58	3.207	0.098
Oth_perish_sale (yes=1)	0.824	0.381	0.877	0.331	0.799	0.402	-0.078
Percent_spoilt (%)	0.176	0.087	0.091	0.050	0.218	0.068	0.127***
Tom_mkt_asso (yes=1)	0.533	0.500	0.506	0.503	0.546	0.499	0.040
In_peak_purc (kg)	2.77	1.985	3.55	1.397	2.38	2.119	-1.165***
In_lean_purc (kg)	2.43	2.191	3.38	1.438	1.96	2.346	-1.417***
Sale_freq_week (#)	6.287	0.865	6.537	0.871	6.165	0.838	-0.373***
Radio use intensity (#)	4.34	9.200	11.75	12.136	0.68	3.689	-11.076***
Know_RPC_seller	0.248	0.433	0.630	0.486	0.073	0.261	-0.556***
Perception_RPC_affordable	0.398	0.490	0.457	0.501	0.368	0.484	-0.089
RPC_awareness	0.325	0.469	0.173	0.380	0.401	0.492	0.228***

Source: Author's compilation from survey data. *** p<0.01, ** p<0.05, * p<0.1
Note: Observations: 245 traders; At the time of the survey, USD 1.00 ≈ Naira 360.

There also exists a significant difference between adopters and non-adopters in terms of their monthly household income – the mean estimated monthly income for adopters is higher than that of non-adopters. This could be an indicator that the RPC technology might have improved the earnings of adopters through higher profits than for non-adopters. The mean years of experience of tomato traders was approximately 13 years which possibly suggests that tomato trading could be a rewarding business that traders chose to engage in the business for a long time. Similar findings were reported in other studies (Haruna et al. 2012; Obayelu et al. 2014; Osuji et al. 2016).

5. ECONOMETRIC RESULTS

5.1 Determinants of reusable plastic container technology adoption

Table 4 presents the first stage binary probit estimation results and post-estimation marginal effects of the covariates evaluated at the mean and median values of each explanatory variable.[4] The predicted marginal effects of the regression covariates show the effect of a unit change in an explanatory variable on the probability of RPC adoption by a trader. The Wald Chi-squared value (118.2), which is statistically significant at a p<0.01 level, shows that the probit model fits the overall data very well. The probit model results indicate that a trader's position in the supply chain, trader's perception about the RPC technology, demographic, economic, and marketing-related factors significantly influence trader adoption decisions of the RPC technology.

[4] Though the marginal effects are evaluated at both mean and median values of each explanatory variable, we focus on marginal effects evaluated at the median values.

Table 4. Probability of reusable plastic container adoption by a tomato trader – probit regression results and post-estimation marginal effects

Variable	Coefficient	Standard error	Marginal Effects dy/dx (mean)	Marginal Effects dy/dx (median)
Retailer_trader (=1)	1.336***	0.495	0.176**	0.278**
Female_trader (=1)	-0.862	0.553	-0.147	-0.224
Age_trader (yrs)	-0.038*	0.022	-0.006	-0.013
ln_education_yrs	-0.112	0.204	-0.019	-0.040
ln_income (Naira)	0.597**	0.233	0.100**	0.211**
ln_experience_yrs	-0.431*	0.248	-0.072*	-0.152
Married (yes=1)	1.437***	0.503	0.133***	0.285**
Hh_size (#)	-0.031	0.043	-0.005	-0.011
Oth_perish_sale (yes=1)	-0.735	0.566	-0.097	-0.202
Percent_spoilt (%)	-21.322***	3.205	-3.557***	-7.540**
Tom_mkt_asso (yes=1)	-0.518	0.340	-0.089	-0.199
ln_peak_purc (kg)	-0.559*	0.332	-0.093	-0.198
ln_lean_purc (kg)	0.505*	0.301	0.084	0.178
Sale_freq_week (#)	0.477**	0.213	0.080**	0.169*
ln_distance_purchase (km)	0.071	0.339	0.012	0.025
Radio use intensity (#)	0.026	0.022	0.004	0.009
Know_RPC_seller	0.586	0.459	0.117	0.226
Perception_RPC_affordable	1.506***	0.399	0.316***	0.533***
RPC_awareness	-0.546	0.494	-0.080	-0.162
Constant	-5.767*	3.418		
Mean dependent variable	0.335			
Pseudo R-squared	0.706			
Chi-square	118.19			
Akaike crit. (AIC)	129.44			

Source: Results from probit model regression using survey data.
Note: Observations: 245 traders. *** p<0.01, ** p<0.05, * p<0.1

Retailers, as against wholesalers, in the fresh tomato supply chain are more likely to adopt RPC – being a retailer in the tomato trade supply chain increases adoption probability by 27.8 percent at the margin (evaluated at median value). The possible explanation for this could be that wholesalers' operations are generally capital intensive (e.g., use of trucks for transportation and improved storage facility) and are conducted in permanent business premises. Thus, the risk of damage to the tomatoes during transportation and sale is lower among wholesalers, implying their relatively lower RPC adoption probability.

Age and trader's experience in the tomato business negatively affects the likelihood of RPC adoption. In terms of marginal effects, an increase in the age of a trader reduces their probability of adoption by 1.3 percent – younger and new entrants into the tomato trading business are more likely to be potential adopters than the older and more experienced traders. A possible explanation is that younger traders are more open and willing to try innovations and are less risk-averse, as evidenced by previous findings (Teklewold et al. 2006; Bokusheva et al. 2012; Elemasho et al. 2017a). On the other hand, experienced traders are less flexible in taking up new technologies and prefer to keep their old habits. A study by Adegbola et al. (2011) showed a similar finding where up to 18 percent of the respondents reported that they were unwilling to change their old habits.

The higher the trader's reported income, the more likely the trader will adopt RPC. As RPC is costlier on a unit basis than the traditional woven basket, it appears intuitive that traders with higher income should be able to afford RPC. This result is in line with findings in other studies (Sulo et al. 2012). Similarly, traders with a high degree of sales frequency (i.e., high turnover in the business) are more likely to adopt RPC. In terms of marginal effects, fresh tomato traders who sell their product for an extra day in the week have an 8 percent higher probability of adopting RPC.

We found that married traders are more likely to adopt RPC in the fresh tomato business. The marginal effect of being married shows that married traders are 13.3 percent more likely to adopt the RPC. This finding is similar to that of Asfaw et al. (2011), who also found that married people made up a significantly larger percentage of the adopters of agricultural technology. The possible explanation could be related to risk cushioning support couples could provide each other in small businesses, i.e., even if a technology is risky which could end up in a loss; the household's livelihood can still sustain from the incomes of the couple who might have engaged in a different livelihood activity. The result is line with the study of Maigida (2012) in Nigeria and Machek et al. (2016) in the Czech Republic, both of which showed that having a spouse plays an important role in technology adoption decisions and profitability.

The seasonality (peak and lean season) and the trade volume (quantity of tomato acquired and sold) are two important factors influencing RPC adoption. During the peak season for tomato in Nigeria, the supply of fresh tomatoes is abundant and market prices are low (Adenuga et al. 2013). In contrast, during the lean season, there is a supply shortage with higher prices. During the peak season, traders are, therefore, more interested in selling as much quantity and as frequently as possible rather than spending money on a large number of RPC to accommodate the large volume of tomato transacted on daily basis. The marginal effects of the coefficients for the two seasons reflect these seasonal phenomena – while a percentage increase in fresh tomato purchased for sale decreases RPC adoption by 19.8 percent in peak season, in contrast, the adoption probability of RPC increases by 17.8 percent in the lean season. Our finding is consistent with the work of Babarinsa et al. (2018) who found that respondents complained that during the peak season trucks was unable to transport as much fresh tomatoes with the use of RPC as compared to the use of woven baskets.

An individual's perception of new technologies, either on technically or financial cost, plays a key role in technology adoption. In the present study, the perception of traders towards the affordability of RPC significantly influences the adoption of RPC. Traders who perceive RPC to be affordable are more likely to adopt the technology by 53.3 percent as compared to traders who perceive RPC as an expensive technology. Other studies have also indicated that farmers or traders who have a positive perception towards the cost of a particular agricultural technology are more likely to adopt that technology (Adegbola et al. 2011; Elemasho et al. 2017b; Izukanne and Chinweota, 2018).

5.2 Endogenous switching regression model results – factors affecting trader's net returns

Table 5 presents the estimation results of the endogenous switching regression (ESR) model using the full information maximum likelihood (FIML) method. The three instrumental variables chosen to improve identification of the selection equation are the number of times a trader listens radio per week ('radio_use_intensity'), the trader's knowledge on the availability and use of RPC technology ('know_RPC_seller'), and the trader's perception on the affordability of RPC ('perception_RPC_affordable'). These variables are chosen based on their local relevance and because they are believed to influence an individual's adoption decision, while not directly affecting the profits they realize, i.e., the regime equations. Radio is the most common and accessible information source that small-scale local traders rely on for vital information. Local suppliers commonly use radio for advertising their products or technologies. The level of traders' knowledge and their perceptions about the availability, use, and affordability of RPC technology is expected to affect their RPC adoption decisions. Thus, these variables were chosen as instruments for identification. All three variables area statically significant, implying that they explain well the selection model fit.

Table 5. Results of endogenous switching regression model on tomato traders' profits based on whether they adopted reusable plastic containers

Dependent variable: **ln_net profit (Naira)**	**OLS model**		**RPC non-adopters**		**RPC adopters**	
	Coefficient	**Standard error**	**Coefficient**	**Standard error**	**Coefficient**	**Standard error**
Trader uses RPC	-0.082	0.076	-	-	-	-
Retailer_trader (=1)	-0.068	0.112	-0.391***	0.118	0.211	0.147
Female_trader (=1)	-0.106	0.086	-0.134	0.087	0.030	0.164
Age_trader (yrs)	-0.004	0.004	-0.003	0.004	-0.009	0.008
ln_education (years)	-0.020	0.043	-0.088**	0.043	-0.013	0.069
ln_income (Naira)	0.005	0.050	0.152***	0.047	-0.166*	0.098
ln_experience (years)	-0.142***	0.042	-0.082	0.052	0.006*	0.073
Married (=1)	0.106	0.079	0.269***	0.092	-0.093	0.125
Hh_size (#)	0.024**	0.011	0.011	0.012	0.025	0.016
Oth_perish_sale (yes=1)	-0.269***	0.087	-0.303***	0.087	-0.094	0.187
Tom_mkt_asso (yes=1)	-0.062	0.063	-0.306***	0.105	0.127	0.098
ln_peak_purc (kg)	0.875***	0.057	0.892***	0.066	0.890***	0.118
ln_lean_purc (kg)	-0.055	0.053	-0.078	0.056	-0.002	0.116
Sale_freq_week (#)	0.213***	0.051	0.189***	0.047	0.265***	0.064
ln_distance_purchase (km)	0.039	0.074	0.041	0.152	0.085	0.075
Constant	9.962***	0.654	9.113***	0.951	11.008***	1.270
SELECTION EQUATION	**Coefficient**	**Std. err**				
Radio use intensity (#)	0.042***	0.012				
Know_RPC_seller	0.792***	0.171				
Perception_RPC_affordable	0.660***	0.213				
Constant	5.673***	0.333				
/lns (/lns_0, /lns_1)			-0.698***	0.111	-0.663***	0.152
/r (/r_0, /r_1)			1.882***	0.308	-0.848***	0.298
sigma ($sigma_0$, $sigma_1$)			0.498***	0.055	0.515***	0.078
rho (rho_0, rho_1)			0.955***	0.027	-0.690***	0.156

Source: Endogenous switching model results using survey data.
Note: Observations: 245 traders. OLS = ordinary least squares regression.

The correlation coefficients between the error term of the selection equation and errors of outcome equations (rho_0 and rho_1) are statistically significant, demonstrating evidence of endogeneity and existence of sample selection bias. In other words, the decision to adopt RPC and the impact of RPC adoption on the profitability of the tomato trader, given the adoption decision, are influenced by both observed and unobserved factors. It has been suggested that the alternative signs of both correlation coefficients suggest that adopters decide to adopt an improved technology-based of the comparative advantages of the technology in line with the outcome of interest (profitability in this case) of the adopter (Abdulai and Huffman 2014; Takam-Fongang et al. 2019; Paltasingh and Goyari 2018). The likelihood ratio tests for joint independence of the equations are also reported at the bottom of Table 5 – the tests show that the equations are dependent.

We present the results generated from the ordinary least squares (OLS) regression in the first two columns of results in Table 5 for comparison with the ESR model results. In the OLS model, the effect of RPC adoption ('Trader uses RPC') is estimated directly by considering adoption as a binary/dummy variable. The coefficient of this dummy is statistically insignificant. This suggests a problem of endogeneity and, consequently, may lead to biased and inconsistent estimates. This is because the OLS approach assumes that RPC adoption is exogenously determined, even though the adoption of agricultural technology among smallholders could be determined endogenously (Kumar et al. 2020).

The results obtained from the ESR model are presented in two rightmost pairs of columns in Table 5. Generally, we find differences between the estimated coefficients of covariates for adopters and non-adopters on the outcome variable ('ln_net profit (Naira)'), indicating the presence of heterogeneity in the sample. Out of the 14 explanatory covariates included in the ESR model, only two variables – the quantity purchased of fresh tomato for sale in a peak season by a trader ('ln_peak_purc (kg)') and the frequency of weekly sales ('Sale_freq_week (#)') – are statistically significant and have a common positive sign on the profitability of both adopters and non-adopters of RPC. This seems intuitive since a large sales volume and a high rate of turnover during the peak period could naturally boost profit levels. This finding corroborates the findings of studies by Sibomana et al. (2016) and Oke et al. (2020), which suggested that the marketing of tomato is highly profitable during the peak season relative to the offseason.

For non-adopters, being a retailer, as against a wholesaler, in the fresh tomato supply chain significantly reduces the profit level. However, this is not the case for adopters. The coefficients of formal education (in years) and membership in a trader's association have an unexpected negative sign and are statistically significant for non-adopters but insignificant for adopters. Though these results seem contrary to expectations and to some previous studies (Jiménez et al. 2015; Longva and Foss 2018; Verhofstadt and Maertens 2015; Posadas-Domínguez et al. 2014; Matchaya and Perotin 2013); the results are consistent with findings in other studies (Bitros and Karayiannis 2010; Khan and Butt 2002; Levie and Autio 2008; Saitgalina et al. 2017). The possible explanation for the education variable could be that profitability in local micro and small-scale enterprises may not necessarily require higher levels of formal education – rather entrepreneurial, managerial, and operational experience obtained through non-formal education may be more important than several years of formal schooling. Several studies document similar findings in that the knowledge gained from managerial and operational experience in small enterprises is essential for the success and performance of the business (Ligthelm and Cant 2003; Marvel and Lumpkin 2007; Toohey 2009). In terms of the association membership effect, commercial associations in developing countries often are bureaucratic, ineffective, and involve high transaction costs, so are counterproductive in the benefits that they offer to small businesses (Saitgalina et al. 2017).

Trader's income level and marital status have positive and significant effects on profitability for non-adopters, but are not significant for adopters. The result of an income effect is in line with other studies (Blanc et al. 2016; Ocholi and Samuel 2017), which may be indicate that an increase in income could lead non-adopters to invest in improved technologies, such as RPC, and consequently increase their profit. As adopters have already invested in such technologies, the income effect on profitability for such traders is not as significant. The results further show that the sale of other perishable produce beside tomato reduces profitability for non-adopters. Xiao and Yang (2016) noted that mass spoilage and associated difficulties in produce quality management reduces the profitability of trade in perishable food items. Moreover, the negative effect of selling other perishable produce on profitability for non-adopters is connected to the fact RPC was not adopted by these traders.

5.3 Endogenous switching regression model results – impacts of reusable plastic containers on trader's net returns

Table 6 presents the expected value of traders' net profit (expressed in natural log) of tomato traders under actual and counterfactual conditions. Cells (5a) and (5d) present the expected value of net profit for adopters and non-adopters of RPC, respectively, showing a higher expected net profit value for RPC adopters than for non-adopters. However, such direct comparisons could be misleading in attributing the difference in profit entirely to RPC technology. The last column in Table 6 presents the treatment effects of RPC adoption on trader's net profit. In the counterfactual case (5c), tomato traders who adopted the RPC container would have lower net profit by about 7 percent (TT ÷ 5c) had they not used RPC. The positive and significant mean difference between cases (5b) and (5d) for non-adopters indicates a similar counterfactual finding. Non-adopters would have increased their net profit by about 5 percent (TU ÷ 5b) if they had adopted RPC containers.

Table 6. Treatment and heterogeneity effects on tomato trader's profits based on whether they adopted reusable plastic containers

	Adopters of RPC (expressed in natural log)	Non-adopters of RPC (expressed in natural log)	Treatment effects
Adopters (RPC)	(5a)1 = 14.94 (0.138)	(5c)1 = 14.02 (0.145)	TT = 0.92***
Non-adopters (RPC)	(5b)1 = 13.52 (0.141)	(5d)1 = 12.88 (0.142)	TU = 0.64***
Heterogeneity effects	BH1 = 1.42	BH2 = 1.14	TH = 0.28***

Source: Post-estimation results (actual and counterfactual means) computed from ESR model.
Notes:
(5a)1 = ATT11 – Observed outcome for adopters, i.e., the expected conditional profit of RPC technology adopters.
(5c)1 = ATT21 – Counterfactual outcomes for adopters. i.e., the expected profit of adopters had they not adopted the technology.
(5d)1 = ATU22 – Observed outcome for non-adopters, i.e., the expected conditional profit of non-adopters of RCP technology.
(5b)1 = ATU12 – Counterfactual outcomes for non-adopters. i.e., the expected profit of non-adopters had they adopted RPC.
TT= Treatment effects on the treated (5(a)-5(c)); TU= Treatment effects on the untreated (5(b)-5(d)); BH=base heterogeneity and TH is transitional heterogeneity (i.e., TH = TT-TU)
*** $p<0.01$ (significant at 1 percent level). Numbers in parentheses are standard errors.

These results show that the use of RPC containers for smallholder tomato traders in Nigeria could significantly increase their net profits. However, the positive transitional heterogeneity (TH) effect (last row in Table 6) on net profit implies that the effect of RPC is larger for adopters relative to non-adopters. This implies the existence of some important sources of heterogeneity that enables adopters to enjoy higher profits than non-adopters. The results presented in Table 7 explore the sources of heterogeneous impacts conditional on the adoption of RPC technology.

5.4 Heterogeneous impacts

The estimated average treatment effect on the treated (ATT) of RPC on profit could differ across different traders. Accounting for such differential effects of RPC technology on adopters is important for addressing specific challenges or constraints that different traders encounter in adopting RPC. To account for the heterogenous impacts on adopters, we run an OLS regression using the predicted value of ATT on profits (the prediction from the endogenous switching regression model) as the dependent variable on the range of covariates used in the ESR regression (Verhofstadt and Maertens 2015; Wossen et al. 2017; Kumar et al. 2020).

The estimated coefficients in Table 7 indicate high levels of heterogeneous effects. The results show that most variables have positive and significant effects on the net profit of adopters. For instance, traders who are older or married obtain lower profits from RPC relative to younger or unmarried traders. Younger traders are expected to be agile in the business; more familiar with modern technology, such as information and communication technologies; more innovative; and willing to take risk. All of these characteristics should enhance their profitability compared to older traders. The possible explanation for the heterogenous effect of RPC on profits of the marital status of traders could be the fact that unmarried people may have less household commitments and responsibilities. Married couples may have to shoulder several domestic responsibilities and commitments, which could have a negative effect on the performance of their tomato trading business.

Table 7. Heterogeneous treatment effects of reusable plastic container technology on the profits in tomato trading realized by adopters

	Coefficient	Standard error	
Retailer_trader (=1)	0.175***	0.040	
Female_trader (=1)	0.001	0.036	
Age_trader (yrs)	-0.009***	0.002	
ln_education (years)	0.002	0.017	
ln_income (Naira)	-0.036**	0.017	
ln_experience (years)	-0.007	0.022	
Married (=1)	-0.121***	0.042	
Hh_size (#)	0.023***	0.005	
Oth_perish_sale (yes=1)	-0.215***	0.059	
Tom_mkt_asso (yes=1)	0.129***	0.027	
ln_peak_purc (kg)	0.868***	0.029	
ln_lean_purc (kg)	0.035	0.028	
Sale_freq_week (#)	0.294***	0.017	
ln_distance_purchase (km)	0.098***	0.021	
Constant	9.111***	0.201	
Mean dependent variable	14.02	SD dependent variable	1.297
R-squared	0.995	Observations	80
F-test	916.54	Prob > F	0.000
Akaike crit. (AIC)	-125.60	Bayesian criterion (BIC)	-89.87

Source: OLS model estimation results (after ESR model) using survey data.
Note: Dependent variable is predicted value of ATT on profits from the ESR model.

Adopters with a large household, those who trade a large quantity of tomato in peak season and with high weekly sales frequency enjoy higher profit from their tomato business than do their counterparts. The plausible explanations for these relationships could be that traders with large households can use household members as a source of labor, thereby reducing their costs of labor and, consequently, reducing their operating cost and increasing their profit margin. That family labor is a crucial factor in the profitability and competitiveness of small-scale enterprise was also suggested by Posadas-Domínguez et al. (2014). A high quantity of tomato traded during the peak period could increase profit margin, ceteris paribus, the higher quantity of tomato traded will lead to higher revenue generation and, subsequently, profitability.

6. CONCLUSION AND POLICY RECOMMENDATIONS

Postharvest loss is a major challenge in food production and supply chains in developing countries like Nigeria. This is particularly acute across value chains for perishable agricultural commodities such as tomato – in Nigeria, about 40 percent of fresh tomatoes are lost annually after harvest. Promoting adoption of appropriate postharvest technologies for packaging, storage, and processing are key to address the problem of postharvest losses. This study investigates the effects of reusable plastic containers (RPC), one such postharvest technology promoted for reducing postharvest losses. We examine the factors influencing its adoption and the impacts of the technology on traders' net profits. Primary data gathered from fresh tomato traders from Lagos state were used in probit and endogenous switching regression models for the analysis.

Our results indicate that a trader's position in the tomato value-chain (retailer versus wholesaler), income, level of sales in the lean season, sales frequency, and perception on the affordability of the technology positively influence adoption. In contrast, the age of the trader, the trader's experience in tomato trading, and level of sales in the peak season negatively influence technology adoption. We found that adoption of RPC technology significantly increases the profits of tomato traders in Nigeria. However, in the counterfactual analysis, the magnitude of the impact of the technology on profits differs among adopters and non-adopters, which indicates unobserved heterogeneity among adopters and non-adopters. Furthermore, the impact of the technology is heterogeneous among adopters due to differences between traders, including their position in the supply chain, income level, demographic factors (age and marital status), experience, sales volume (frequency), and seasonality.

Based on our results we suggest three policy recommendations:

- Addressing the problem of postharvest losses could significantly contribute to improving food security and smallholders' livelihoods across agricultural value chains. Thus, policy interventions aimed at promoting postharvest technologies should be considered a key policy priority alongside promotion of agricultural productivity technologies.
- Besides reducing significant food losses, postharvest technologies could create substantial job opportunities across value chains for unemployed youth. Thus, the government's youth employment and job creation policy should give due attention to interventions in postharvest technology.
- The cost of the RPC technology is the major barrier to adoption among tomato traders and new entrants to the agribusiness. Thus, policy interventions to reduce costs should be put in place to ensure the technology is affordable to traders and to increase wider adoption. Such interventions might include low-cost financing options, subsidies, financial incentives for RPC suppliers and local RPC producers, or permitting duty-free importation of the technology.

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