IFPRI Discussion Paper 2409

March 2026

Cooling Technologies and Long-Term Efficiency Improvement of Horticulture Market Agents

Panel Data Evidence from a Solar-Powered Cold Storage Intervention in Nigeria

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Abstract

Modern cooling technologies that use renewable energy sources have been increasingly recognized as a promising tool to address a multitude of challenges emerging in progressively complex food systems in developing countries. When provided as cold storage inside horticulture markets, cooling technologies can contribute to improved quality of products and strengthened vertical linkages. Knowledge gaps about the medium- to long-term impacts of these technologies in developing countries remain, especially in Africa south of the Sahara (SSA). This study partly fills this knowledge gap by revisiting the 2021 short-term impact evaluation study (Takeshima et al. 2023) to assess the medium- to longer term impacts of interventions in northeast Nigeria in which 7 small solar-powered cold storages were installed across 7 horticulture markets. Combinations of difference-in-difference and variants of propensity score-based methods suggest that using cold storage significantly increased horticulture sales volumes and revenues of market agents. Using cold storage also reduced the share of food loss and lengthened the products' shelf-life while raising prices received by both market agents and farmers, which were associated with improved product quality, expanded value-adding activities by market agents, and increased use of advance payments. We find no evidence of negative spillover effects inside horticulture markets. Observed effects are driven by the technical improvements that raise the efficiency of the use of purchased raw commodities, enabled by cold storage, based on modified efficiency analyses. At the same time, the efficiency of cold storage use remains low despite some improvement over time, and scopes exist to enhance this efficiency.

Keywords: Solar-powered cold-storage, horticulture, market agents, efficiency, medium-to-long-term effects, Nigeria

Acknowledgments

This work was undertaken as part of the CGIAR Science Program on Better Diets & Nutrition (BDN) led by the International Food Policy Research Institute (IFPRI). BDN aims to identify, co-design, and test food system solutions that tackle major constraints to delivering sustainable, healthy diets and improving nutrition outcomes for people in low and middle-income countries. Other CGIAR centers participating in BDN include the International Potato Center (CIP), the International Maize and Wheat Improvement Center (CIMMYT), the International Water Management Institute (IWMI), and the Alliance of Bioversity International and CIAT. We would like to thank all funders who supported this research through their contributions to the CGIAR Trust Fund: https://www.cgiar.org/funders/. We also thank the Japanese government for providing additional funding, which enabled this study. Authors are responsible for all remaining errors.

1 Background

Modern cooling technologies, including cold storage, are considered one of the critical tools to address increasingly complex agrifood systems in developing countries, including improving not only poverty and economic growth but also food loss and waste, food and nutrition security, and environmental sustainability outcomes (for example, IFPRI 2020; Kashyap & Agarwal 2020). Effective use of cold storage can also contain most human pathogens, ensuring enhanced food safety (Uçar & Özçelik 2013) and greater consumption of micronutrient-rich horticulture crops like vegetables and fruits (Ali & Tsou 1997; Schreinemachers et al. 2018). Cooling technologies, including cold storage, also have the potential to contribute to improved market functioning by enabling higher and more stable prices received by suppliers in the domestic market (Rakshit 2011; Schreinemachers et al. 2018), combined with increased sales achieved through reduced loss (Allen & de Brauw 2018). Cooling-chain development has been a significant part of food systems transformation outside Africa south of the Sahara (SSA), including Japan during the second half of the 20th century (McDonald 2000), Bangladesh (Lewis 1996), and India (IFPRI 2020). By 2010, 90 percent of potato producers in India had begun using cold storage. Similar technologies may become more broadly relevant in SSA in the near future (Tschirley et al., 2015).

Traditionally, the use of cold storage has also been associated with increased energy consumption requirements and environmental effects like carbon emissions (Coley et al. 2009; Pueyo et al. 2020). In South Africa, cold storage has emerged as one of the largest energy consumers for potato production in recent years (Steyn et al. 2016). However, a growing set of potential solutions are being proposed and introduced on a pilot basis, including solar power (Takeshima et al. 2023).

Evidence generally remains scarce as to the viability of these technologies in developing countries like Nigeria, which are characterized by often vastly different conditions in terms of effective demand for increased freshness and other quality attributes, availability of alternative cooling methods and electricity sources, and value-adding practices and institutional linkages among actors along the value-chains–all of which are often critical elements of post-harvest agrifood systems (for example, Fafchamps et al. 2008; Minten et al. 2012; Vandeplas & Minten 2015). Takeshima et al. (2023) is among the first studies to fill this knowledge gap through a short-term impact evaluation of 7 small-scale, solar-powered cold storages installed across horticulture markets in northern Nigeria in January 2021 through collaboration between the International Food Policy Research Institute (IFPRI) and Nigerian social enterprise, Cold Hubs. Takeshima et al. (2023) found significant short-term impacts of these installed cold storages between December 2020 (pre-installment) and March 2021 (post-installment) on gross revenues, profit, sales volumes, loss reduction, and the adoptions of quality enhancing practices by market agents transacting horticulture commodities. Their findings also indicate that producers benefited from receiving higher sales prices resulting from higher demand by market agents, without significant negative spillover effects suffered by market agents in the control group.

Despite the positive short-term impacts, questions remain as to the longer-term impacts, as well as year-on-year impacts, after removing potential seasonality biases. This study attempts to fill this knowledge gap by providing updated evidence of the longer-term impacts of the same interventions evaluated by Takeshima et al. (2023), using data from December 2022, two years after the initial baseline survey. As in Takeshima et al. (2023), we re-apply a combination of the difference-in-difference (DID) method and variants of propensity score-based (PS)methods to panel data of market agents collected before and after the installation of cold storages in 7 horticulture markets. In addition, unlike Takeshima et al. (2023), this study also assesses the technical changes associated with cold storage use, as well as the remaining efficiency issues which may materialize in the more medium to long terms. We do so by applying methodologies within the stochastic frontier framework (Reinhard et al. 1999; Zhu et al. 2023) combined with recent developments in methods that address endogeneity issues in the stochastic frontier literature (for example, Greene 2005; Tran & Tsionas 2015; Yu & Jaenicke 2020; Tirkaso & Hailu 2022).

This study contributes to various strands of literature. By providing evidence on field-level impacts in developing countries, this study contributes to the literature on cooling technologies in food systems in developing countries (Minten et al. 2014; Schreinemachers et al. 2018; Kashyap & Agarwal 2020). This study also contributes to the literature on the potential of modern cooling technologies using renewable off-grid electricity, namely solar power (Takeshima et al. 2023). The study also offers insights into addressing issues of food loss and waste through cooling technologies (e.g., Yu & Jaenicke 2020; Smith & Landry 2021). By focusing on cold storage use and market agents' behaviors, this study also contributes to the literature on horticulture value-chain development, including the relationship between producers and market agents (Minten et al. 2012) and the nature of premiums on quality (Fafchamps et al. 2008; Vandeplas & Minten 2015). Lastly, through the application to the context of post-harvest handling techniques of horticulture products, this study contributes to the literature on input use efficiency within the stochastic frontier framework that also addresses the potential endogeneity of input variables (Reinhard et al. 1999; Zhu et al. 2023; Greene 2005; Tran & Tsionas 2015; Yu & Jaenicke 2020; Tirkaso & Hailu 2022).

The paper proceeds as follows: Section 2 quickly describes the interventions to install cold storage; Section 3 discusses empirical approaches and data; Section 4 presents the estimated results; and lastly, section 5 concludes our findings.

2 Interventions to install solar-powered cold-storages[1]

A total of 7 cold storages were installed in 7 horticulture markets in northeast Nigeria in January 2021. The project was intended by the donor (the Japanese Government) to be an emergency response to rebuilding livelihoods destroyed by insurgent groups in a conflict-affected region of northeast Nigeria. Among 14 markets across 5 states (Adamawa, Bauchi, Gombe, Jigawa, and Yobe states) selected given their eligibility as horticulture markets that operate daily, 7 horticulture markets were randomly chosen for cold-storage installation (*intervention markets*), leaving the remaining 7 as *comparison markets* (Figure 1).

The installed cold storage can store up to 3 tons of common horticulture products. Each cold storage is powered by 5.6-kilowatt solar panels (18 of 380-watt photovoltaic panels manufactured by Panasonic). The surplus electricity generated during the day is stored and released at night to enable continued refrigeration. The cold storage also uses propane as a refrigerant, which is less harmful to the ozone layer and thus environmentally friendly. Within the intervention market premises, these cold storages were installed in spaces negotiated with market authorities, that is, in a leveled space with generally easy access from most market stalls, and far from any objects that can block sunlight.

[1]This section is a compressed version of Takeshima et al. (2021, section 2).

Selection of the initial set of users

The cold-storage installation was advertised by each market's horticulture traders associations and horticulture producers associations. All market agents selling horticulture crops belong to one of these associations. Anyone interested in potentially becoming a cold-storage user was required to participate in the 5-days postharvest management training first. A total of 350 market agents from intervention markets participated in the training; 251 of these eventually became cold-storage users, while 99 decided not to use it after receiving the training.

Operation of cold storage

The inside temperature is kept at 4 degrees Centigrade at all times. Users pay ₦100 per day per crate (which can typically hold 20 kilograms of products) stored. ColdHubs manages the operations of cold storage at each site, including use-fee collections, remote monitoring of storage conditions, ensuring security through contributions to market security guards, and maintenance work, which involves occasional cleaning of solar panels (such as removing dust and sand).

Investment and operational costs of cold storage

The installed cold storage typically costs US$40,000 per unit. Once built, variable costs are generally about $150 per month (Takeshima et al. 2021, Table 1). Maintenance costs primarily consist of remote monitoring costs, payment for operators in charge of fee collections and other miscellaneous work, security guards, land rental fees, and simple cleaning of solar panels.

Solar panels

The solar panels used are the 380-watt Monocrystalline (PERC) Solar PV Module manufactured by Panasonic, with a conversion rate of solar energy to electricity outputs of approximately 19.6 percent and a temperature coefficient of –0.39 percent (an indicator of how electricity output capability drops as the panel temperature rises above 25°C). Panasonic solar panels used are also resistant to dust and sand (certified through the International Electrotechnical Commission (IEC) 60068), which is a common challenge in the Sahel region like northeast Nigeria, and resistant against ammonium (certified through IEC 627168), which is important in horticulture markets that handle agricultural products. The electricity generation capacity can remain at least 90 percent and 80 percent of initial capacity levels even after 12 years and 25 years, respectively.

3 Empirical analyses

We evaluate the impacts of cold storage through data collected from market agents in the pre- and post-intervention periods and apply several econometric methods to these data. The intervention project was not implemented in a standard randomized controlled trial and involves self-selection of market agents into the treatment group (cold storage users) and the control group (non-users within the same markets). We therefore apply estimation methods aimed at mitigating potential biases.

3.1 Quasi-experiment impact evaluation approach[2]

We estimate the impacts of cold storage through difference-in-difference (DID) methods combined with a propensity score-based model, including the propensity score matching (PSM) estimator (DID-PSM). DID-PSM improves over a standard PSM, as the former can control for unobserved agents' fixed effects, partly adding validity to the unconfoundedness assumption of PSM (Heckman et al. 1997; Heckman et al. 1998; Smith & Todd 2005).

Specifically, the average treatment effects on the treated (ATT) for using cold storage is estimated as (modified from exposition in Villa 2016),

$$DID_{PSM} = \{E(Y_{i,t=2}|D_{i,t=2} = 1, C_i = 1) - w_i \times E(Y_{i,t=2}|D_{i,t=2} = 0, C_i = 0)\} - \{E(Y_{i,t=0}|D_{i,t=0} = 0, C_i = 1) - w_i \times E(Y_{i,t=0}|D_{i,t=0} = 0, C_i = 0)\} \quad (1)$$

where $Y_{i,t}$ is the set of outcomes of interest for market agent i at period $t = 0$ (pre-intervention; December 2020) or $t = 2$ (post-intervention; December 2022). We denote our post-intervention period in this study as $t = 2$, to distinguish the period from March 2021 ($t = 1$) which was used to assess short-term impacts by Takeshima et al. (2023). $C_i = 1$ if agent i are those who end up using cold-storage at $t = 2$ ($C_i = 0$ if otherwise), and $D_{i,t}$ denotes the actual use of cold storage.

The method (1) improves over standard DID by weight w_i, which is defined in various ways by agent i's propensity to use a cold storage,

$$p_i = \Pr(C_i = 1|X_{i,t=0}) \quad (2)$$

which is a function of i's exogenous, observable characteristics X_i at $t = 0$. The translation of p_i to w_i depends on the matching method. In our primary specification, we use a nearest neighbor method with a caliper, which are generally more consistent than other matching methods (for example, Caliendo & Kopeinig 2008). We then also estimate kernel matching methods robustness checks.

Variables X_i are identified from the past studies focusing on horticulture market agents and include key characteristics of market agents and key characteristics of market stalls where they conduct trading activities (for example, Fafchamps et al. 2008; Minten et al. 2012; Vandeplas & Minten 2015). Market agents' characteristics include age, gender, household size, and education levels, as well as whether the market agent is a native of the local government area (LGA) where the market is located. In addition, having similar market agents among relatives proxies trading skills and knowledge, access to market information, and additional social networks. The number of credit sources with ready access for borrowing money when needed (both formal and informal sources) proxies the agent's financial capacity.

The capacity of conventional storage (ambient, non-cold) owned and the total values of business assets (mechanical scales, processing equipment, generator, motorized and non-motorized transportation equipment) proxies the agent's capacity to affect the use of cold storage. Greater values of own non-cold storage and assets can raise returns from cold storage or lower returns if they are primarily substitutes. While the agent rents the market stalls from market authorities, having the market stalls for exclusive use rather than shared space may also affect the decision to use cold storage.

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[2]This subsection is largely extracted from Takeshima et al. (2021, subsection 3.1).

One of the key characteristics of market stalls is the distance to where cold storage was later installed. Other market stall characteristics include distances to various key public facilities (market entry gate, public toilet, canteen, meeting room, market representative's office, and nearest piped water source). These can affect the ability to spend time at the market stalls to conduct business transactions and the congestion level, affecting decisions to use cold storage in complex ways.

Other market stall characteristics include their quality, such as whether the floor is made of superior materials (asphalt/tar, cement, or ceramic), whether the stall has a roof, whether the road in front of the stall is paved, whether there is drainage around the stall and the drainage is covered or not, and lastly, whether the stall has access to the electricity grid.

In addition, X includes market dummy variables. Among these variables, all distance variables, capacity of non-cold storage owned, and value of business assets are transformed into natural logarithms to reduce excess skewness.

DID-PSM (1) provides consistent estimates for market agent-level outcomes Y_i. However, estimating effects measured at both market agent and crop levels can require further addressing potential self-selection biases of crop choice at pre- and post-intervention periods. We therefore employ DID bivariate-IPW (DID-BIPW) for outcomes ($Y_{i,k}$) at the market agent (i) and crop (k) level. BIPW has been proposed as an extension of IPW (Imbens & Wooldridge 2009; Huber 2014) and applied by other studies (for example, Takeshima et al. 2023). Through a bivariate probit regression, we first estimate the joint probability p that agent i uses the cold storage and handles crop k ($\hat{p}_{i,k}$) and the joint probability that i does not use cold storage and still handles crop k ($p^*_{i,k}$) as a function of same set of $X_{i,t=0}$. From this, we calculate inverse probability $\widehat{w}_{i,k} = 1/\hat{p}_{i,k}$, and $w^*_{i,k} = 1/p^*_{i,k}$.

We then estimate

$$\Delta Y_{i,k} = Y_{i,k,t=1} - Y_{i,k,t=0} = \alpha + \beta \cdot D_{i,k,t} + \gamma \cdot X_{i,k,t} + \varepsilon_{i,k} \tag{3}$$

by applying weights $\widehat{w}_{i,k}$ to a cold storage-using market agent, and $w^*_{i,k}$ to a non-using market agent. $D_{i,k,t}$ indicates whether a cold storage is used by agent i for crop k. $X_{i,k,t}$ include market and crop dummies. Standard errors are then estimated through paired bootstrap. By incorporating weights $\widehat{w}_{i,k}$ and $w^*_{i,k}$, (3) consistently estimates the effect of cold storage on improved product handling practices, β. Notations α and γ are intercept and other estimated coefficients, and $\varepsilon_{i,k}$ is idiosyncratic error.

With a stronger assumption that the use of cold storage is exogenous to specific outcomes when the model controls for unobserved fixed effects of associated market agents and crops, one can also estimate the effects of cold storage through a fixed effects model using post-intervention period data alone,

$$Y_{i,k} = \alpha + \beta \cdot D_{i,k} + \gamma \cdot X_{i,k} + \varepsilon_{ik} \quad \text{(only for } t = 2) \tag{4}$$

in which outcomes ($Y_{i,k}$) for market agent i and crop k are regressed on cold storage use $D_{i,k}$. Under the assumption that $D_{i,k}$ is exogenous to $Y_{i,k}$ conditional on unobserved, market agent–crop fixed effects, the effects of cold storage use β can be estimated consistently and efficiently. We, therefore, show results from (4) as supplementary results.

3.2 Efficiency analyses

We then assess the associations between cold storage use and efficiency in revenue generation (conditional on purchased goods and other inputs), as well as how the efficiency of cold storage use itself has changed over time. We do so in the stochastic frontier framework, which can capture the underlying economic structure of market agents. Such key structures include, for example, returns to scale, which may complicate how the use of cold storage affects business outcomes beyond the changes in average marketing margins captured in the regressions (1) and (2) above.

Applying Reinhard et al. (1999) and Zhu et al. (2023) to our context, we first estimate stochastic frontiers models of overall gross revenues

$$\ln Y_{it} = \beta_0 + \beta_R \ln R_{it} + \frac{1}{2}\beta_{RR}(\ln R_{it})^2 + \beta_K \ln K_{it} + \beta_L \ln L_{it} + \beta_T Z_{it} + V_{it} - U_{it}. \quad (5)$$

where Y_{it} is the total weekly gross revenue earned by market agent i in round t (December 2020, March 2021, and December 2022), R_{it} is the purchase value of raw commodities, K_{it} is the value of business capital, and L_{it} is the labor inputs. T_{it} is the average maximum daily temperature, and Z_{it} is a vector of other variables, namely, average daily maximum temperature during the reference period and the survey round dummy variables (for rounds 2 and 3). V_{it} is the normally distributed idiosyncratic error term. U_{it} (≥ 0) is the inefficiency term that follows half-normal distribution. Parameters β are estimated coefficients. Note that equation (5) is written in restricted translog form, due to significant multicollinearity observed among squared/interacted terms.

We assume that the raw commodities R_{it} are used with efficiency η_{it}, so that $R_{it} = \eta_{it} \cdot R_{it}^*$ (in which R_{it}^* is the value of raw commodities before any losses). Extending Reinhard et al. (1999) and Zhu et al. (2023), we can estimate η_{it} using the estimates from (5), as

$$\eta_{it} = \exp\left[\frac{-b_{it} + \sqrt{b_{it}^2 - 2\hat{\beta}_{zz}\hat{U}_{it}}}{\beta_{zz}}\right] \quad (6)$$

where $b_{it} = \hat{\beta}_R + \hat{\beta}_{RR} \ln R_{it}$ and $\hat{U}_{it}$ are the estimated value of U_{it} in (5).

We then estimate, following Zhu et al. (2023),

$$\eta_{it} = \gamma_0 + \gamma_D \cdot D_{it} + \gamma_X \cdot X_{it} + \theta_i + \varepsilon_{it} \quad (7)$$

whereby the parameter γ_D measures the role of cold storage use on the efficiency of raw material use. θ_i represents market agent fixed effects, and ε_{it} is idiosyncratic error. Given the potential endogeneity of D_{it}, equation (7) is estimated using the proximity to cold storage interacted with round dummy variables as instrument variables.

Addressing potential endogeneity in stochastic frontier regression (5)

Literature has raised growing concerns regarding the potential endogeneity biases of inputs variables in stochastic frontier regressions (e.g., Greene 2005; Tran & Tsionas 2015). To address this, we estimate (5) using two methods: (a) Greene's (2005) true random effects model, and (b) a Copula--based method originally proposed by Tran & Tsionas (2015) and applied in later studies (for example, Yu & Jaenicke 2020; Tirkaso & Hailu 2022). Method (a) partly addresses potential endogeneity by controlling for market agent-specific effects as random effects. Method (b) essentially addresses potential endogeneity by exploiting the identification enabled by the assumption of normality in V_{it} and non-normality in all explanatory variables. Both models also allow for time-varying inefficiency term U_{it}.

Efficiency of cold storage use within the stochastic frontier framework

We also obtain related insights into the efficiency of cold storage use itself. We first estimate

$$\ln Y_{it} = \beta_0 + \beta_R \ln S_{it} + \frac{1}{2}\beta_{RR}(\ln S_{it})^2 + \beta_R \ln R_{it} + \beta_K \ln K_{it} + \beta_L \ln L_{it} + \beta_T Z_{it} + V_{it} - U_{it} \text{ (among cold storage users only)} \quad (8)$$

in which S_{it} is the extent of weekly cold storage use (quantity times the number of days products were stored in cold storage). We then estimate the cold storage use efficiency, and this efficiency changed over time (between March 2021 and December 2022). Similar to (5) through (7), we apply a Copula-based model (we also tried Greene's (2005) true random effects model but failed to obtain convergence in results.).

Regressions (1) through (8) are run across different samples and units to provide insights across relevant dimensions collectively. Table 12 in the Appendix summarizes the samples used in each analysis.

4 Data and descriptive statistics[3]

Our primary sample consists of three types of market agents: cold storage users in intervention markets, non-users in intervention markets, and those in comparison markets. The baseline survey was conducted in December 2020. In each of the 7 intervention markets, 100 market agents were interviewed, while 50 market agents were randomly selected in each of the 7 comparison markets. At intervention markets and prior to the pre-intervention survey, we were provided with the list of the 350 market agents who decided to participate in the postharvest management training (aforementioned pre-requisite to use cold storages). We interviewed them in the pre-intervention survey so that we would likely have a sufficient sample size of eventual cold storage users, given that most eventual users would belong to these groups. This would ensure sufficient statistical power in our impact evaluation analyses. As described earlier, of the 350 market agents who attended training, 251 market agents eventually became the initial group of cold storage users. We then randomly selected additional market agents from the list of all market agents in each market so that a total of 100 market agents were interviewed in intervention markets. These sample sizes were determined based on the typical number of cold storage users observed in other horticulture markets in Nigeria, where similar cold storages had already been in operation by ColdHubs. We thus interviewed a total of 1,050 respondents (= 100 × 7 intervention markets + 50 × 7 comparison markets).

Two rounds of post-intervention surveys were conducted in March 2021 and then again in December 2022, interviewing the same 1,050 market agents. The timing for the first post-intervention survey was determined based on a number of factors. We aimed to allow sufficient time for market agents to become familiar with the use of cold storages so that their benefits become more identifiable. Two months post-installation was considered sufficient given the relatively short production season for many horticulture crops (especially vegetables). The timing for the second post-intervention survey was determined to minimize seasonality bias (by

[3]This section draws largely on Takeshima et al. (2021, section 4).

focusing on the December period again). Remarkably, we were able to track and interview all 1,050 cold storage users who had been interviewed in the baseline survey.

Importantly, sample breakdowns of cold storage users and non-users in intervention markets are outcomes of agents' self-selection. Furthermore, while market agents in control markets are selected randomly from all agents registered with corresponding associations in comparison markets, their characteristics may still differ significantly from market-agents in intervention markets. As described above, our empirical methods mitigate potential biases due to these sampling procedures through the combination of DID and matching estimators.

Out of 700 and 350 market agents interviewed in the intervention markets and comparison markets, 22 and 28, respectively, had to be dropped due to missing values for key explanatory variables. For each market agent, we also asked for information about 20 horticulture commodities. After dropping the observations from crop-specific information, our primary final samples therefore consist of 678 market agents in intervention markets (243 cold storage users and 435 non-users), supplemented by information from 322 market agents in comparison markets. However, since our analyses deal with varying units and missing outcome values, sample sizes are discussed in more detail in the results section.

4.1 Descriptive statistics

At baseline, most market agents were traders and wholesalers, while some were farmers who would bring products directly from their farms. Typical crops included tomatoes, spring onions, and green peppers, traded by at least one–third of all three types of respondents. Among fruits, watermelons and oranges are relatively commonly traded.

Table 1 summarizes the descriptive statistics of pre-intervention variables X_{it}. Respondents were around 40 years old and were typically natives in the area where the markets are located. On average, they had completed 6 years of formal education. About half of them had relatives who were likewise engaged in trading activities.

Few respondents owned capital assets like non-cold storage space, generators, or motorized vehicles. Inside the market, they typically had access to small market stalls (about 10 m^2 in area) located a couple of minutes away from the market entry gate, covered with a roof or ceiling, and with access to drainage. Some, though not all, also had access to electricity, paved roads in front of their stalls, and piped water. These variations in infrastructure access, including paved roads or piped water, were common in market premises in Nigeria due to insufficient public investment in agricultural infrastructure in general, as well as inadequate resources for maintenance and repairs (Takeshima et al. 2023). Lastly, only some had previously used cold storage.

Table 2 and Table 3 present the key horticulture commodities trading practices for both the pre-intervention period of December 2020 and post-intervention period of December 2022. Typically, during the pre-intervention period, market agents earned gross revenues of \$394 per week from selling 495 kg of horticulture commodities, of which 6.8 percent was net revenue, while these transaction revenues and volumes somewhat declined in the post-intervention period (Table 2). Gross revenue refers to total earnings from sales in a week, while net revenue here is the gross revenue minus costs, including the purchase costs of horticulture commodities they transact, as well as any other expenses (labor, chemicals, packages, market-stall rents, etc.), converted to a 1-week equivalent. Since almost all market agents exclusively transact the horticulture commodities, the costs incurred are also almost solely for horticulture trading activities.

Typically, respondents lose 9.6 percent of all horticulture commodities due to waste before sales. In the pre-intervention period, cold storage users were selling and generally earning less, wasting a larger share of their commodities than non-users in the intervention markets. However, during the post-intervention period, cold storage users enjoyed a relative increase in transaction volumes and revenues while both non-users in the intervention markets and those in comparison markets saw a significant decline in transactions compared to the pre-intervention period. Cold storage users also saw a significant reduction in the share of commodities wasted in the post-intervention period relative to other agents.

Most agents engaged in pre-sales practices like grading/sorting, bagging/boxing/packaging, and cleaning (removing stones and foreign materials, and washing) (Table 3). Some market agents also treated products with pesticides and chemicals, often to preserve commodity quality, including delaying the ripening process (Gibbs & Steele 2018, p.60). About 20 percent of agents were receiving advance payments from buyers. In the post-intervention periods, treatment group market agents saw relative improvement in the quality and value-adding practices, compared to comparison group market agents, consistent with the empirical results presented in a later section. The patterns in Table 3 are generally similar across commodities.

5 Results

5.1 DID-PSM estimates of the long-term effects between December 2020 and December 2022

Table 4 presents the results from the first stage regression of DID-PSM at the pre-intervention period, presented as in Takeshima et al. (2021, Table 7). A greater likelihood of using cold storage is associated with the proximity to cold storage. Inside market premises that are typically densely populated, transactions costs of moving products between cold storages and respective market stalls can be substantially high, as products are exposed to the sun and can be damaged when moved. Using cold storage is also associated with greater proximity to certain market facilities and access to drainage at the stall.

Cold storage is also more likely to be used if the market stall is further away from the nearest piped water source, possibly because greater access to stable water that can keep products cool can sometimes substitute for cold storage. More educated market agents may also readily accept relatively new technologies like solar-powered cold storages. Having more sources of credit, which can potentially allow taking loans for longer periods, may also encourage market agents to avoid distress sales and instead keep products in cold storage until prices improve.

Additionally, cold storage is more likely to be used if market stalls are far from the market representatives' office. This may be because cold storages tend to be installed further away from market representatives' offices, likely because offices tend to be in taller buildings that block the sunlight needed for solar-powered cold storages, or because there is more competition for space around these offices. Cold storage use is also more likely if the market agent speaks fewer languages, has fewer business assets, does not have exclusive space, or does not have electricity in his or her stall. This may be because speaking fewer languages or having fewer business assets makes it more difficult to sell products more quickly without cooling. Not having exclusive stalls may induce cold storage use as additional standard storage space and a lack of electricity in the stalls may also induce using cold storage for not only cooling purposes but also other electricity needs like charging phones.

PSM also successfully achieves balancing properties (Table 13 in Appendix). Table 13 shows that, in PSM samples, only 1 out of 30 variables exhibit a statistically significant difference in means at the 10 percent statistical significance level between treatment and control samples, which we would observe under the assumption of a null hypothesis that two samples are balanced.

5.2 Market agent-level outcomes on sales revenue, profit, and food loss

Table 5 summarizes the effects of using cold storage on sales revenue, profitability, and sales volume, as well as perceived reduction of food loss, estimated at the market agent level. Table 5 suggests that using cold storage led to statistically significant improvements in many of these outcomes. It has led to net increases in gross sales revenues and sales volumes by as much as 65 percent and net increases in the share (%) of net revenues to gross revenues by 8 percentage points. It has also led to a net reduction in the share (%) of the value of loss to total gross revenue by 9 percentage points for items put in cold storage, which was substantial enough that, even when considering all items sold by market agents, the loss was reduced by 6 percentage points at the market-agent level. These effects are largely consistent with other PSM specifications. The estimated Rosenbaum bounds suggest that statistical significance holds even when the odds ratio of using cold storage changes by about 40 percent or more, meaning that the results are reasonably robust against hidden bias, which PSM results are sometimes sensitive to. As discussed in subsequent sections, the increase in sales may not only be due to reduced loss but also to supply responses to increased prices.

5.2.1 Effects of using cold storage on prices, shelf-life, quality, and value-adding practices

Table 6 through Table 8 present the estimated effects on prices, quality-enhancing practices by market agents between purchase and sales, relations with buyers, and how farmers also improved quality when selling to cold storage using market agents. These are estimated at the market agent and crop levels, through equations (3) and (4).

In Table 6 through Table 8, samples for fixed-effects methods consist of 1,429 price observations reported, differentiated by cold storage use and crops, for each of the 678 market agents in the post-intervention period. The sample size for the first stage of DID-BIPW is 13,560, which consists of 678 market agents in intervention markets multiplied by the 20 horticulture crops of our focus. The second stage of DID-BIPW only uses observations for crops that were sold during both the pre-intervention and post-intervention periods, and thus are significantly smaller: 318 observations for all crops combined (of which 132 of these observations are for tomato). This means that a majority of market agents changed their crops between the pre-intervention and post-intervention periods. This validates our DID-BIPW models, which address potential biases arising from attrition and accretion of crops between the survey rounds.

Table 6 suggests that using cold storage increased sales price by approximately 13 percent and increased price margins by 19 percentage points. These results are consistent in both estimation methods (3) and (4). The increased prices and price margins are consistent with the hypothesis that price premiums exist for the improved freshness of perishable horticulture products enabled by cold storages. In addition to raising sales price, Table 6 also suggests that the effects on purchase price are also somewhat positive—that is, using cold storage also induced market agents to pay higher prices to farmers. On average, market agents perceived that using cold storage allowed them to keep the products fresh for approximately 4 to 14 days longer.

Table 7 suggests that using cold storage also induces various value-adding practices before sales by market agents, including grading and sorting; packaging, including bagging and boxing; washing and cleaning, like removing stones or foreign materials; and application of chemicals and pesticides. Effects on grading and sorting are particularly consistent across estimation methods, including tomato which is most commonly sold across markets. These results are consistent with the hypothesis that access to cooling technologies that preserve freshness and attract price premiums induce improved trading practices.

Table 7 also shows that using cold-storage technologies increases the likelihood of receiving advance payments from buyers. This reflects buyers' demand for fresher commodities and trust in cold technologies, and is often considered an indicator of institutional modernization of horticulture value chains (for example, Minten et al. 2012).

Table 8 shows that use of cold storage by market agents for certain commodities also often induced farmers to sell horticulture products of improved quality in terms of size, shape, color, flavor, taste, moisture content, skin texture, and density. These results are consistent with the hypothesis that cooling technologies enhance economic returns to quality attributes, and farmers respond to such premiums.

5.2.2 Relative absence of (negative) spillover effects

Even when cold-storage usage has significant impacts, these impacts may simply reflect the reallocation of profits from non-users of cold storage, due to negative spillover effects within the horticulture markets. One way to investigate the presence/absence of such negative spillover effects is to compare the patterns among market agents who decided not to use cold storage in intervention markets with those of market agents in comparison markets by adjusting for self-selection among the former respondents. Specifically, we compare whether the average Δy_{it} differs statistically significantly in intervention markets among market agents not using cold storage, and among market agents in comparison markets, by adjusting the values for the former through IPW. Statistically significantly lower values for the former would suggest that they experienced worse outcomes than the latter, which would indicate evidence of negative spillovers within intervention markets. However, statistically insignificant differences point to the relative absence of such negative spillovers. Results are shown in Table 9. The sample size for Table 9 consists of 757 market agents, including 435 non-users in intervention markets and 322 market agents in comparison markets.

Table 9 shows the statistical significance in differences for key outcome variables, such as sales volume, gross revenues, profit margins, and the proportion of the loss. None of these differences are statistically significant. Our results therefore indicate that negative spillover effects are relatively absent within intervention markets. The absence of differences in the changes in sales volumes, gross revenues, or profit margins suggest that prices received by non-users in intervention markets also were unaffected by the introduction of cold storage.

5.3 Efficiency analyses

Table 10 and Table 11 provide additional evidence on the technical efficiency of market agents' business transactions and linage with cold storage (equations (5) through (8)).

5.3.1 Efficiency of revenue generation/the use of purchased raw commodities, and associations with cold storage use

Table 10 summarizes the estimated stochastic frontier function of gross revenue (5) for both Greene's (2005) true random effects model and Copula-based endogenous stochastic frontier model, estimated technical efficiency of the use of purchased raw commodities (6), and the effects of cold storage use on the technical efficiency (7) (bottom part of Table 10).

The most important result here are in regards to equation (7) (bottom part of Table 10), that is, using cold storage has statistically significant positive effects on the technical efficiency of the use of purchased raw commodities. In other words, the adoption of cold storage use constitutes an explicit technical improvement in marketing activities that leads to more efficient use of purchased raw commodities in revenue generation for the market agent. Table 10 also shows that there is explicit scope for enhancing the efficiency of the use of purchased raw commodities (which can be as low as 0.7 or less on average in Copula-based model),[4] and cold storage explicitly enhances this efficiency. Table 10 therefore sheds more light on the underlying mechanisms of technical changes that lead to observed effects in Table 5.

Of secondary importance, results in Table 10 also indicate that purchased raw commodities exhibit revenue elasticity of around 0.8 ~ 0.9, significantly less than 1 as expected (squared term is positive but negligible).

5.3.2 Trend in cold storage use efficiency over time

Table 11 shows the results of efficiency of cold storage uses, estimated through (8). The results indicate that efficiency of cold storage use varies considerably among users, with average efficiency of around 0.23 ~ 0.24 in both round 2 (March 2021) and round 3 (December 2022); in other words, market agents using cold storage could reduce the extent of cold storage (in terms of volume stored or the number of days stored) by 76 ~ 77 percent and can still potentially earn the same level of revenues. Nonetheless, the bottom part of Table 11 shows that higher average outdoor temperatures still lead to higher cold storage use efficiency (with respect to revenue generation), because quality deteriorates faster when stored outside cold storage. A positive coefficient for the December 2022 dummy indicates that, after controlling for temperature effects, cold storage use efficiency has improved in December 2022 from March 2021, possibly indicating that there may be learning effects that raise cold storage use efficiency over time. While the relatively low efficiency of cold storage use should not be interpreted against the use of cold storage itself (which still generates overall positive impacts), they do suggest significant scope for improving the cold storage use efficiency among users, through training and other technical support.

6 Conclusions

Cooling technologies are becoming increasingly integral elements of global agrifood system transformation. For example, these technologies can potentially lead to a greater and more stable supply of perishable horticulture commodities and a reduction in food loss and waste, income growth for low-income producers and traders through strengthened linkages with more modern markets, and food and nutrition security through increased consumption of

[4]The estimated efficiency is generally higher in Greene's (2005) true random effects model possibly because most of residual variations in outcomes is treated as heterogeneity (random effects) rather than variations in efficiency. Nevertheless, using cold storage still has significantly positive effects on the use efficiency of purchased raw commodities.

micronutrients. The declining cost of off-grid solar electricity in recent years has enhanced the potential economic viability of providing such cooling technologies in poor regions like northeast Nigeria, where access to a conventional source of electricity has remained costly. Improved efficiency of solar panels in high-temperature environments has also enhanced the potential for successfully transferring these technologies to tropical countries. However, the knowledge gap regarding the impacts of certain cooling technologies, such as solar-powered modern cold storage in developing countries, is still vast.

This study provided critical evidence to fill this knowledge gap by evaluating an intervention to install solar-powered cold storage in northeast Nigeria. Using these cold storages led to a significant increase in horticulture products sold and profits earned by market agents while significantly reducing the share of products lost or wasted before the sale. These increases in quantity sold by market agents are not simply due to reduced loss but also supply responses to higher prices that market agents were able to command when using cold storage and were then able to pass through to farmers selling products to them. These benefits were realized without negative spillovers to non-user market agents in the same intervention markets. Higher prices were also likely to have provided economic incentives to improve the quality of horticulture products farmers sell to market agents and to engage in other value-adding practices by market agents. Efficiency analyses indicate that the observed effects are driven by the technical improvements that raise the efficiency of the use of purchased raw commodities, enabled by the cold storage. At the same time, efficiency of cold storage use remains low despite some improvement over time, and scopes exist for enhancing this efficiency through, for example, additional training and technical support.

These improvements characterize essential elements of agrifood system modernization. Solar-powered cold storage can be one of the potentially viable technological triggers for such a process, particularly in developing regions like northeast Nigeria. Solar-powered cold storage can be a viable technology to address the dual goals of meeting growing electricity needs for transforming the global agrifood system while mitigating climate change through reduced carbon emissions.

Lastly, our analyses inspire various policy options to capitalize on solar-powered cold storage. First, small subsidies or grants/loans for setting up similar solar-powered cold storages, as part of the support for small and medium enterprises (SMEs) in Nigeria (for example, McKenzie 2017), may be worthwhile to lower the initial hurdles for investments which can potentially bring higher returns. Second, the public sector can play facilitating roles in negotiating with the market and local authorities for setting aside suitable spaces within the market premises for solar-powered cold storage. Third, as is often recommended in promoting agricultural mechanization (for example, Diao et al. 2020), it may be worthwhile to reduce the importation costs of solar panels and other parts like inverters and batteries for agricultural purposes, as well as to reduce bottlenecks associated with cumbersome importation processes at borders, such as Lagos port. These measures can promote further investments in similar solar-powered cold storage in Nigeria. Fourth, and most importantly, governments should invest in agricultural R&D and information sharing of better cold-storage technologies elsewhere. For example, in India, the spread of cold storage since the 2000s has been triggered by the introduction of high-speed compressors in cold storage operations at the beginning of the early 2000s, which reduced time and electricity costs for reducing temperatures (Minten et al. 2014). Public–private partnerships in further R&D for improving cold storage technologies may offer significant returns in developing countries, including Nigeria.

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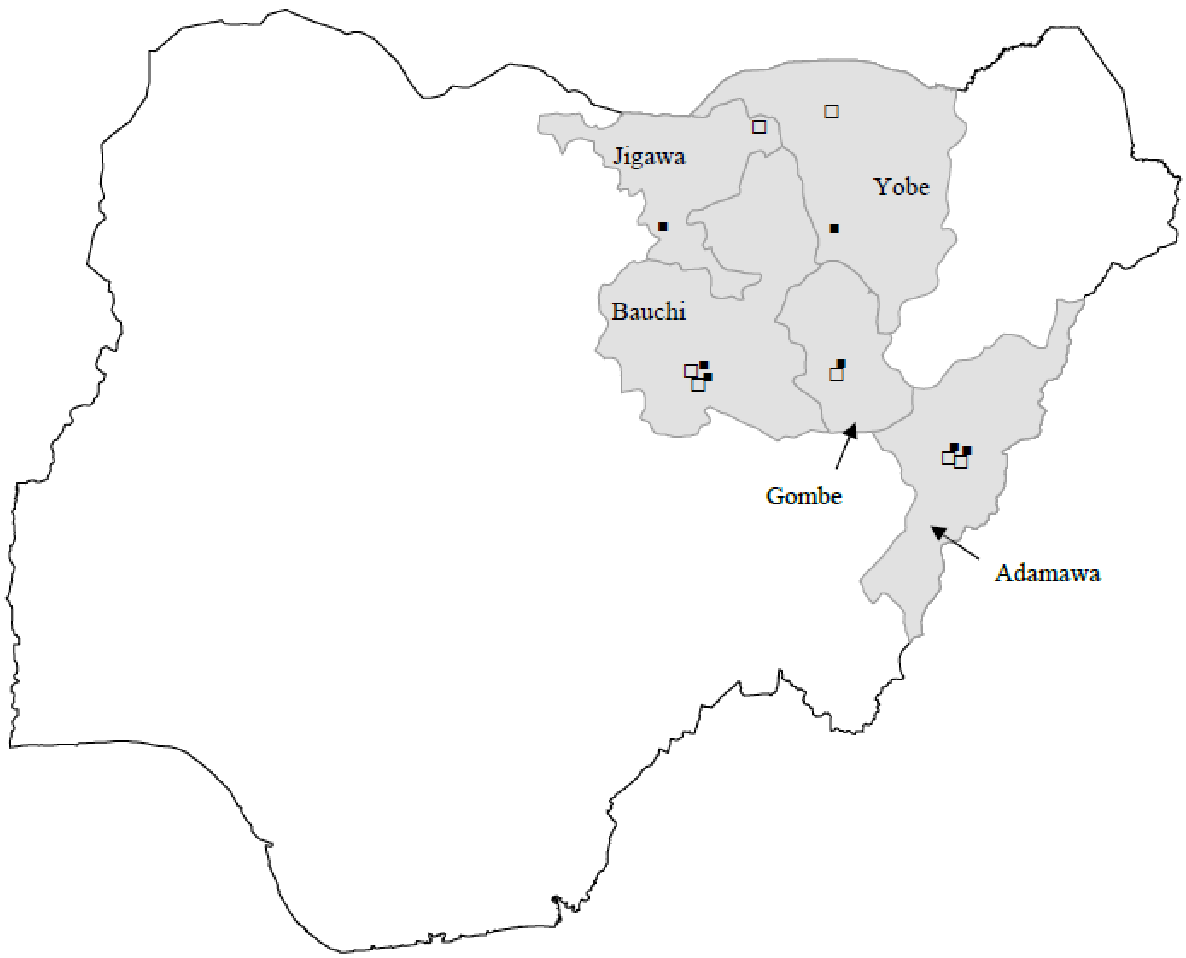

Figure 1. Locations of horticulture markets where cold storages were installed (intervention markets)

Source: Authors based on IFPRI Survey (2020).

Note: ■ = Intervention markets; □ = Comparison markets

Table 1. Descriptive statistics at baseline (December 2020)

Variables	Market agents in intervention markets		Market agents in comparison markets
	Market agents who later become cold storage users	Market agents who remain as non-users	
Sample size	**243**	**435**	**322**
Age (years)	41.720	38.762	41.834
Female (yes = 1)	0.028	0.056	0.149
Household size (count)	10.544	10.947	11.191
Education completed (years)	5.708	6.713	6.289
Native of the LGA of the market (yes = 1)	0.584	0.533	0.557
Number of languages spoken (number)	1.888	2.009	2.326
Traders among relatives (yes = 1)	0.520	0.629	0.417
Access to ready credit sources (number)	2.896	1.796	2.497
Capacity of own storage (ton)	2.551	1.717	0.984
Business assets (US$)	62.111	27.424	19.383
Having exclusive space in market stall (yes = 1)	0.476	0.727	0.717
Distance to cold-hub storage from market stalls (Euclidean distance)	0.134	0.243	N/A
Distance to entry gate (travel time, minutes)	5.580	7.769	4.272
Distance to public toilet (travel time, minutes)	5.215	8.054	6.617
Distance to canteen (travel time, minutes)	4.504	5.581	4.842
Distance to meeting room (travel time, minutes)	5.241	5.964	7.093
Distance to market representative's office (travel time, minutes)	5.592	5.885	7.052
Distance to the nearest piped water source (travel time, minutes)	15.313	8.298	26.563
Market stall has improved floor (yes = 1)	0.344	0.256	0.337
Market stall has a roof (yes = 1)	0.812	0.678	0.583
Market stall has paved road in front (yes = 1)	0.200	0.300	0.220
Market stall has drainage (yes = 1)	0.532	0.393	0.840
Market stall has covered drainage (yes = 1)	0.164	0.147	0.120
Market stall has electricity (yes = 1)	0.204	0.220	0.177
Market 1 (Dutse Daily Market: Jigawa State)	0.192	0.116	N/A
Market 3 (Gombe Main Market: Gombe State)	0.064	0.187	N/A
Market 6 (Jimeta Modern Market: Adamawa State)	0.116	0.158	N/A
Market 8 (Muda Lawal Market: Bauchi State)	0.060	0.189	N/A
Market 9 (Potiskum-Mamudo Market: Yobe State)	0.184	0.120	N/A
Market 11 (Wunti Market: Bauchi State)	0.188	0.118	N/A
Market 14 (Yola Bypass Market: Adamawa State)	0.196	0.113	N/A

Source: Authors based on IFPRI (2020, 2021, and 2022).

Note: N/A = not applicable.

Table 2. Key characteristics at the market agent level

Variables	Pre- or post-intervention	Month	Cold storage users in intervention markets	Non-users in intervention markets	Market agents in comparison markets	All
Sample size[a]			**243**	**435**	**322**	**1,000**
Gross revenue (US$/week)	Pre-	Dec 2020	369	438	360	394
	Post-	Mar 2021	272	167	143	178
		Dec 2022	435	372	330	371
Net revenue margin (proportion)	Pre-	Dec 2020	0.058	0.070	0.064	0.068
	Post-	Mar 2021	0.111	0.059	0.050	0.065
		Dec 2022	0.047	–0.014	–0.014	0.001
Sales volume (kg/week)	Pre-	Dec 2020	379	696	448	495
	Post-	Mar 2021	414	398	270	370
		Dec 2022	623	700	410	571
Wastage (proportion of unsold commodities due to wastage to total quantity purchased, all crops combined)	Pre-	Dec 2020	0.143	0.095	0.091	0.096
	Post-	Mar 2021	0.089	0.123	0.135	0.107
		Dec 2022	0.083	0.179	0.147	0.136

Source: Authors.
Note: [a]Due to omission of invalidate sample, the total sample size is less than the total number interviewed of 1,050.

Table 3. Improved practices and product quality (all crops combined, limited to same commodities transacted in both pre- and post-intervention periods)

Variables	Period	Cold storage users in intervention markets	Non-users in intervention markets	Those in comparison markets	All
All commodities combined					
Improved practices by market-agents					
Grading/sorting before sales (yes = 1)	Dec 2020	0.766	0.869	0.934	0.876
	Mar 2021	0.981	0.708	0.930	0.848
	Dec 2022	0.997	0.911	0.979	0.956
Bagging, boxing, packaging before sales (yes = 1)	Dec 2020	0.893	0.652	0.647	0.660
	Mar 2021	0.963	0.767	0.754	0.799
	Dec 2022	0.977	0.870	0.980	0.935
Cleaning like removing stones, foreign materials, washing before sales (yes = 1)	Dec 2020	0.972	0.873	0.889	0.907
	Mar 2021	1.000	0.852	0.917	0.905
	Dec 2022	0.984	0.897	0.884	0.915
Treating products with pesticides / chemicals before sales (yes = 1)	Dec 2020	0.103	0.042	0.031	0.049
	Mar 2021	0.243	0.038	0.031	0.074
	Dec 2022	0.310	0.240	0.206	0.245
Receiving advanced payment from buyers (yes = 1)	Dec 2020	0.374	0.229	0.079	0.196
	Mar 2021	0.533	0.229	0.162	0.259
	Dec 2022	0.345	0.260	0.175	0.251
Quality of products sold by farmers to market-agents (perceptions by market-agents) – all crops combined					
Size (high quality = 1)	Dec 2020	0.701	0.691	0.679	0.690
	Mar 2021	0.963	0.648	0.500	0.648
	Dec 2022	0.890	0.882	0.511	0.754
Shape (high quality = 1)	Dec 2020	0.664	0.574	0.659	0.625
	Mar 2021	0.869	0.551	0.504	0.592
	Dec 2022	0.852	0.818	0.529	0.725
Color (high quality = 1)	Dec 2020	0.730	0.631	0.657	0.665
	Mar 2021	0.888	0.725	0.504	0.667
	Dec 2022	0.971	0.791	0.516	0.738
Smell (high quality = 1)	Dec 2020	0.651	0.626	0.663	0.645
	Mar 2021	0.888	0.526	0.526	0.671
	Dec 2022	0.958	0.789	0.509	0.732
Taste (high quality = 1)	Dec 2020	0.612	0.644	0.654	0.639
	Mar 2021	0.907	0.695	0.522	0.665
	Dec 2022	0.929	0.783	0.509	0.732
Moisture content (high quality = 1)	Dec 2020	0.571	0.616	0.659	0.618
	Mar 2021	0.832	0.712	0.526	0.660
	Dec 2022	0.977	0.775	0.509	0.731
Skin texture (high quality = 1)	Dec 2020	0.682	0.636	0.674	0.660
	Mar 2021	0.897	0.703	0.518	0.665
	Dec 2022	0.958	0.800	0.516	0.739
Density (high quality = 1)	Dec 2020	0.585	0.610	0.670	0.623
	Mar 2021	0.822	0.691	0.526	0.650
	Dec 2022	0.913	0.777	0.496	0.711

Source: Authors.

Table 4. Factors associated with propensity scores of using cold storage (first-stage; standard probit) (marginal effects of a one-standard deviation change of each variable on the probability (yes = 1), evaluated at sample means of all other exogenous variables)

Variables	Coef.	Standard error
<u>*Demographics*</u>		
Age	0.069	(0.089)
Female	0.059	(0.071)
Household size	–0.059	(0.090)
Education completed (years)	0.149*	(0.081)
Native of the LGA of the market	–0.011	(0.071)
Number of languages spoken	–0.257***	(0.074)
Traders among relatives	–0.075	(0.075)
Number of credit sources	0.248***	(0.095)
Asset		
Capacity of own storage	–0.032	(0.070)
Business assets (natural log)	–0.804***	(0.099)
Exclusive space	–0.412***	(0.075)
Location		
Distance to cold-hub storage from market stalls	–0.197*	(0.112)
Distance to entry gate	–0.039	(0.094)
Distance to public toilet	–0.370***	(0.138)
Distance to canteen	–0.123	(0.124)
Distance to meeting room	–0.116	(0.145)
Distance to market representative's office	0.255*	(0.135)
Distance to the nearest piped water source	0.430***	(0.105)
Facilities		
Improved floor	0.119	(0.114)
Roof	0.064	(0.081)
Paved road	–0.188	(0.146)
Drainage	0.417***	(0.151)
Covered drainage	0.072	(0.137)
Electricity	–0.201**	(0.097)
Market dummies	Included	
Sample size	678	
Pseudo-R^2	.418	
p-value (H0: variables are jointly insignificant)	.000	
Variance inflation factor	2.87	

Source: Authors.
Note: *10% **5% ***1%.

Table 5. Impacts of cold storage on at the market agent level (DID-PSM, between pre-intervention period in December 2020 and post-intervention period in December 2022)

Estimation methods	Outcome variables				
	Revenue (gross)	Share (%) of net revenue to gross revenue	Sales volume	Share (%) of the value of loss to total gross revenue[a]	Share (%) of the value of loss to total gross revenue (among cold-stored items only)[a]
	Percent increase	Percentage point change	Percent increase	Percentage point	Percentage point change
Primary method					
Nearest neighbor (4) + caliper (0.01)	64.992** (25.968) [2.30]	7.977* (4.693) [1.40]	63.534*** (15.583) [3.10]	–5.917*** (1.574) [2.90]	–9.144*** (3.285) [2.80]
Robustness check using more consistent but less efficient method[b]					
Nearest neighbor (1) + caliper (0.01)	68.921** (26.426) [2.20]	11.284** (5.739) [1.40]	46.304*** (16.942) [2.00]	–5.477*** (1.866) [2.30]	–7.513** (3.467) [2.45]
Sample size			678		

Source: Authors.

Note: *10% **5% ***1%. Numbers in brackets are Rosenbaum bounds (Rosenbaum 2002). [a]"Loss" includes loss for items kept outside cold-storage by cold-storage-user. "Loss among cold-stored commodities only" excludes loss for items kept outside cold-storage by cold-storage-user. [b]Kernel matching methods had slightly poorer balancing properties than our primary method of nearest neighbor methods combined with caliper. Therefore, results should be interpreted with caution.

Table 6. Effects on price margins, prices (sales/purchase), and shelf life

Estimation methods	Outcome variables			
	Price	Price margin	Price paid to farmers	Shelf life
	Sales price	Share (%) of price margin to purchase price	Purchase price	Number of days products remain fresh
	Percent increase	Percentage point increase	Percent increase	Days
Market agent–crop fixed effects methods	13.025*** (3.102)	19.128** (7.806)	2.226** (1.116)	4.215*** (0.399)
Sample size	1,846			
DID-BIPW (Tomato)	Insignificant	Insignificant	Insignificant	14.083*** (5.625)
Sample size	129			
Sample size of first-stage bivariate probit	13,560			

Source: Authors.
Note: *10% **5% ***1%.

Table 7. Effects on quality enhancing practices and receipt of advance payments from buyers

Estimation methods	Grading/sorting before sales	Bagging, boxing, packaging before sales	Cleaning products before sales, like removing stones, foreign materials, washing	Applying pesticides/chemicals before sales	Receive an advance payment from the buyer
	Yes = 1	Yes = 1	Yes = 1	Yes = 1	Yes = 1
Market agent–crop fixed effects methods	0.033*** (0.009)	0.033*** (0.009)	0.019** (0.009)	0.106*** (0.018)	Insignificant
Sample size			1,846		
DID-BIPW	0.210** (0.085)	0.106 (0.075)	0.291*** (0.090)	0.333*** (0.085)	Insignificant
Sample size			272		
DID-BIPW for tomato	0.022 (0.100)	–0.181 (0.152)	0.273* (0.144)	0.168** (0.085)	Insignificant
Sample size			129		

Source: Authors.

Note: *10% **5% ***1%.

Table 8. Effects on product quality sold by farmers (dependent variable = 1 if the quality of products sold to market agents is "high quality" in various attributes)

Estimation methods	Quality attributes of products sold to market-agents							
	Size	Shape	Color	Flavor	Taste	Moisture content	Skin texture	Density
Market-agent-crop fixed effects methods	0.039*** (0.009)	0.097*** (0.013)	0.113*** (0.014)	0.109*** (0.014)	0.097*** (0.014)	0.092*** (0.013)	0.103** (0.014)	0.113*** (0.014)
Sample size	1,846							
DID-BIPW	0.081 (0.091)	0.029 (0.096)	0.086 (0.090)	0.139* (0.082)	0.205** (0.088)	0.219** (0.090)	0.103* (0.059)	0.144* (0.084)
Sample size	272							

Source: Authors.
Note: *10% **5% ***1%.

Table 9. Indicators of the absence of negative spillover effects within the intervention markets

	Sales volume	Revenue	Profit margin	Loss
Differences	–0.110 (0.121)	–0.059 (0.142)	0.150 (0.174)	0.079 (0.050)
p-value (H0: differences are insignificant)	.363	.676	.327	.114
Sample size	757	757	757	757

Source: Authors.

Table 10. Efficiency in overall revenues and the use of purchased raw commodities

Variables	Greene (2005) true random effects model	Copula-based endogenous stochastic frontier
	Coef. (std.err)	Coef. (std.err)
Stochastic frontier function of gross revenue (5)		
Purchased raw commodities	0.806***(0.024)	0.887***(0.032)
Purchased raw commodities ^ 2	0.007***(0.001)	0.004***(0.001)
Capital	0.001 (0.001)	0.001 (0.001)
Labor	0.0003 (0.003)	0.009*** (0.003)
Round dummy	Yes	Yes
Intercept	Yes	Yes
σ_v	0.295***(0.005)	0.534***(0.027)
σ_u	0.099***(0.007)	0.950***(0.004)
Log-likelihood	–754.750	–708.297
Technical efficiency in overall revenues (mean)		
Round 1	0.909	0.616
Round 2	0.928	0.630
Round 3	0.904	0.630
Technical efficiency of the use of purchased raw commodities (6)		
Round 1 (mean)	0.898	0.662
Round 2 (mean)	0.899	0.670
Round 3 (mean)	0.900	0.672
Associations between cold-storage uses and technical efficiency in the use of purchased raw commodities (7) (through GMM – panel fixed effects model, that treat cold-storage uses as endogenous, using proximity to cold-storage as an IV)		
Cold storage uses	**0.010***(0.002)**	**0.065***(0.022)**
Round dummy – March 2021	–0.004** (0.001)	–0.023* (0.012)
Round dummy – December 2022	–0.008*** (0.002)	–0.031***(0.012)
Round dummy*Market dummy	Yes	Yes
Market-agents fixed effects	Yes	Yes
Intercept	Yes	Yes
Number of observations	3,000	3,000

Source: Authors.
Note: *10% **5% ***1%.

Table 11. Trends in efficiency of cold storage uses (among cold storage users)

Variables		Copula-based endogenous stochastic frontier
		Coef. (std.err)
Stochastic frontier function of gross revenue (8)		
Cold storage uses		0.179*** (0.046)
Cold storage uses squared		–0.049** (0.020)
Other expenses including purchased commodities		0.965*** (0.006)
Capital		0.007*** (0.003)
Labor		–0.004 (0.005)
Year dummy		Included
Intercept		Included
σ_v		0.480*** (0.018)
σ_u		0.692*** (0.022)
ρ		0.912*** (0.009)
Log-likelihood		
Technical efficiency in overall revenues		
	Round 2 (mean)	0.565
	Round 3 (mean)	0.565
Technical efficiency of the use of cold storage		
	Round 2 (mean)	0.238
	Round 3 (mean)	0.234
Trends in cold storage use efficiency		
Round dummy – December 2022 (base = March 2021)		0.131** (0.057)
Average temperatures[a]		0.061** (0.026)
Market agents fixed effects		Yes
Intercept		Yes
Number of observations		486

Source: Authors.

Note: *10% **5% ***1%. [a]Temperature is for corresponding periods surveyed in each round (December 2020, March 2021, December 2022 for round 1, 2 and 3, respectively).

Appendix A: Additional results

Table 12. Summary descriptions of samples used in each regression model and results tables

Results Table	Regression model equation number	Treatment group sample in intervention markets	Control group sample in intervention markets	Control group sample in non-intervention markets	Total sample
Table 4	(2)	243 agents	435 agents		678
Table 5	(1), (2)	243 agents	435 agents		678
Table 6	(4)	680 (= 243 agents * 2.8 crops transacted on average in t = 2)	1,166 (= 435 agents * 2.7 crops transacted on average in round t = 2)		1,846
	(3) for tomato only	50 observations of tomato transactions that happened in both t = 0 (baseline) and t = 2 (endline)	79 observations of tomato transactions that happened in both t = 0 (baseline) and t = 2 (endline)		129
	First stage bivariate probit preceding (3)	4,860 (= 243 agents * 20 crops included in the survey out which some were transacted by agents)	8,700 (= 435 agents * 20 crops included in the survey out which some were transacted by agents)		13,560
Table 7	(4)	680 (= 243 agents * 2.8 crops transacted on average in t = 2)	1,166 (= 435 agents * 2.7 crops transacted on average in round t = 2)		1,846
	(3)	102 observations of crops that were transacted in both t = 0 (baseline) and t = 2 (endline)	170 observations of crops that were transacted in both t = 0 (baseline) and t = 2 (endline)		272
	(3) for tomato only	50 observations of tomato transactions that happened in both t = 0 (baseline) and t = 2 (endline)	79 observations of tomato transactions that happened in both t = 0 (baseline) and t = 2 (endline)		129
Table 8	(4)	680 (= 243 agents * 2.8 crops transacted on average in t = 2)	1,166 (= 435 agents * 2.7 crops transacted on average in round t = 2)		1,846
	(3)	102 observations of crops that were transacted in both t = 0 (baseline) and t = 2 (endline)	170 observations of crops that were transacted in both t = 0 (baseline) and t = 2 (endline)		272
Table 9	5.2.2		435	322	757
Table 10	(5), (6), (7)	729 (= 243*3 rounds)	1,305 (= 435*3 rounds)	966 (= 322*3 rounds)	3,000
Table 11	(8)	486 (= 243*2 rounds)			486

Source: Authors.

Table 13. Balancing properties (single PSM)

Variables	Non-adjusted raw sample		IPW-sample (common support)	
	Cold storage user	Non-user	Cold storage user	Non-user
Demographics				
Age	40.775	39.170	40.775	39.705
Household size	10.938	10.654	10.938	10.962
Education completed	6.318	7.390*	6.318	6.942
Native of the LGA of the market	0.605	0.549	0.605	0.694
Number of languages spoken	1.892	1.967	1.892	1.943
Traders among relatives	0.566	0.615	0.566	0.524
Number of credit sources	0.950	0.809*	0.950	0.861
Asset				
Capacity of own storage	0.406	0.518	0.406	0.410
Business assets	1.484	2.111	1.484	1.208
Exclusive space	0.543	0.582	0.543	0.499
Location				
Distance to cold-hub storage from market stalls	–7.073	-6.932	–7.073	–6.961
Distance to entry gate	2.416	2.448	2.416	2.407
Distance to public toilet	2.542	2.538	2.542	2.517
Distance to canteen	2.426	2.346	2.426	2.382
Distance to meeting room	2.548	2.503	2.587	2.485
Distance to market representative's office	2.587	2.485*	2.587	2.563
Distance to the nearest piped water source	2.342	2.127	2.342	2.357
Facilities				
Improved floor	0.357	0.269*	0.357	0.402
Roof	0.736	0.643*	0.736	0.714
Paved road	0.240	0.275	0.240	0.298
Drainage	0.473	0.341**	0.473	0.485
Covered drainage	0.178	0.165	0.178	0.241
Electricity	0.233	0.148*	0.233	0.176
Markets				
Market 1	0.192	0.116*	0.124	0.167
Market 3	0.124	0.176	0.124	0.139
Market 6	0.132	0.165	0.132	0.167
Market 8	0.116	0.220**	0.116	0.161
Market 9	0.171	0.154	0.171	0.185
Market 11	0.155	0.099	0.155	0.163
Market 15	0.132	0.099	0.132	0.048**

Source: Authors.

Note: *10% **5% ***1%. Asterisks indicate statistically significant differences from the figures among cold storage users.

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