Evaluating Seasonal Food Storage and Credit Programs in East Indonesia[☆]

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Abstract

Predictable annual lean seasons occur in many rural areas, including West Timor in Indonesia. Imperfections in savings and credit markets make it difficult for staple farmers to convert harvest season output into lean season consumption. We conduct a randomized evaluation of a seasonal food storage program and a food credit program. By providing improved ways to transfer assets across seasons, each program functions as a subsidy on lean season consumption. We find that neither program had effects on staple food consumption. The storage program increased non-food consumption. The credit program increased reported income and reduced seasonal gaps in consumption. Our results are consistent with positive income effects through the expansion of budget sets, but suggest that the average household could be close to staple food satiation.

Keywords: Seasonality, Food policy, Food storage, Food credit
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1. Introduction

Seasonality is a concern for many households engaged in rain-fed agriculture.[1] Farmers whose incomes vary over the agricultural cycle need access to instruments–savings or credit–to transfer assets across seasons. Imperfections in savings and credit markets can lead to low consumption

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[1]Seasonal food shortages have been documented in parts of Sub-Saharan Africa, South Asia and Southeast Asia. See Khandker and Mahmud (2012) and Devereux et al. (2012) for an overview.

levels and predictable annual lean seasons.[2] Yet, there is limited evidence on the impacts of programs that address market imperfections related to seasonality.[3]

We conduct a randomized evaluation of two seasonal programs–food storage and food credit–in West Timor. This island in East Indonesia has historically suffered from an annual lean season between November and January. We focus on farmers who produce staples–maize or rice–which serve both as a form of consumption and a tradable asset. Many farmers have difficulty borrowing against future harvests, use poor storage methods, and face seasonal price variation. These features, which we call *seasonal frictions*, have two effects–they skew consumption away from the lean season and they limit annual consumption possibilities.

We build a stylized model that encapsulates these seasonal frictions in a low harvest-to-lean season marginal rate of transformation (MRT). The lower a household's MRT, the more harvest consumption it must forgo to provide for lean season consumption. The problem of seasonality is therefore framed as a technological one–seasonal frictions lower MRT, increasing the opportunity cost of lean season consumption and making it difficult to transfer assets across seasons.

We address this problem by offering improved access to savings or loans, both of which can raise farmers' MRT. In 2008, we randomly assigned 96 villages to receive a food storage program, a food credit program, or no program. Assignment was stratified by four districts, and two NGOs implemented the programs in two districts each. The storage program offered households free food storage equipment–weather-sealed drums and sacks–with high retention rates. For the credit program, women's microcredit groups were formed and offered loans of staples during the lean season, which were to be repaid in kind after the following harvest. Repaid grain was stored in sealed facilities for disbursement in the following lean season.

Increases in the MRT effectively serve as subsidies that lower the opportunity cost of lean season consumption and thereby expand the overall budget set. As a result, first, substitution effects serve to raise lean season consumption and lower harvest season consumption. Second, income effects from the expansion in the budget set can raise consumption in either season.

Beyond the above-described parallels between the two programs, each operated through different mechanisms and had relative strengths and weaknesses. Storage directly improved MRT by raising the retention rates of stored staple. Furthermore, the program could serve as a commitment device to help households save because the technology reduced visibility of assets and made frequent withdrawals cumbersome. These commitment benefits could apply to both self-control problems and social pressures to share. But it was possible that benefits would be limited within our three-year study–it could take time to accumulate a buffer stock or there might be nothing to store if there were harvest failures.

The credit program improved MRT by allowing households to borrow against future harvests

[2] There is a large literature on the challenges to consumption smoothing in the presence of credit or savings constraints, notably Deaton (1991) and Townsend (1994). See Khandker and Mahmud (2012) for a discussion focused on seasonality and Zeller et al. (1997) for an overview that relates food security policies to the consumption smoothing literature.

[3] Seasonal food deprivation has been described as the "cycle of quiet starvation" and the "father of famine" (Devereux et al., 2008) and "one of the most persistent and intractable aspects of global food insecurity" (Khandker and Mahmud, 2012). Yet, according to two surveys on this topic, "[o]f all the dimensions of rural deprivation, the most neglected is seasonality" (Devereux et al., 2008), and, "[a] focus on seasonality is often missing" in social protection schemes (Khandker and Mahmud, 2012). There is a small but growing literature on policies to mitigate seasonal food shortages. We discuss this later in the introduction.

relatively cheaply. It had risk-mitigating features that storage lacked–it provided implicit insurance against harvest risks through limited liability; the group structure encouraged risk-sharing across participants; and unlike storage, it offered a fixed and explicit MRT. This implies that the credit program could have stronger effects on reducing consumption variability, including across seasons. However, by providing an up-front benefit with delayed repayment, it had the potential to increase the debt burden of households if they over-borrowed. The viability of the credit program depended on repayment rates since it was funded with a one-time grant.

To investigate the impacts of food storage and credit, we built a large scale seasonal household panel that tracked 2,870 households during each harvest and lean season over three years. We test for two categories of treatment effects. First, we look at the mean effects on consumption-related outcomes, which could also have consequences on health. Second, we look at seasonal gaps between harvest and lean season consumption. We report Intent-to-Treat (ITT) effects below.

The storage program raised the *Consumption and Income Index* by 0.097 units. This is driven by a 13.4% and a 14.2% increase in non-food expenditure in the lean and harvest seasons, respectively. We find a null effect on staple food consumption (0.6% effect, s.e. 2.9%), with a 95 percent confidence interval on calories consumed per capita per day of -18 to 23 calories. Further analysis shows that the positive effects on the index are strongest for individuals who we identify as the most savings constrained; i.e. those who face relatively low initial MRTs.

For storage, we find no effects on consumption smoothing across seasons. This is consistent with the discussion above on its relative lack of risk protection mechanisms compared to credit. Storage also had no effects on health.

The credit program raised the *Consumption and Income Index* by 0.087 units, but only in the harvest season. This is driven by a 26.8% rise in reported income in the harvest season, with no detectable changes in consumption levels. Since our measure of consumption is incomplete, this increased income might translate into higher consumption in categories that we do not measure. Again, we estimate null effects on staple food consumption (2.4%, s.e. 3.6%), with a 95 percent confidence interval of -95 to 196 calories per capita per day.

Additionally, the seasonal gap in monthly non-food expenditure narrowed by 0.066 units, with significant reductions in the overall *Seasonal Gap Index* for districts administered by one NGO. However, there were moderately negative health effects in the harvest season. The *Health Index* is 0.075 units higher in the lean season and is 0.130 units lower in the harvest season. Health effects are statistically insignificant in the lean season and when we pool both seasons.

The null effects on staple food consumption are striking considering our focus on raising the MRT of these goods. The positive effects on non-food consumption and reported income suggest that each program did raise household assets for staple farmers. But this rise in assets did not translate into greater staple consumption, which implies that the average household in our study could be close to staple food satiation. This is consistent with preferences where the marginal utility of staples drops rapidly relative to the marginal utility of other consumption (see Banerjee and Duflo (2007) and Jensen and Miller (2008) for related discussions of preferences).

This finding is also notable in light of transaction costs associated with the buying and selling of staples, which are relevant given our focus on remote rural households. Under standard food subsidy programs, transaction costs of converting cash (or vouchers) to staples might incentivize households against raising staple consumption. In contrast, our programs directly expand in-kind income, so households could have minimized transaction costs by raising staple consumption instead of converting it to other goods.

This paper demonstrates some ways in which staple programs can affect outcomes for staple farmers despite leaving staple consumption unchanged. This has implications for the design and interpretation of staple food policy, which plays a major role in many developing countries.[4] Increases in harvest season consumption are consistent with dominant income effects from budget set expansions, and a consequent rise in welfare.

To better understand the mechanisms, we analyze how each program affects intermediate outcomes. In Sections 4.1 and 4.2, we extend our stylized model to develop hypotheses for the programs' effects on "first-stage" outcomes that precede consumption–staple inventory and staple sales. In Section 4.3, we discuss how the programs might interact with risks, social pressures and behavioral biases. We also consider other budget set effects that could counteract the effects of the programs.

In Section 7, we discuss first-stage effects on staple sales and inventory. While each program affects sales, we do not detect effects on inventory. The latter has two explanations. First, stocks are difficult to measure precisely and are highly sensitive to timing. Second, some of our theoretical predictions on sales and inventory are themselves ambiguous. In particular, for both storage and credit programs, the signs of first-stage effects in the harvest season depend on the household's initial method of saving.[5]

Despite the fact that we do not observe effects on inventory, the following patterns shed some light on mechanisms. For storage, we find increases in income from staple sales in districts under one NGO. In particular, higher lean season staple sales are consistent with expanded inventory. Also, since consumption effects are stronger for savings-constrained households, it appears likely that the storage program facilitated expanded stock retention. Finally, storage reduced the share of festival expenditures that was spent on neighbors. These factors combined suggest that the benefits of the storage program derived from both higher returns to savings and reduced vulnerability to social pressures.

For credit, we again find increases in income from staple sales. These, combined with no reduction in staple consumption, are consistent with the credit program improving MRT. We find no evidence of over-borrowing, and apart from instances of harvest failures, the credit program sustained high repayment rates. Under one NGO, credit also resulted in a reduction in the share of festival expenditures spent on neighbors' festivities. This suggests that, relative to traditional storage methods, credit too offers some protection from social pressures to share.

[4]In the Philippines, the rice subsidy program accounts for 70% of public social protection expenditures (Jha and Ramaswami, 2010). Indonesia and India too have large and expensive staple subsidy programs.

[5]While our model makes clear predictions on first-stage effects in the lean season, harvest season effects are theoretically ambiguous. Under the storage program, in the lean season both sales and inventory should rise–more inventory due to the higher retention rate and more sales to fund other consumption. However, harvest season predictions depend on initial methods of saving–when income effects dominate, effects on intermediate steps are opposite-signed for cash savers versus in-kind savers. As we explain in Section 4.3, in-kind savers should store less and sell more to fund greater non-food consumption in the harvest season, but cash savers who switch to saving in-kind should store more and sell less.

Under credit, in the lean season, sales should rise as under storage. In the harvest season, again, predictions for staple sales are ambiguous. Staple sales for consumption increase but sales for savings drop for cash savers, since they now have to repay in kind. But in contrast to storage, inventory in both seasons should fall since credit reduces the need to maintain one's own stock.

Our paper relates to the literature on consumption seasonality,[6] and to the literature on food policy in developing countries.[7] Angelucci and Attanasio (2013) and Attanasio et al. (2012) find positive effects of conditional transfers on food consumption for poor urban households in Mexico and for urban and rural households in Colombia. Hidrobo et al. (2014) find that food transfers, food vouchers and cash transfers in urban centers in Ecuador significantly improved the quantity and quality of food consumed. These programs are relatively less comparable to ours as the cash transfers were conditional and, in the case of Hidrobo et al. (2014), included a nutrition sensitization component. Our results are closer to those of Jensen and Miller (2011), who find no evidence that price subsidies (in the form of food vouchers for staples) improved nutrition for poor urban households in two provinces in China.

The food storage and food credit programs can be viewed as potentially compelling ways to address seasonal frictions. Other approaches to the problem have been examined in a number of studies. Khandker et al. (2011) find that government social safety nets reduce both seasonal and non-seasonal insecurity to a limited extent. Stephens and Barrett (2011) and Burke (2014) study the relationship between credit constraints and seasonal price fluctuations in crops. As ways to cope with lean seasons, Pitt and Khandker (2002) and Khandker et al. (2010) study cash-based credit programs and Bryan et al. (2014) study seasonal migration.

While our programs generate subsidy-like income and substitution effects, the mechanisms are different from standard price subsidies. By introducing new products that target the sources of seasonal frictions, the programs can persistently improve the rate at which farmers transfer assets across seasons. These "technologies" raise the MRT of staples as assets that can be both consumed and traded for other goods, thereby subsidizing even non-staple consumption. Since the up-front fixed costs (to purchase storage equipment and seed capital for credit) can be amortized over time, persistent benefits would raise the implied cost-effectiveness of the programs.[8]

We provide some background on West Timor in Section 2, present the theoretical framework in Section 3, describe the treatments in Section 4, discuss data in Section 5, lay out the empirical framework in Section 6, discuss results in Section 7, and conclude in Section 8.

2. Background

West Timor occupies half of the island of Timor and is in one of Indonesia's poorest provinces. According to the 2008 annual *Susenas* household survey, on average, rural farm households in West Timor consume around 2255 calories per capita per day (slightly above the minimum recommended daily limit of 2100), with 1400 (62%) calories coming from staples. Our study focuses on

[6]There is a small but growing literature on consumption smoothing across seasons within an agricultural cycle. See, for example, Sahn (1989); Paxson (1993); Alderman and Garcia (1993); Handa and Mlay (2006); Chaudhuri and Paxson (2002); Alderman and Sahn (1989); Behrman (1988); Pinstrup-Anderson and Jaramillo (1989); Khandker (2012). More recently, there have been some randomized controlled trials related to consumption seasonality (Beaman et al. (2014); Bryan et al. (2014); Fink et al. (2014)).

[7]See Barrett (2002), Dréze et al. (1995) and Zeller et al. (1997) for an overview of the literature on food policies. There is a long literature investigating the targeting properties and treatment effects of food policies, especially food price subsidies (see, for example, Besley and Kanbur (1990) and Jha and Ramaswami (2010)).

[8]By contrast, standard in-kind and cash transfers and direct food subsidy programs incur per period, recurring costs that do not amortize over time.

smallholder staple farmers, many of whom are dependent on rain-fed agriculture.[9] The climate is characterized by a brief monsoon (typically between November and January) followed by a long dry spell. While rice is the primary staple across Indonesia, maize has traditionally been the primary staple consumed in West Timor.[10] Maize is also the primary crop grown in West Timor, followed by rice.[11] The main harvest seasons occur in April for maize and May-June for rice.

There is a recurring, annual lean season between the months of November and January that is known locally as *musim paceklik*. As Fox (1977) describes, farmers expect an "ordinary hunger period" of a few months before each harvest.[12] We find the following seasonal patterns in our harvest and lean season surveys. First, 48% of households report lacking food in the past month in our lean season surveys, and 37% do so in the harvest season. On average, staple calories consumed per capita per month are around 38 kCals in the lean season and 42 kCals in the harvest season. Households report monthly per capita expenditures that are 20% higher in the harvest season compared to the lean season. On average, respondents expect maize prices to be 58% higher in January (lean) than in April (harvest). Table 1 shows that these seasonal differences are statistically significant using household fixed effect regressions.[13] As we explain next, there is suggestive evidence that farmers face savings and credit constraints that could partly explain this recurring seasonal variation as well as the low overall levels of consumption.

First, existing storage methods have high depreciation rates. The most prevalent practice of hanging smoked maize from the ceiling leaves it exposed to insects, rodents and moisture, resulting in an annual depreciation rate of approximately 34% (FAO, 2003). Rice, while less vulnerable than maize, is generally stored in sacks that provide inadequate protection from infestation. Possibly due to transportation costs or a lack of infrastructure, inter-island trade is limited. This could also explain why newer storage technologies have not been introduced locally.

These methods also leave the grain highly visible and subject to what might be termed "social depreciation", which emerges from community pressures to share.[14] We collected data on seasonal festival expenditures including amounts spent on own and others' festivities. Festival expenditures are important and constitute 20% of non-food expenditures for the control group. On average, 57% of festival expenditures are incurred on other households' festivities.

Furthermore, there are two types of difficulties associated with saving in cash (equivalent to selling staple in the harvest season and buying it back the lean season). First, maize prices are

[9]Smallholder subsistence farmers and landless agricultural laborers can both experience consumption seasonality but with possibly different patterns (see, for example, Sen (1981a,b); Ravallion (1987); Khandker and Mahmud (2012)). Landless laborers must deal with variation in labor demand while smallholder subsistence farmers experience food shortages when their food stock depletes before the harvest season.

[10]In the 1983 village census, 73% of villages in West Timor reported maize as their primary staple while 17% reported rice.

[11]According to the 2003 village census, in the average village in West Timor, maize is planted on 53% of village area and rice is planted on 17%.

[12]Fox (1977) describes this annual recurrence further: "On Timor, in particular, it is usually expected as a kind of annual inevitability that there will be a hunger period of a month or more as food supplies dwindle before the next harvest. If in the previous year crops have failed to any great extent, the hunger period becomes a famine."

[13]We provide more details about the data in Section 5 and more details about the regression in the footnote of the table.

[14]Consider norms that create pressure on households to share visibly stored assets, as in Baland, Guirkinger and Mali (2011).

Table 1: Seasonality Patterns with Household Fixed Effects

Dependent Variable:	Staples consumed	Non-food expenditures	1(Lacked food)	Expected maize price
	(1)	(2)	(3)	(4)
1(Harvest season)	3.989***	3.358***	-0.116***	-1340.954***
	(0.893)	(0.526)	(0.013)	(15.168)
Number of observations	7,152	7,152	7,152	14,304
R^2	0.450	0.390	0.348	0.420
Harvest season mean	42	24	0.366	2334
Lean season mean	38	20	0.483	3675
Overall mean	40	22	0.424	3005

* p<0.1, ** p<0.05, *** p<0.01

Notes: Each column reports results from an OLS regression at the household-season level with household fixed effects and a dummy for the harvest season. Standard errors are clustered at the household level. These regressions pool households in control villages in all rounds and households in storage villages in the first two survey rounds. We do not include credit villages as there is no within household variation (we only have one pre-treatment round). Columns 1 to 3 examine seasonal patterns for staples consumed (per capita per month kCals), monthly non-food expenditure items (in thousands of Rupiahs) and an indicator for whether households lacked food in the past month. Column 4 reports results for households' expectations for prices in future harvest (April) and lean (January) seasons. Column 4 has more observations because price expectations for future harvest and lean seasons are asked in both harvest and lean season surveys.

low in the harvest season and high in the lean season. Second, households are constrained by their remoteness–the average household in our dataset is 25.6 km from the nearest market. This suggests significant transaction costs associated with converting food to cash and back to food.

Credit, when available, is offered at high rates. Informal annual credit interest rates in West Timor range from 30% to 50%. Indonesia also has a long association with microfinance. However, Johnston and Morduch (2008) argue that in most cases it remains unsustainable given the small average loan size. Together, these local features point to seasonal frictions, whether borrowing against future harvests or saving in cash or in-kind.

The Indonesian government's efforts on food security are centered around a national rice subsidy program called Raskin. Under this program, basic selection criteria are applied to all households. Eligible households receive a monthly allowance of rice (up to 20 kg per household) at subsidized prices. In addition to the high fiscal costs,[15] the program suffers from high leakage (Olken, 2006), possibly due to poor targeting. Finally, as a national program, the timing and provisions under Raskin are not adjusted to seasonal needs in West Timor.

3. Theoretical Framework

We use a stylized model to illustrate how local seasonal frictions highlighted in Section 2 can be summarized using the marginal rate of transformation (MRT). We first demonstrate that a "no-seasonality" benchmark has a harvest-to-lean season MRT of staples equal to one. In contrast, with seasonal frictions, MRT is less than one. This gives rise to two problems–consumption patterns

[15] In 2009, the cost of Raskin amounted to 0.23% of GDP (Trinugroho et al., 2011).

that are tilted towards the harvest season, and low overall consumption due to the costs associated with any lean season consumption.

We model food storage and food credit as technology shocks that raise MRT, thereby functioning as a subsidies on lean season consumption. This section builds a framework to analyze the consumption effects of such technology shocks. In Section 4, we describe each program separately and in detail, and discuss additional distinct predictions associated with each.

3.1. Seasonal Frictions

In any year, there is a harvest period (H) and a lean period (L). In each period, utility is a function of staple consumption (m) and consumption of a non-food numeraire good (c). We assume an additively separable utility function: utility in period t is given by $U_t \equiv u_{m,t}(m_t) + u_{c,t}(c_t)$, where each $u_{i,t}$ is twice differentiable and strictly concave. For each good i and period t, $u'_{i,t}(0) = \infty$ (there are no corner solutions).

Income is seasonal. In any harvest period, the farmer receives an endowment of e units of the staple.[16] She must allocate the endowment to consumption in both harvest and lean periods. For clarity, since we have an in-kind program, we measure units of consumption in terms of the staple, so that M_H represents the amount of endowment allocated to the harvest season and M_L represents the amount allocated to the lean season. Within each season, the allocated asset amount is divided across the staple (which has a cash price of p_H and p_L in harvest and lean, respectively) and non-food (which has a price of 1).

To isolate the mechanisms that generate variation within, rather than across, agricultural cycles, we assume for now that there is no harvest risk. Since endowments are identical in each harvest season, the farmer essentially faces a two-period problem because there is never an incentive to carry resources from one agricultural cycle to the next. For simplicity, we assume there is no discounting across consecutive periods.

The farmer solves the following utility maximization problem:

$$\max_{M_H \in [0,e]} V_H(M_H) + V_L(M_L) \tag{1}$$

$$\text{s.t. } M_L = \eta\,(e - M_H) \tag{2}$$

Here, the indirect utility functions $V_H(M_H)$ and $V_L(M_L)$ each represent the maximized utility subject to the budget constraint *within* a period. In any period t, $V_t(M_t)$ is:

$$\max_{m_t \in [0,M_t]} u_{m,t}(m_t) + u_{c,t}(c_t) \tag{3}$$

$$\text{s.t. } c_t = p_t\,(M_t - m_t) \tag{4}$$

The slope of the farmer's inter-seasonal budget constraint (equation (2)) is key to our analysis. Given an allocation in H, the resulting asset level in L depends on η, the marginal rate of transformation (MRT). The inverse of the MRT is the relative cost of lean season consumption–each unit of asset allocated to the lean season requires forgoing $\frac{1}{\eta}$ units in the harvest season.

In practice, η depends on the individual's choice of technology used to transfer assets across seasons–saving in kind, saving cash, or borrowing. If she saves in kind, $\eta = \gamma$, which we define

[16]This setup can also accommodate labor income in both harvest and lean seasons, which is ignored for simplicity.

as the retention rate on stored staples. If she saves in cash, staples are sold in the harvest season and re-purchased in the lean season, so $\eta = \frac{p_H}{p_L}$. If she borrows, $\eta = \frac{1}{r}$, where r is defined as the amount (in staple units) that must be paid in the harvest season for a staple loan in the lean season. In this case, the farmer allocates a part of her harvest towards repaying the loan from the *previous* lean season, rather than towards consumption in the following lean season as under saving. The farmer chooses the technology with the highest MRT, so that $\eta = \max\left\{\gamma, \frac{p_H}{p_L}, \frac{1}{r}\right\}$.

The utility maximization problem yields the following first-order conditions:

$$u'_{m,H}(m_H) = (\eta)\, u'_{m,L}(m_L) = (p_H)\, u'_{c,H}(c_H) = (p_L \eta)\, u'_{c,L}(c_L) \tag{5}$$

In the absence of frictions, $\eta = 1$. This is the "no-seasonality" benchmark. For our target population in West Timor, seasonal frictions imply that the MRT is strictly less than one.

We illustrate the consumption-savings problem due to this low-MRT technology in Figure 1. Since $V_H(M_H)$ and $V_L(M_L)$ must be strictly concave, the problem can be described in two dimensions with a budget constraint and well-behaved indifference curves. The horizontal and vertical axis depict asset allocations (in staple units) to the harvest and lean seasons, respectively. The horizontal intercept depicts the staple endowment, e. Without seasonal frictions, the slope of the budget constraint is -1. If preferences were identical across seasons, the utility-maximizing bundle for the "no-seasonality" benchmark would be at the intersection of the budget constraint and the 45-degree line, M^0.[17]

With seasonal frictions, the budget constraint is flatter and the budget set shrinks. As a consequence, the agent's utility maximizing bundle moves to a point such as M^*.

3.2. Storage and Credit: Overall Effects

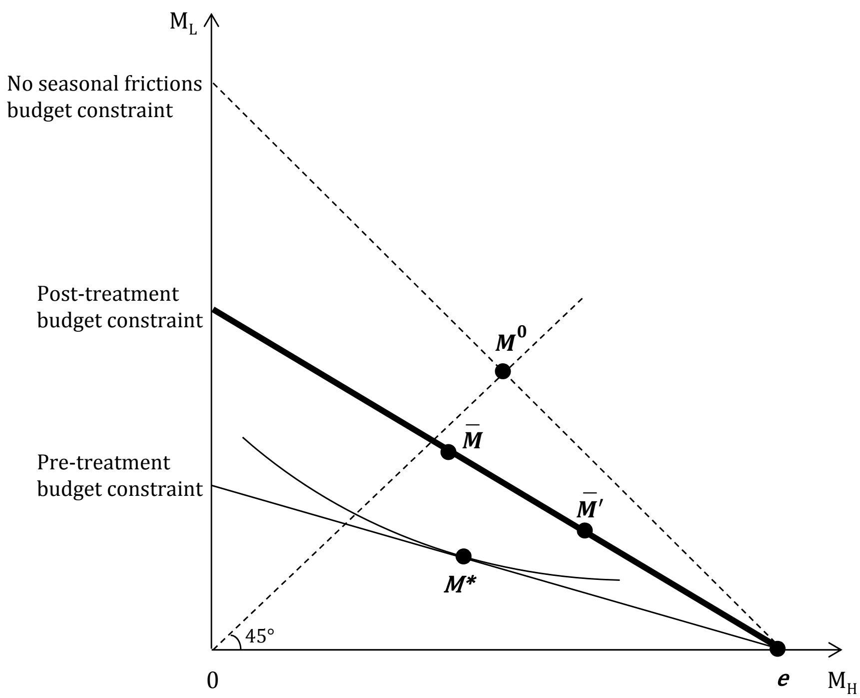
Storage and credit programs differ in their implementation. However, in the abstract, both programs can be interpreted as technological innovations that help farmers more effectively convert staple output in the harvest season to lean season consumption through a higher γ or lower r. By raising the MRT, both programs lower the cost of lean season consumption ($\frac{1}{\eta}$). Treatment effects can be analyzed within this framework of lean season subsidies (illustrated in Figure 1).

First, there are across-season effects. Since lean season consumption becomes relatively cheaper, the slope of the budget line changes, leading to substitution effects that serve to increase lean season consumption (M_L) and decrease harvest season consumption (M_H). In addition, the swivel of the budget line results in an expansion of the budget set, leading to income effects that increase both M_L and M_H. The post-treatment consumption bundles depend on the relative magnitudes of substitution and income effects.

We therefore expect total lean season consumption to weakly rise in response to the programs, whereas total harvest season consumption may rise or fall since income and substitution effects oppose each other. If substitution effects dominate, the farmer moves to a point such as $\bar{M}$ (west of M^*); if income effects dominate, we expect a move to a point such as $\bar{M}'$ (east of M^*). Increases in harvest season consumption point to budget set expansions and unambiguous welfare improvements. However, decreases in harvest season consumption have ambiguous welfare implications. They would be consistent with dominant substitution effects but also with budget set contractions.

[17] This framework also accommodates the possibility that preferences and consumption needs vary across the agricultural cycle, as in Behrman et al. (1997). For expositional simplicity, we do not separately model the cases of consumption for inferior and Giffen foods, as in Jensen and Miller (2008).

Figure 1: Allocation Across Seasons



Notes: The inter-seasonal asset allocation problem. Assets (in staple units) allocated to harvest season consumption are on the x-axis and assets allocated to lean season consumption are on the y-axis. The endowment is e. M^0 indicates the allocation if there are no seasonal frictions and utility functions are identical across seasons. M^* is a hypothetical allocation under seasonal frictions. Possible post-treatment allocations are $\bar{M}$(if substitution effects dominate) and $\bar{M}'$ (if income effects dominate).

Second, the new levels of M_H and M_L result in new allocations of food and non-food consumption *within* each season. How a change in M_t is allocated across m_t and c_t depends on rates of change of marginal utilities ($u'_{m,t}$, $u'_{c,t}$). Under homothetic utility, we expect a rise in both forms of consumption. On the other hand, if individuals are close to food satiation, most changes will be captured by non-food consumption. A quasilinear utility function helps demonstrate this point: the first tranches of income are allocated to food, but additional income gains are directed towards non-food consumption. The predictions are summarized in the table below, where the asterisk serves as a reminder that there could be no effect for staple consumption under quasi-linear utility.

Storage/Credit	**Harvest**	**Lean**
If income effect dominates:		
Non-food consumption (c)	↑	↑
Staple consumption (m)*	↑	↑
If substitution effect dominates:		
Non-food consumption (c)	↓	↑
Staple consumption (m)*	↓	↑

4. Program Design

Given global concerns about food security and the high costs of food programs, we were approached by the World Bank to design and evaluate new solutions in West Timor, a setting with historical food insecurity and predictable seasonal patterns. While both programs have features that are tailored to West Timor, they share similarities with other food programs. See Gelay (2008), Lines (2011) and Zeller (2001) for examples of food storage programs and Khandker and Mahmud (2012) and Mohan et al. (2007) for examples of credit programs for consumption purposes.

The implementation and evaluation of the programs were funded by the Japanese Social Development Fund. The treatments were implemented in September 2008 and lasted 3 years. The programs were implemented by two local NGOs, Yayasan Alfa Omega (YAO) and Yayasan Tanaoba Lais Manekat (TLM), each of which operated independently in two districts. YAO operated in the districts of Kupang and Timor Tengah Utara (TTU) while TLM operated in districts of Timor Tengah Selatan (TTS) and Belu. Maize is the primary crop on the island, but some regions also plant rice, depending on the growing conditions. In TLM districts, a larger proportion of farmers exclusively grow maize than in YAO districts.[18]

Both NGOs were selected because they had experience implementing cash-based savings and microcredit programs in West Timor. Participants were informed that the food storage and food credit programs were part of a three-year pilot, sponsored by the World Bank. Both were introduced as new programs, with no ties to other programs sponsored by the NGOs. All facilitators on the field were newly hired and trained.

The project covered 24 rural villages in each of the four districts, or *kabupaten*s, in West Timor. These villages were selected by the NGOs, who were instructed to choose villages that were far enough from each other to avoid contamination effects.

[18] In our data, 96% of households report some maize production during our sample period. During the first harvest, 62% of farm households in TLM districts reported producing maize only and 10% produced both maize and rice. By contrast, 34% of farm households in YAO districts reported producing maize only and 43% reported producing both maize and rice.

Treatment assignment was conducted by us and stratified by district. Within each district, six villages were randomly assigned to the control group (no treatment), twelve to the storage treatment, and six to the credit treatment. To be eligible for storage or credit programs, the NGOs required participants to be married (or once-married) female farmers.

While the impacts on consumption, for both storage and credit, can be analyzed within the framework of income and substitution effects provided in Section 3, each is distinct in its implementation. Below, we describe in detail the implementation of each program and associated theories of change.

4.1. Storage

4.1.1. Design

The storage treatment was designed to subsidize lean season consumption by raising the retention rate which, as described in Section 2, is constrained by physical depreciation, social pressures, and price variation. The program provided new storage equipment for free. Participants were offered a choice of high capacity drums (180 kg), lower capacity jerrycans (40 kg), and sacks.

In total, there were 2,433 members under YAO and 2,529 members under TLM. Groups of up to 108 women per village were formed through public announcements in the lean season. While training was provided at the group level, grain was stored privately. Participants were trained in drying methods and provided with warnings about aflatoxins which can destroy large quantities if the grain is exposed to moisture. Compared to traditional methods of hanging smoked maize, these technologies discouraged frequent withdrawals (which would expose the dried maize to moisture and air). Drums were the most popular method of storage, and more than 80% of stored staples were maize.[19]

For the first year, we imported storage products from another island. Materials arrived too late to be used in the harvest season of that year. This meant that storage treatments in most areas started in the harvest season of the second year. For the second year, our agricultural specialists managed to locally source sufficiently secure storage materials.

Given these delays and the finiteness of our survey timeline, we were left with a limited window of opportunity to evaluate the effects of storage. This is a potential concern since the potential benefits of storage are realized only after adequate harvests. In the short run, harvest failures leave households with little to store.

[19] We had initially designed two storage treatments: a "pure storage" treatment in which participants were free to withdraw at any time, and a "commitment storage" treatment in which they agreed to a restriction on withdrawals until a self-specified date. Each was assigned to a quarter of the villages. Under commitment storage, individuals were required to sign a contract under which they agreed to a restriction on withdrawals until a self-specified date. The contract allowed for early withdrawals only in the case of explicitly defined and verifiable emergencies. Storage equipment was then sealed. The implementing NGOs were tasked with carrying out random audits to check the seal. If the seal was broken before the contracted date, and if the individual did not have a verifiable emergency, she would be denied future access to the program.

In practice, however, the implementing NGOs did not adhere to this distinction. Under even the pure storage treatment, participants were required to maintain written records specifying anticipated withdrawal dates. While these were not contractually binding, they served to discourage them from making intermediate withdrawals. For these reasons, we do not distinguish between the pure storage and contract storage treatments in our analysis. We repeated the empirical analysis treating pure and contract villages separately. There were no differences between the two treatment groups.

On the other hand, a particular advantage of the storage program is that it might reduce household vulnerability to self-control problems and social pressures (Ashraf et al., 2006). This is because the nature of the technology both discourages frequent withdrawals and reduces visibility of stored assets.

4.1.2. Predicted First-Stage Effects for Storage

Section 3 maps out the overall change in consumption that is predicted through participation in either program. Consumption must be preceded by intermediate choices, which are affected differentially by storage and credit. Here, we extend our model to predict how each program affects the following intermediate outcomes which are potentially observable: stored staple stocks after harvest and at the start of the lean season, and staple sales. We first conduct this exercise for storage.

Figure 2 serves as a guide to farmers' decisions that ultimately result in consumption. The variables that we analyze in our data analysis are indicated in capital letters. Consider choices in the absence of storage and credit programs. The top panel of the figure shows decisions made in the harvest season. Harvested staple must be allocated across harvest and lean seasons. The amount allocated to the harvest season can be consumed in kind (m_H) or as non-food (c_H) for which staples are sold. The portion of harvested staple that is not immediately consumed must be transferred to the lean season. As described in Section 3, this can be done using any of three technologies (in-kind savings, cash savings, in-kind credit). In the lean season, the farmer observes her assets and converts them into consumption.

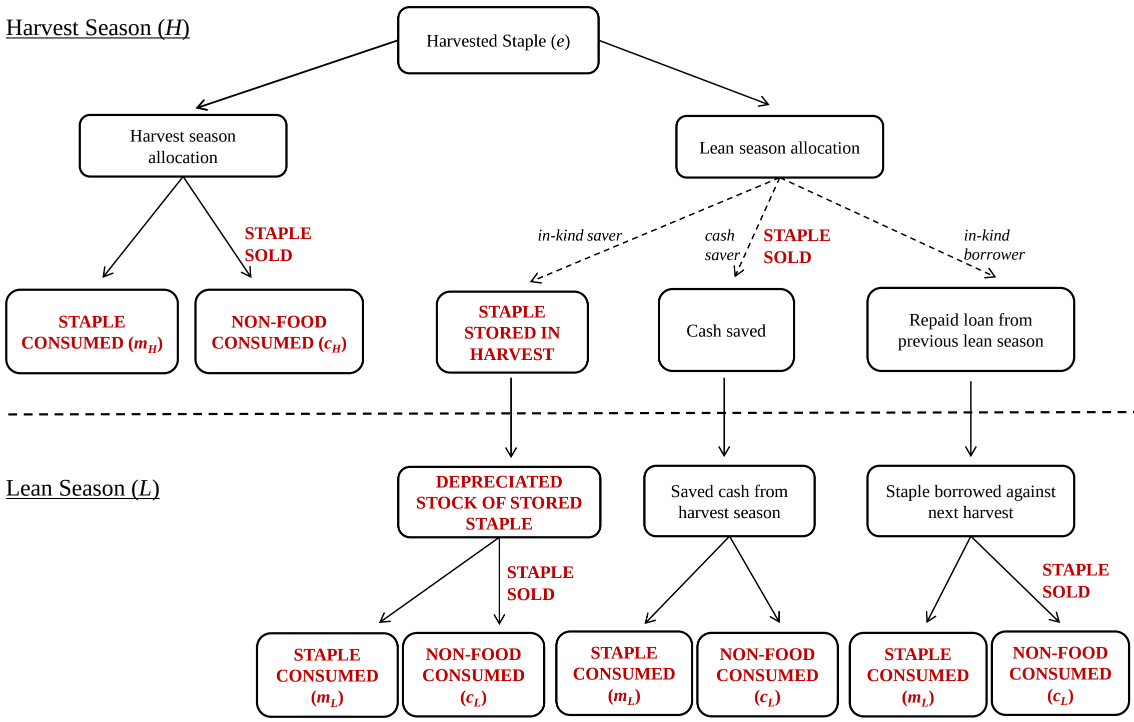
Now, consider the impact of the storage program, which raises the staple retention rate to some $\bar{\gamma}$. Assume households were initially saving in kind or in cash at some $\eta < \bar{\gamma}$ (since credit use was rare). The resulting changes in behavior depend on whether income or substitution effects dominate, and whether households were originally saving in kind or in cash. The following table summarizes the predicted changes in behavior.

Storage	**Harvest**	**Lean**
If income effect dominates:		
Staple sales	$\uparrow$ (in-kind savers), $\downarrow$ (cash savers)	$\uparrow$ (to fund non-food consumption)
Staple stock	$\downarrow$ (in-kind savers), $\uparrow$ (cash savers)	$\uparrow$ (higher retention rate)
If substitution effect dominates:		
Staple sales	$\downarrow$ (more saved in kind)	$\uparrow$ (to fund non-food consumption)
Staple stock	$\uparrow$ (less consumed)	$\uparrow$ (more stored, higher retention rate)

The impacts on consumption are as described in Section 3.2. The table above allows us to make some additional observations relevant to the data analysis. First, lean season predictions are straightforward. Stocks should unambiguously expand, regardless of the initial technology. Lean season staple sales should also rise to fund the increase in non-food consumption that results from an expanded lean season budget.

Second, harvest season predictions are ambiguous if income effects dominate–in this case, harvest season consumption increases. The changes on intermediate outcomes depend on the initial technology used. Stored stocks could fall or rise: those who were initially saving in kind will store less to fund greater consumption in the harvest season, but those who were initially saving in cash

Figure 2: From Endowment to Consumption through Intermediate Choices



Notes: This figure shows how a harvest endowment is converted into harvest and lean season consumption. Lean season consumption depends on how the individual chooses to transfer assets across seasons–by saving in kind, saving in cash, or through lean season credit.

will switch to saving in kind and therefore store more. Second, staple sales could fall or rise. More will be sold to fund greater non-food consumption. But for those who initially saved in cash, this effect will be drowned out by the fact that they no longer sell staples for the purpose of savings.

Third, the lower the farmer's initial MRT (η), the greater will be the difference between the new MRT ($\bar{\gamma}$) and η, resulting in a larger budget set expansion and stronger effects of the storage program. In particular, all else equal, we expect benefits to be weakly larger for households with a lower baseline staple retention rate, γ.

4.2. Credit

4.2.1. Design

As the storage program aimed to subsidize lean season consumption by loosening the savings constraint, the food credit program aimed to loosen the credit constraint. It was designed as a staple-based microcredit program, with repayment schedules that target local seasonal patterns. The program was similar to the cash-based women's microcredit program created under the Kecamatan Development Project (see Olken (2007) for more details), except that we offered staple food rather than cash loans and focused on financing lean season staple consumption instead of income-generating activities.

In September 2008, the NGOs introduced the program at churches and through local leaders' networks. Credit groups of up to 108 eligible women were formed in each treated village. Groups then elected their internal leaders and administrators. In total, there were 1229 and 1374 credit participants in YAO and TLM villages, respectively.

Disbursement and repayment were timed to match seasonal patterns. During each lean season (typically between December and January), participants filled out forms to request loans. The loans were to be repaid in kind, with interest, after the following harvest (typically between April and June). The credit groups held meetings to determine a common date for the disbursement of food. The repayment date was determined by the anticipated timing of the participant's harvest. In practice, most loan terms were approximately 6 months.

The seed capital for the credit program was gifted to the groups. This was used to facilitate grain procurement and storage equipment. Group members voted to borrow either rice or maize. Grain to be used for credit was then sourced from nearby districts by the NGOs and the group leaders. In our data, 45% of all loans issued were rice and 55% were maize.

Facilitators collected data on plot size and previous harvests to determine loan capacity, which ranged from 50 kg to 250 kg per member. This externally imposed loan ceiling ensured that participants could not borrow unlimited amounts for the purposes of arbitrage. For maize, the mean loan was 85 kg and the median was 50 kg. For rice, the mean loan was 95 kg and the median was 100 kg.

Loans accumulated simple interest at the rate of 1.5% per month (measured by weight) with a loan fee of 1.5%. In general, households paid an accumulated 10.5% interest in the harvest season.[20] This suggests an improved MRT, given existing estimates of retention rates under traditional storage. While training and monthly meetings happened at the group level, lending and liability were individual. The punishment for default was permanent expulsion from the groups. Exceptions were made for natural catastrophes and harvest failures. In these cases, households were permitted to roll over debt to the following agricultural cycle.

Repaid grain was stored in drums and sacks until the next round of disbursement. While the program grant was used as seed money to provide the first round of loans, repaid food was expected to sustain future loans. Since the credit program also took advantage of superior storage technologies, relatively low interest rates were sustainable. Furthermore, the credit contract provided implicit insurance in several ways. First, by allowing households to roll over debt, it protected borrowers from harvest risk. Second, by lending at a fixed interest rate, it protected borrowers from the storage risk they would face if storing on their own, as discussed further below.

Naturally, the viability of the credit program depended on repayment rates. Our initial concerns about repayment stemmed from two factors. First, loans were for consumption rather than income generation. Second, repayment was lump-sum and scheduled for several months after disbursement, unlike under typical microcredit programs. However, repayment rates were 100% except in instances of harvest failure, when debt was deferred to the following harvest. In the first and third years, TLM villages faced major harvest failures (repayment rates in these harvest periods were initially 60% and 4%). In the second year, some YAO villages faced harvest failures (repayment rates were initially 80%). For harvest failures in the first two years, full repayment was received within one year of default. We do not have data on repayment following harvest failures in the

[20]The terms were based on standard contracts under SPP (the women's microcredit program under KDP) and other microcredit programs (including those offered by TLM and YAO).

third year as the formal program had ended by that time. The high repayment rates suggest that such a program can be self-sustaining.

4.2.2. Predicted First-Stage Effects for Credit

With credit, the agent has the option to borrow maize in the lean season at some interest rate r'. If, as we assume, r' is sufficiently low, the farmer will fund lean season consumption by borrowing against the next harvest rather than saving from the previous one (as shown in Figure 2).

Now, any amount not consumed in the harvest season is used to repay the loan from the previous lean season. In the following lean season, another cycle of borrowing begins: the household funds consumption using credit against the next harvest. The table below summarizes the changes.

Credit	**Harvest**	**Lean**
If income effect dominates:		
Staple sales	$\uparrow$ (in-kind savers), $\downarrow$ (cash savers)	$\uparrow$ (to fund non-food consumption)
Staple stock	$\downarrow$ (no more storing)	$\downarrow$ (no more storing)
If substitution effect dominates:		
Staple sales	$\downarrow$ (less non-staple consumption)	$\uparrow$ (to fund non-food consumption)
Staple stock	$\downarrow$ (no more storing)	$\downarrow$ (no more storing)

Staple stocks drop in both seasons since the program does not require households to save on their own. Suppose income effects dominate. There should be greater staple sales in the lean season, and predictions on sales in the harvest season are ambiguous. For households that originally saved in-kind, staple sales for consumption rise, with continued zero sales for savings. For households that originally saved in cash, staple sales for consumption rise while staple sales for savings drop (since instead of saving in cash they now repay in kind).

4.3. Comparing Storage and Credit

Since the problem of seasonality is repetitive, storage and credit can to some extent be viewed as substitutes.[21] Each program raises the rate at which assets can be transferred from the harvest season to the lean season, whether these transfers occur from a harvest season to the subsequent lean season (storage) or to the *previous* lean season (credit). However, beyond this abstract similarity, the two programs operate through distinct mechanisms.

The above observable changes in behavior were directly based on the simplified model provided in Section 3. They show how storage and credit programs make different predictions on intermediate outcomes. In the lean season, we predict a rise in staple stocks under the storage program and a drop under the credit program. If income effects dominate, under storage the changes in both harvest stocks and harvest sales are ambiguous. Under credit, the changes in harvest sales remain ambiguous, but harvest stocks are predicted to drop. Next, we highlight some additional implications and differences between the storage and credit programs.

[21] See Afzal et al. (2014) for a similar argument in a setting with lump-sum expenditure needs, which can be funded through both credit and savings.

4.3.1. Risk

Risk can matter differently for credit and storage. We argue that credit is better than storage at dampening the fluctuations associated with risky outcomes. This happens through the programs' interaction with both harvest risk and storage risk.

First, the benefits of storage depend on the realized harvest. Under harvest failure, if there is nothing to store, there is nothing to be gained from improved storage. Credit, on the other hand, provides implicit insurance through limited liability. Furthermore, the group lending aspect of credit encourages risk sharing across members.

Second, under storage, households face a risk even conditional on harvest since the technologies are not foolproof. For example, under certain conditions, stored maize could be damaged by aflatoxins. While the storage treatment is expected to raise the MRT, the actual rise in MRT is uncertain. This can limit the ability of households to precisely close seasonal gaps through storage. Under credit, this risk is absorbed by the program since the interest rate is fixed and is independent of storage risk. In effect, credit offers households a fixed MRT while storage does not. Therefore, when comparing consumption between any two consecutive harvest and lean seasons, we expect seasonal gaps to be lower under credit than under storage.

4.3.2. Social and Behavioral Factors

Recent literature in behavioral economics examines how savings and credit decisions are influenced by one's preferences (which might be time-inconsistent) and social relations (which result in pressures to share, on the one hand, and provide discipline, on the other). These considerations play out differently in our storage and credit programs.

Storage provides informal commitment of two kinds. First, the technology and treatment design discourage frequent withdrawals (Ashraf et al., 2006). Second, households have an opportunity to reduce the visibility of their assets, and thus potentially protect themselves from social taxes (Baland et al., 2011).

Under credit, there is a concern about over-borrowing if individuals are time-inconsistent (Basu, 2014). Time-inconsistent preferences imply a desire to consume more in the present than is optimal under some reasonable notions of long-run welfare. By offering consumption with delayed payments, credit could help individuals indulge their taste for instant gratification, resulting in high debt burdens in the harvest season.

To some extent, this might be prevented by institutional limits to loan size. While a determination of the optimal loan size is beyond the scope of this paper, we provide some evidence from the annual Indonesian *Susenas* household survey to suggest that our program loan limits leave room for over-borrowing. We find that the maximum loan of 250 kg provides more than 4 months of the average staple consumption for farm households in West Timor.[22] It is therefore possible that the program would enable households with self-control problems to consume more in the lean season than would be in their long-run interest.

[22] According to the Susenas household survey in 2008, the average farm household in West Timor consumes 1400 calories per day from staples. To provide this, households require about 0.39 kg of rice or maize per day (1 kg of rice and maize provide roughly 3600 calories). For a lean season period lasting 3 months (Dec-Feb), a household of 5 would need 176 kg (0.39 kg *90 days*5 members). For 4 months (Nov-Feb), the equivalent number is 234 kg.

5. Data

Enumerators visited 2,877 agricultural households twice each year for three years, once during the lean season and once during the harvest season.We had two main surveys–a household survey (the main survey) and a short individual survey. The surveys were administered by the agricultural institute of a local university, *Lembaga Penelitian Undana.* We had to drop 7 households because we could not merge information from the two sets of surveys. There was no attrition. Therefore, our final sample comprises 2,870 households (713 from control villages, 720 from credit villages and 1,437 from storage villages) and 17,220 observations (at the household-season level).

Figure 3: Timeline of Surveys and Treatment by Year and Month

		Survey	Credit	Storage
		(1)	(2)	(3)
YEAR 1	Sep '08	Round 1		
	Oct '08			
	Nov '08			
	Dec '08		Disbursement	
	Jan '09			
	Feb '09			
	Mar '09			
	Apr '09		Repayment	
	May '09			
	Jun '09			
	Jul '09	Round 2		Distribute equipment
	Aug '09			
YEAR 2	Sep '09			
	Oct '09			
	Nov '09	Round 3		
	Dec '09		Disbursement	
	Jan'10			
	Feb '10			
	Mar '10			
	Apr '10		Repayment	
	May '10			
	Jun '10			
	Jul '10	Round 4		
	Aug '10			Distribute equipment
YEAR 3	Sep '10			
	Oct '10			
	Nov '10	Round 5		
	Dec '10		Disbursement	
	Jan'11			
	Feb '11			
	Mar '11			
	Apr '11	Round 6		
	May '11			

Notes: Months that are in italics (bold) correspond to the lean (harvest) season.

Figure 3 describes the timing of the surveys in relation to harvest seasons (April to June) and lean seasons (November to January). There were six survey rounds. Odd-numbered rounds correspond to lean season surveys and even-numbered rounds correspond to harvest season surveys.

Column 1 shows that the first round was conducted between September and November 2008, just before the start of the lean season. Because many of the villages were extremely remote, each survey round took two to three months to complete. Due to budget delays, the first two harvest season surveys (rounds 2 and 4) were delayed by three months and began in July.

The following columns in Figure 3 show how the timing of the surveys coincided with the treatments. For credit, food disbursements occurred between the months of December and January (the peak of the lean season) and repayments were around harvest months (April to June). Comparing columns 1 and 2, we can see that credit has five rounds of post-treatment surveys (rounds 2 to 6) and one pre-treatment round that was conducted in the lean season. We do not have a pre-treatment harvest season survey for credit.

For storage, the final column shows that equipment only arrived between July and August of 2009 (coinciding with round 2, in column 1). Since this was already several months after the first harvest, little was stored until the subsequent harvest season (round 4). Therefore, we define rounds 4 to 6 as post treatment rounds for storage. We have one pre-treatment harvest survey and two pre-treatment lean surveys.

Key outcomes

We constructed the following measures to test whether our treatments improved well-being by raising consumption and health or reducing seasonal fluctuations. We first construct measures to test for consumption effects discussed in Section 3.2, including *log(Staple consumed, kCal)*,[23] *log(Non-food expenditure)*, *log(Reported income)* and an indicator that is one if the household reported lacking food in the previous month. All continuous consumption measures are scaled to per capita per month units. *Reported income* is the amount households report as their income (from harvest sales, wages, remittances and gifts). We explain how these variables are constructed and related data issues (such as outliers and missing values) in Table A1 in the appendix.

We also included self-reported measures related to health. We have three variables–an indicator variable of whether the household was unable to afford health expenditures in the past month, the number of household members who reported any sickness in the past three months, and the total number of sick days reported (totaled over all members who reported they were sick in the past three months). The last two health outcomes are scaled to per capita per month units.

Next, we measure seasonal fluctuations using the absolute difference between consumption in the harvest and lean seasons within each agricultural cycle.[24] Reductions in seasonal gaps can be interpreted as a welfare improvement, under the assumption of identical, separable, and concave utility functions for both seasons. We provide more details in the appendix where we also report results using other measures of consumption variability.

To address concerns associated with having many outcomes, we follow Kling et al. (2007) and use mean effects analysis. We discuss mean effects analysis in the appendix.

One limitation of our data is that our food intake information is incomplete. We have consumption measures for primary staples and other major food items (cassava, fruits and beans). Rice and

[23] Staple consumption is calculated as rice consumed plus maize consumed (both in calories), as these are the two main staples.

[24] For example, the seasonal gap in *log(Staple consumed)* is measured as the absolute difference between rounds 2 and 3 and the absolute difference between rounds 4 and 5. For seasonal differences, we use differences in the *monthly* non-food expenditure items only. See Table A1 in the appendix.

maize represent more than 60% of the average per capita per day calories for farmers in rural West Timor, based on our calculations using the 2008 annual *Susenas* household survey. Other studies have also found that about 60% to 70% of calories in the typical poor person's diet comes from the primary staple in the region (see, for example, Jensen and Miller (2011)). For budgetary reasons, we did not collect data on other foods such as meat and seafood. As a result, we are unable to build a truly comprehensive measure of food consumption. If households substituted towards consuming non-staples not measured by us, our analysis will miss this margin of adjustment.

Another limitation lies in the measurement of staple inventory. Since the traditional storage method involves hanging smoked maize in the attic, it was hard to measure the weight of the maize inventory, especially in the control villages. Also, the timing of measurement was crucial. As discussed in Section 4, we would ideally measure whether the storage treatment expanded the stock of inventory at the beginning of the lean season, before any sales or consumption of the staple stock. In practice, we often surveyed the villages closer to the peak of the lean seasons (late November to January), when most households would have already sold or consumed some of their staple stock.

Balance checks

Table 2 reports results from tests of whether treatment and control villages are balanced, using the first survey round. Column 1 of Table 2 reports the means of the control group in the baseline (round 1, lean season). The average amount of calories consumed per capita per month is 40.88 kCals. The average absolute difference in staples consumed across seasons is 24.52 kCals. On average, 6.7% of households report some savings in a bank, 11.8% of households report having some debt, the maize inventory is 29% of the maize produced and the rice inventory is 24% of the rice produced.

Columns 3 to 5 report results from OLS regressions comparing storage to control villages, controlling for district fixed effects and clustering standard errors at the village level. We report p-values for tests of the coefficient on the treatment indicator being zero. Columns 6 to 8 report results for credit versus control villages. The full estimation samples include 2,150 households for storage and 1,433 households for credit. The outcomes are organized into five panels: Panel A includes consumption and income, Panel B includes health outcomes, Panel C examines agricultural production and storage behavior and Panel D reports baseline household characteristics and Panel E reports baseline seasonal differences.

For storage, one outcome out of 23 tests has a p-value below 5%. In Panel D, *Number of motorcycles owned* has a mean difference of 0.051 and a p-value of 0.8% (compared to the control group mean of 0.067). However, a difference of 0.051 motorcycles seems small and economically insubstantial. For credit, Table 2 shows no p-values below 5%.

6. Estimation

We use an Intent-to-Treat (ITT) specification that compares treatment and control villages:

$$y_{ivd} = \alpha + \beta TREAT_{vd} + \theta_d + \varepsilon_{ivd} \tag{6}$$

where y_{ivd} is the outcome for household i, in village v in district d, $TREAT_{vd}$ is the treatment assignment indicator and θ_d represents district fixed effects (treatment assignment was stratified by districts). We estimate the regressions separately for credit and for storage and pool all post treatment survey rounds. Standard errors are clustered at the village level. The take-up rate for credit was 40% and the take-up rate for storage was 42%.

The key parameter of interest, β, represents the average treatment effect of being in a village that was assigned either credit or storage (compared to no treatment). We expect an improvement in well-being to be associated with increases in consumption levels and improvements in health and decreases in seasonal differences. As discussed in Section 3.2, for consumption in the harvest season, we expect $\beta > 0$ if the income effect dominates and $\beta < 0$ if the substitution effect dominates. For consumption in the lean season, we expect $\beta > 0$.

Unfortunately, due to a mis-communication, TLM assigned the wrong treatment for six villages.[25] To address this, we report our main results using only the initial intended assignment. We believe the non-compliance is orthogonal to unobserved village characteristics. The assignment was performed by the authors who were based in the United States at the time of assignment. The treatment assignment was sent via email but one NGO mistakenly used the treatment assignment from an older email.

We also report heterogeneous treatment effect estimates by NGO districts. Since assignment was stratified by districts ex ante and both NGOs were operating independently, these results remain internally valid. These regional patterns are worth examining for the following reasons. First, harvest risks are related to regional rainfall patterns, resulting in widespread harvest failures that can encompass entire districts. In the first two harvests, close to a fifth of maize farmers reported zero maize production.[26] In the final harvest, a prolonged rainy season linked to La Nina in 2010-2011 resulted in widespread harvest failures, with 70% of maize farmers reporting zero maize production.

Second, TLM districts were more suitable for maize so that most farmers only planted maize (the riskier crop) while YAO districts had regions that were suitable for both maize and rice. Therefore, TLM districts experienced more harvest failures and the lack of crop diversification also meant that harvest failures were more costly. In the first harvest season, for example, maize farmers in TLM districts reported a 7 p.p. higher incidence of harvest failures, which is close to a third of the sample mean (22%). Relatedly, take-up rates tended to be lower in TLM than in YAO. For storage (credit), take-up was 35% (32%) for TLM compared to 49% (47%) for YAO. The greater salience of harvest risks in TLM districts could explain the lower take-up. Farmers may not participate in credit because they are worried about their ability to repay, and farmers who experienced harvest failures have nothing to store. This is less important for YAO districts because more farmers also produce and store rice. In the data collected by the NGOs, only 2% of households under TLM report storing any rice compared to 48% of households for YAO.

Finally, the mis-assignment problem was unique to TLM districts. We do not think the mis-assignment introduced systematic biases that can explain our results. In fact, we find stronger effects for YAO districts which suggests that our results are not driven by mis-assignment problems. However, the mis-assignment problem remains significant for TLM districts (6 out of 48 villages in TLM districts were mis-assigned) which could introduce more noise.

[25] Two villages assigned credit were implemented as storage villages, two villages assigned storage were implemented as credit and storage and credit were each implemented in a control village.

[26] Here, we define maize farmers as any farmer who produced some maize during our study period, which covers 96% of households. Since maize is the primary staple and primary crop in West Timor, our assumption is that farmers plant maize every cycle, so that reports of zero maize production are most likely harvest failures.

Table 2: Baseline Summary Statistics and Balance Check

	Control		Storage-Control			Credit-Control		
	Mean	SD	Coeff.	p-value	N	Coeff.	p-value	N
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Consumption and Income								
Staple consumed in kCal	40.880	25.576	-0.064	0.245	2147	-0.063	0.261	1427
Non-food expenditure	34.242	27.808	0.068	0.299	2145	0.073	0.311	1431
Reported income	76.174	90.806	0.205	0.488	1970	0.270	0.377	1296
1(Lacked food last month)	0.590	0.492	-0.027	0.598	2150	0.053	0.339	1433
Panel B: Health								
1(Health expenditure shortages last month)	0.158	0.365	0.008	0.771	2150	0.005	0.856	1433
Number of sick days	0.180	0.557	0.059	0.115	2150	0.022	0.550	1433
Number of sick household members	0.024	0.050	0.004	0.331	2150	0.0004	0.925	1433
Panel C: Agricultural Yields and Storage								
Amount of maize produced in kg	145.137	179.054	7.662	0.717	2150	-5.080	0.826	1433
Amount of maize stored in kg	35.045	45.998	-4.542	0.384	2150	-9.709*	0.069	1433
Amount of rice produced in kg	132.165	282.393	-11.229	0.729	2150	-11.219	0.789	1433
Amount of rice stored in kg	27.408	61.887	-3.218	0.578	2150	3.987	0.666	1433
Ratio of maize stored	0.287	0.481	-0.017	0.596	1722	-0.057*	0.057	1145
Ratio of rice stored	0.236	0.416	-0.034	0.399	748	-0.031	0.419	519
Panel D: Household Characteristics								
1(Graduated primary school)	0.780	0.415	0.00001	1.000	2150	-0.007	0.826	1433
1(Graduated lower secondary school)	0.241	0.428	0.042	0.181	2150	0.0004	0.990	1433
Age	44.800	12.564	0.445	0.591	2106	0.028	0.977	1403
Number of chickens owned	3.116	3.584	-0.123	0.653	2150	-0.316	0.240	1433
Number of cows owned	0.470	0.988	-0.046	0.521	2150	0.077	0.379	1433
Number of pigs owned	1.269	1.218	-0.178*	0.059	2150	-0.005	0.969	1433
Number of motorcycles owned	0.067	0.251	0.051***	0.008	2150	0.019	0.259	1433
Household size	4.832	1.830	-0.143	0.314	2150	-0.030	0.854	1433
1(Has savings in a bank)	0.067	0.251	-0.007	0.612	2150	0.003	0.810	1433
1(Has debt)	0.118	0.323	0.005	0.851	2150	0.014	0.567	1433
Panel E: Seasonal Differences, |Harvest - Lean|								
Staple consumed in kCal	24.520	33.102						
Monthly nonfood expenditure	10.406	13.709						
Reported income	80.726	108.684						
1(Lacked food last month)	0.498	0.500						

* p<0.1, ** p<0.05, *** p<0.01

Notes: Columns 1 and 2 report means and standard deviations for control villages in the baseline. Columns 3 to 5 report results from an OLS regression comparing households in storage and control villages in the baseline, controlling for district fixed effects and clustering standard errors at the village level. Columns 3 and 4 report the coefficient and p-value corresponding to the storage dummy and column 5 reports the sample size for each regression. The full estimation sample for the storage versus control comparison includes 2150 households. Some dependent variables have missing values. Columns 6 to 8 report results comparing credit and control villages. The full estimation sample for the credit versus control comparison has 1433 households. In Panel A, we report means and standard deviations of consumption and income in levels (columns 1 and 2) but the regressions reported in columns 3 to 8 are in logs. All expenditure and income values are in thousands of Rupiahs (1 USD=9000 Rupiahs). All continuous outcomes in Panels A, B and E are in per capita per month units.

7. Results

We present the main results for the storage treatment in Section 7.1 and the results for the credit treatment in Section 7.2. We describe mechanisms in 7.3, provide cost benefit calculations in 7.4 and discuss implications for future work in Section 7.5.

7.1. Main Results for Storage

Table 3 reports results for consumption and reported income. Columns 1-3 report ITT estimates for the storage treatment compared to the control group. Each pair of cells in this table reports the ITT estimate of β in equation 6 and its standard error. We report results using all post treatment seasons (column 1), lean seasons only (column 2) and harvest seasons only (column 3). Column 4, labeled N(All), reports sample sizes for regressions in column 1. Panel A reports results for all districts. Panels B and C report results for YAO and TLM districts, respectively.

We find a statistically significant increase in the *Consumption and Income Index* by 0.097 (s.e. 0.042) units for storage for all seasons (Panel A, column 1). The treatment effects are similar for both lean (0.101, s.e. 0.054) and harvest seasons (0.095, s.e. 0.042). As discussed in Section 3.2, these increases, particularly in the harvest season, are consistent with dominant income effects due to budget set expansions. The improvements are driven by a 13.4% (s.e. 7.7%) and a 14.2% (s.e. 5.3%) increase in non-food expenditure in the lean and harvest seasons, respectively as well as a 7.4 percentage point (s.e. 4.2. p.p.) decrease in the likelihood of food shortages in the lean season. The most responsive expenditure items seem to be discretionary personal consumption items. By comparison, Bryan et al. (2014) report ITT estimates implying that an US$8.50 migration subsidy in Bangladesh to encourage seasonal migration increased monthly per capita non-food consumption by 10.1% to 12.7%.

We estimate null effects on staple food consumption. The effects on consumption of staple calories are 0.6% (s.e. 2.9%), with a 95 percent confidence interval of -5.1% to 6.3%. In caloric levels scaled to per capita per day units, the 95 percent confidence intervals are -18 calories to 23 calories, compared to the minimum daily recommendation of 2100 calories (commonly used to construct poverty estimates). Jensen and Miller (2011) study the impact of staple price subsidies in China and find no evidence that subsidies improved nutrition, including calories consumed. They estimate 95 percent confidence intervals of a similar magnitude, -31 to 22 calories per person per day, for a ten percentage point increase in the subsidy of staple prices.[27] Bryan et al. (2014) estimate calorie consumption effects of 4.5% to 5.1% and 95 percent confidence intervals of 82 to 178 calories per capita per day.[28]

Given that the policy reduced the relative cost of lean season staple consumption, substitution effects should increase staple consumption in the lean season. However, we do not detect this increase. Moreover, transaction costs (which are likely to be significant for rural households)

[27] This was calculated using the -0.027 (s.e. 0.076) price elasticity estimate reported in Panel A in Table 4 for Jensen and Miller (2011). To calculate the impact on caloric levels, we use the average calories consumed per capita per day for the control group (1752 calories reported in Table 2). Therefore, the confidence intervals in calories per person per day (for a 10 percentage point increase in the price subsidy) are calculated as $-\frac{0.027}{100} * 10 * 1752\,calories \pm 1.96 * \frac{0.076}{100} * 10 * 1752\,calories$. A ten percentage point price subsidy is roughly 0.11 RMB (US\$0.01, 1RMB=\$0.13), using the average price in the two provinces in China, 1.1 RMB per 500 g of staple (see p1207 in Jensen and Miller (2011)). Each household received one month's supply of vouchers for 750 g per person per day.

[28] Both Jensen and Miller (2011) and Bryan et al. (2014)) include staple and non-staple calories.

Table 3: Impact of Storage and Credit on Consumption

Treatment:	Storage				Credit			
Season:	All	Lean	Harvest	N(All)	All	Lean	Harvest	N(All)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: All Districts								
Consumption and Income Index	0.097**	0.101*	0.095**	5907	0.061	0.020	0.087*	6565
	(0.042)	(0.054)	(0.042)		(0.042)	(0.047)	(0.049)	
Log(Staple consumed in kCal)	0.006	-0.015	0.017	6009	0.024	-0.028	0.058	6741
	(0.029)	(0.045)	(0.030)		(0.036)	(0.043)	(0.044)	
Log(Non-food expenditure, in 1000 Rp)	0.139**	0.134*	0.142***	6042	0.049	-0.006	0.084	6791
	(0.054)	(0.077)	(0.053)		(0.050)	(0.060)	(0.056)	
Log(Reported income)	0.221	0.187	0.239	5943	0.221**	0.152	0.268*	6615
	(0.144)	(0.115)	(0.194)		(0.103)	(0.101)	(0.142)	
1(Lacked food last month)	-0.033	-0.074*	-0.013	6450	-0.016	-0.031	-0.005	7165
	(0.026)	(0.042)	(0.026)		(0.027)	(0.030)	(0.034)	
Panel B: Alfa Omega Districts								
Consumption and Income Index	0.115**	0.128	0.109***	3001	0.093**	0.035	0.131**	3311
	(0.045)	(0.081)	(0.037)		(0.044)	(0.054)	(0.052)	
Log(Staple consumed in kCal)	0.022	-0.013	0.039	3056	0.028	-0.022	0.060	3383
	(0.034)	(0.057)	(0.033)		(0.038)	(0.044)	(0.048)	
Log(Non-food expenditure, in 1000 Rp)	0.141**	0.153	0.136**	3063	0.063	-0.002	0.105	3391
	(0.067)	(0.115)	(0.060)		(0.063)	(0.079)	(0.074)	
Log(Reported income)	0.106	0.145	0.086	3010	0.190**	0.142	0.221**	3316
	(0.105)	(0.162)	(0.104)		(0.079)	(0.122)	(0.079)	
1(Lacked food last month)	-0.070*	-0.105	-0.052	3210	-0.062	-0.048	-0.072	3565
	(0.037)	(0.065)	(0.034)		(0.038)	(0.041)	(0.047)	
Panel C: TLM Districts								
Consumption and Income Index	0.079	0.074	0.082	2906	0.028	0.005	0.042	3254
	(0.071)	(0.073)	(0.076)		(0.073)	(0.079)	(0.083)	
Log(Staple consumed in kCal)	-0.010	-0.016	-0.006	2953	0.021	-0.034	0.057	3358
	(0.047)	(0.070)	(0.049)		(0.061)	(0.074)	(0.076)	
Log(Non-food expenditure, in 1000 Rp)	0.136	0.115	0.147	2979	0.035	-0.010	0.064	3400
	(0.086)	(0.103)	(0.087)		(0.080)	(0.093)	(0.086)	
Log(Reported income)	0.336	0.228	0.392	2933	0.252	0.162	0.316	3299
	(0.268)	(0.166)	(0.375)		(0.192)	(0.164)	(0.277)	
1(Lacked food last month)	0.003	-0.043	0.026	3240	0.031	-0.015	0.061	3600
	(0.034)	(0.053)	(0.039)		(0.038)	(0.044)	(0.044)	

* p<0.1, ** p<0.05, *** p<0.01

Notes: Results for consumption and income levels. Column 1 reports the results from OLS regressions where the main regressor is the storage dummy, with district fixed effects and standard errors clustered at the village level. Column 1 pools all seasons, column 2 only includes lean season surveys and column 3 only includes harvest season surveys. Each pair of cells reports the coefficient estimate and standard error for the treatment dummy. The full estimation sample has 6450 observations, including households in storage and control villages from rounds 4 to 6 but the number of observations change for outcomes in logs (more details are in the appendix), the sample sizes pooling all seasons are reported in column 4. Columns 5 to 8 report results for credit versus control villages. The full estimation sample has 7165 observations, including households in credit and control villages from rounds 2 to 6. All consumption and income values are in thousands of Rupiahs (1 USD=9000 Rupiahs), scaled to per capita per month units. Panel A includes all districts. Panels B and C include Alfa Omega and TLM districts respectively. The index is defined so that an increase represents more consumption (the indicator for lacking food enters negatively).

should bias us towards finding effects on staple consumption (relative to other goods), since the storage treatment focuses on in-kind staples directly, instead of providing vouchers or cash. This makes the null effects on staples noteworthy. We cannot rule out increases in other food items due to data limitations. However, we did collect data on a few other food items (fruits, beans and cassava) and do not detect any changes on their consumption patterns.

The null treatment effects along the staple food margin are consistent with the marginal utility of staples diminishing more rapidly than marginal utilities of other forms of consumption. In our model, the generalized utility function is agnostic on this, but more specific functional form assumptions (such as quasilinear utility, a reasonable conjecture in this setting) could explain this pattern.

Panels B and C report heterogeneous treatment effect estimates by region for YAO districts (Panel B) and TLM districts (Panel C). Results are weaker in TLM districts, possibly due to the greater exposure to maize as the primary crop, the lower take-up rate and mis-assignment by TLM (as discussed above).

Table 4 shows null health effects for storage (-0.00008, s.e. 0.031) with a 95 percent confidence interval from -0.61 to 0.61 standardized units. Table 5 reports effects on seasonal differences. Columns 1 to 3 report ITT estimates for all districts, YAO districts and TLM districts, respectively. Panel A shows that storage has statistically insignificant effects on the *Seasonal Gap Index* (-0.031, s.e. 0.036). This is consistent with our discussion about how risk smoothing may take time for storage as the program lacks direct risk protection features, households need time to accumulate a buffer stock which is further complicated by the delay in the delivery of the storage equipment. Table 6 reports IV estimates, which are around twice as large as ITT estimates (the take-up rate is 42%). Tables A3 and A4 report IV estimates by NGO districts.

7.2. Main Results for Credit

Column 5 of Table 3 shows that the credit program increases the *Consumption and Income Index* by 0.087 (s.e. 0.049) units in the harvest season. This is driven by increases in reported income (26.8%, s.e. 14.2%). As we do not observe decreases in consumption, the higher reported income is consistent with increases in the consumption of other goods not measured by us (this could include other food items, such as meat, other non-food consumption, or savings). Again, we estimate null effects on staple food consumption (2.4%, s.e. 3.6%) with a 95 percent confidence interval of -4.6% to 9.5% (or -95 to 196 calories per capita per day). Panels B and C show that there are stronger effects for YAO districts than for TLM districts, possibly due to more instances of low repayment rates in TLM (as discussed in Section 4), the lower take-up rate and mis-assignment by TLM.

Column 5 of Table 4 shows that credit had a statistically insignificant effect on the *Health Index* when we pool both seasons. The *Health Index* is 0.075 (s.e. 0.059) units higher in the lean season (though this is not significant), but is lower by 0.130 units (s.e. 0.045) in the harvest season. This is driven by a 4.2 p.p. (s.e. 1.4 p.p.) greater likelihood of households reporting a difficulty to meet health expenditure payments, 0.073 (s.e. 0.042) more sick days per capita per month and 0.007 (s.e. 0.003) more household members who reported any sickness in a month. While the deterioration in health in the harvest season is a concern, it is reassuring that the magnitudes are not large and that the overall health effects (combining all seasons) are insignificant.

Table 5 shows that the credit treatment had relatively stronger effects on seasonality outcomes, compared to storage. As discussed in Section 4, credit provides households with better tools to

Table 4: Impact of Storage and Credit on Health

Treatment:	Storage				Credit			
Season:	All	Lean	Harvest	N(All)	All	Lean	Harvest	N(All)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: All Districts								
Health Index	-0.00008	0.056	-0.028	6450	-0.048	0.075	-0.130***	7165
	(0.031)	(0.036)	(0.038)		(0.041)	(0.059)	(0.045)	
1(Health expenditure shortages last month)	0.002	-0.022	0.014	6450	0.023*	-0.006	0.042***	7165
	(0.011)	(0.016)	(0.011)		(0.012)	(0.016)	(0.014)	
Number of sick days	0.014	-0.014	0.028	6450	0.019	-0.063	0.073*	7165
	(0.025)	(0.020)	(0.034)		(0.037)	(0.056)	(0.042)	
Number of sick household members	-0.002	-0.004	-0.0002	6450	0.003	-0.005	0.007***	7165
	(0.002)	(0.003)	(0.002)		(0.002)	(0.003)	(0.003)	
Panel B: Alfa Omega Districts								
Health Index	-0.057	0.052	-0.111*	3210	-0.053	0.115	-0.165**	3565
	(0.051)	(0.062)	(0.061)		(0.061)	(0.088)	(0.069)	
1(Health expenditure shortages last month)	0.016	-0.022	0.034**	3210	0.021	-0.0009	0.035*	3565
	(0.017)	(0.029)	(0.016)		(0.016)	(0.019)	(0.019)	
Number of sick days	0.048	-0.026	0.085	3210	0.033	-0.111	0.129*	3565
	(0.042)	(0.031)	(0.060)		(0.060)	(0.090)	(0.067)	
Number of sick household members	0.002	-0.002	0.004	3210	0.002	-0.007	0.008**	3565
	(0.003)	(0.005)	(0.003)		(0.003)	(0.005)	(0.004)	
Panel C: TLM Districts								
Health Index	0.056	0.060	0.053	3240	-0.044	0.035	-0.096	3600
	(0.034)	(0.039)	(0.042)		(0.056)	(0.080)	(0.058)	
1(Health expenditure shortages last month)	-0.011	-0.022	-0.006	3240	0.024	-0.011	0.048**	3600
	(0.014)	(0.016)	(0.016)		(0.019)	(0.026)	(0.020)	
Number of sick days	-0.020	-0.002	-0.029	3240	0.005	-0.016	0.018	3600
	(0.024)	(0.026)	(0.032)		(0.044)	(0.067)	(0.049)	
Number of sick household members	-0.005**	-0.006	-0.005	3240	0.003	-0.002	0.006*	3600
	(0.002)	(0.004)	(0.003)		(0.003)	(0.004)	(0.004)	

* p<0.1, ** p<0.05, *** p<0.01

Notes: Repeats the analyses in Table 3 but for health outcomes. The index is defined so that an increase represents better health. Number of sick days and number of sick household members are scaled in per capita per month units.

Table 5: Impact of Storage and Credit on Seasonal Differences

Treatment:	Storage				Credit			
NGO Districts:	All	YAO	TLM	N(All)	All	YAO	TLM	N(All)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Seasonal Difference Index	-0.031	-0.067	0.005	1834	-0.050	-0.103*	0.005	2444
	(0.036)	(0.057)	(0.045)		(0.033)	(0.051)	(0.040)	
Log(Staple consumed in kCal)	0.007	-0.024	0.039	1909	0.001	-0.012	0.015	2593
	(0.033)	(0.039)	(0.052)		(0.038)	(0.031)	(0.072)	
Log(Monthly nonfood expenditure)	0.003	0.043	-0.038	1934	-0.066**	-0.067	-0.065	2615
	(0.040)	(0.068)	(0.039)		(0.032)	(0.044)	(0.047)	
Log(Reported income)	-0.035	-0.052	-0.017	1858	-0.024	-0.087	0.039	2472
	(0.064)	(0.066)	(0.110)		(0.054)	(0.067)	(0.083)	
1(Lacked food last month)	-0.036	-0.087	0.015	2150	-0.003	-0.062	0.056	2866
	(0.042)	(0.061)	(0.057)		(0.040)	(0.055)	(0.057)	

* p<0.1, ** p<0.05, *** p<0.01

Notes: Results for seasonal differences. Column 1 reports the results from OLS regressions at the household-cycle level where the main regressor is the storage dummy, with district fixed effects and standard errors clustered at the village level. Column 1 pools all districts, column 2 only includes Alfa Omega districts and column 3 only includes TLM districts. Each pair of cells reports the coefficient estimate and standard error for the treatment dummy. The full estimation sample has 2150 households for one post treatment cycle (round 4 minus round 5), including households in storage and control villages. The number of observations change for outcomes in logs (more details are in the appendix), the sample sizes pooling all districts are reported in column 4. Columns 5 to 8 report results for credit versus control villages. The full estimation sample has 2866 observations, including households in credit and control villages from two post treatment cycles (round 2 minus round 3, round 4 minus round 5). All consumption and income values are in thousands of Rupiahs (1 USD=9000 Rupiahs), scaled to per capita per month units. The index is defined so that a decrease represents smaller seasonal fluctuations.

reduce seasonal variation and smooth consumption. The effect on the *Seasonal Gap Index* is statistically insignificant for all districts but there is a significant decline of 0.103 units (s.e. 0.051) for YAO districts. The reduction seems to be strongest for seasonal differences in the *log of monthly non-food expenditure items* which declines by 6.6% (s.e. 3.2%) for all districts. Table 6 reports IV estimates, which are around twice as large as ITT estimates (the take-up rate is 40%).

In summary, both storage and credit increased consumption or income, consistent with each program expanding budget sets, especially in the harvest season. Storage resulted in consumption increases in both seasons but with no seasonal smoothing and health effects. Credit had some seasonal smoothing effects but there was also moderately worse reported health in the harvest season, with no effects on overall health when we pool both seasons.

7.3. Additional Tests

Here, we discuss first-stage effects and additional implications as described in Section 4.

Staple sales

For storage, changes in income from harvest sales are statistically insignificant for all districts but, for YAO districts, sales income increased by 18,000 Rp (s.e. 10,160) in the lean season and by 12,000 Rp (s.e. 5,506) in the harvest season (available upon request). This increase in sales income is consistent with households selling staples to fund their larger non-food expenditures. We do not detect changes for storage villages in TLM districts.

For credit, sales income increased by 14,000 Rp (s.e. 5,459 Rp) overall, with increases of 17,000 Rp (s.e. 7,314) in the lean season and 12,000 Rp. (s.e. 5,553) in the harvest season for all districts (column 1, Table 7). The increase in sales income in the harvest season is net of repayment to the credit program, which, as we discuss further down, suggests that households are not over-borrowing.

Staple stocks

We do not detect any changes in the overall stock of stored staples in either season for credit or storage. Measuring the stock of stored maize is hard for reasons described in Section 5 and we lack high frequency data on inventory. The increase in sales in the lean seasons for storage villages in YAO is consistent with expanded inventory in the lean season.

We also conduct a heterogeneous treatment effects analysis that suggests that the storage program served as a way to improve stock retention. We compare results for households that are ex ante savings constrained versus households that are not. While this is not necessarily indicative of the household's actual MRT (η), all else equal we predict stronger program effects for households with below median retention rates (which are more likely savings constrained). Indeed, Table A5 in the appendix shows that the effect is stronger amongst households who are ex ante savings constrained (the interaction terms with indicators for low-retention-rate households are statistically significant). We explain the heterogeneous treatment effect regressions in the appendix.

This suggests that the main mechanism behind the effects of storage on consumption is an alleviation of the savings constraint, as discussed in the model. We cannot construct baseline retention rates for credit since there is no pre-treatment harvest season data.[29]

[29] To construct baseline retention rates, we need pre-treatment data for both harvest and lean seasons (round 2 and round 3 for storage).

Table 6: IV Impact of Storage and Credit on Outcomes

Treatment:	Storage				Credit			
Season:	All	Lean	Harvest	N(All)	All	Lean	Harvest	N(All)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Panel A: Consumption and Income								
Consumption and Income Index	0.224**	0.233*	0.222**	5907	0.149	0.049	0.216*	6565
	(0.100)	(0.127)	(0.100)		(0.100)	(0.111)	(0.115)	
Log(Staple consumed in kCal)	0.014	-0.034	0.039	6009	0.060	-0.067	0.145	6741
	(0.066)	(0.103)	(0.068)		(0.086)	(0.103)	(0.109)	
Log(Non-food expenditure, in 1000 Rp)	0.324**	0.311*	0.332**	6042	0.120	-0.015	0.209	6791
	(0.135)	(0.183)	(0.133)		(0.124)	(0.146)	(0.137)	
Log(Reported income)	0.515	0.431	0.560	5943	0.543**	0.371	0.662*	6615
	(0.339)	(0.272)	(0.456)		(0.249)	(0.242)	(0.347)	
1(Lacked food last month)	-0.079	-0.177*	-0.030	6450	-0.040	-0.080	-0.013	7165
	(0.061)	(0.099)	(0.063)		(0.067)	(0.075)	(0.083)	
Panel B: Health								
Health Index	-0.0002	0.134	-0.067	6450	-0.122	0.188	-0.330***	7165
	(0.074)	(0.084)	(0.091)		(0.103)	(0.148)	(0.116)	
1(Health expenditure shortages last month)	0.005	-0.053	0.034	6450	0.057*	-0.015	0.105***	7165
	(0.026)	(0.038)	(0.027)		(0.032)	(0.040)	(0.037)	
Number of sick days	0.033	-0.033	0.066	6450	0.047	-0.160	0.185*	7165
	(0.059)	(0.047)	(0.082)		(0.092)	(0.140)	(0.104)	
Number of sick household members	-0.004	-0.010	-0.0005	6450	0.006	-0.012	0.018***	7165
	(0.005)	(0.008)	(0.005)		(0.006)	(0.008)	(0.007)	
Panel C: Seasonal Differences, |Harvest - Lean|								
Seasonal Difference Index	-0.070			1834	-0.118			2444
	(0.082)				(0.076)			
Log(Staple consumed in kCal)	0.016			1909	0.003			2593
	(0.074)				(0.091)			
Log(Monthly nonfood expenditure)	0.006			1934	-0.160**			2615
	(0.091)				(0.079)			
Log(Reported income)	-0.079			1858	-0.058			2472
	(0.146)				(0.127)			
1(Lacked food last month)	-0.085			2150	-0.008			2866
	(0.099)				(0.100)			

* p<0.1, ** p<0.05, *** p<0.01

Notes: Repeats the analyses in Tables 3 to 5 (for all districts) but using an instrumental variable regression where the main independent variable is a take-up dummy instrumented with the treatment assignment. The estimate reported is for the take-up dummy.

Social and behavioral considerations

We examine each program through the social and behavioral lens described in Section 4. We investigate a proxy for social pressures to share–the need to contribute to neighbors' festival expenditures. Storage participants could circumvent this constraint by committing to store harvest for the lean season. To test this, we calculate the share of a household's annual festival expenditures that is used for neighbors' festivities. We find that households in YAO storage villages report a 10 p.p. reduction (s.e. 3.7 p.p.) in the share of festival expenditures spent on others. This reduction for YAO villages is consistent with the mechanism described above, where commitment (formal or informal) associated with storage raised storage retention rates, γ.

We also find similar results for credit–for YAO villages, there was a 9.1 p.p reduction (s.e. 4.4 p.p.) in the share spent on others. This suggests that both programs play some role in reducing visibility of assets and consequent vulnerability to social pressures.

For credit, we see no evidence of over-borrowing. First, we find that loans are always repaid, though in some cases after a permitted delay due to harvest failures. Second, there are increased sales in the harvest season. Since repayment is in-kind, these sales are indicative of surplus stock that must go towards additional consumption or savings.

Other budget set effects

In the model, the budget constraint (equation 2) included only agricultural endowments and assumed away other sources of revenue that could give rise to income effects, including wages and private transfers (gifts and remittances). We see that neither program affected other budget set factors, providing further support that the income effects above are directly due to the programs' effect on the MRT of staples. One concern is that the null staple effects might arise because our transfers are exactly offset or crowded out by other income sources. Table 7 shows that neither program affected transfers or wage income. Another concern is that staple consumption might have increased at the household level but not at the per capita level if household size increased but there are no effects on household size.

7.4. Cost Benefit Analysis

The main cost component for storage includes the procurement costs to purchase the storage equipment. These represent direct transfers to households. For storage, the average procurement cost per eligible household was 134,553 Rp. We calculate this by first dividing the total procurement cost per NGO by the total number of eligible households, and then averaging across both NGOs. For credit, the average procurement cost was 325,845 Rp. This was used to purchase and transport the first loan disbursements to the credit villages.

The benefit-to-cost ratio for storage, using annualized benefits and average procurement costs, is 43% (=58,000 Rp/134,553 Rp). To calculate annualized benefits for storage, we use the result that storage had statistically significant effects on *ln(Non-food expenditures)* in *both* harvest and lean seasons (Table 3).[30]

[30] The ITT estimate of the treatment effect on non-food expenditure levels for households is 29,000 Rp. The annualized benefit, then, is 58,000 Rp. We repeated the exercise using expenditure levels for households instead of per capita units since program participation is at the household level (this includes observations with zero non-food expenditures, which is more conservative).

Table 7: Other Budget Set Items

Dependent Variable:	Sales	Gifts	Remittances	Wage	Household size
	(1)	(2)	(3)	(4)	(5)
Panel A: Storage					
Storage	3.044	0.668	-0.128	2.915	-0.057
	(5.711)	(1.984)	(1.662)	(4.559)	(0.148)
Number of observations	6,450	6,450	6,450	6,450	6,450
R^2	0.002	0.001	0.010	0.003	0.023
Dependent variable mean	33	14	11	45	5
Panel B: Credit					
Credit	13.772**	0.552	-1.085	-0.095	-0.023
	(5.459)	(1.698)	(1.201)	(3.544)	(0.154)
Number of observations	7,165	7,165	7,165	7,165	7,165
R^2	0.008	0.001	0.006	0.008	0.011
Dependent variable mean	36	14	9	39	5

* p<0.1, ** p<0.05, *** p<0.01

Notes: Panel A (Storage) repeats the OLS estimation in column 1 of Table 3 and Panel B (Credit) repeats the analysis in column 5 of Table 3. Each column is a regression where the dependent variable is reported in the column header. The sample sizes for each regression are reported in the bottom of the panel.The dependent variables for columns 1 to 4 are the per capita per month income from staple sales, gifts, remittances and wages (in thousands of Rupiahs), including zeros. In column 5, household size is the number of household members.

For credit, the benefit-to-cost ratio is 46%. Credit had a statistically significant effect on *ln(Reported income)* in the harvest season (Table 3).[31] Therefore, the benefit-to-cost ratio is 151,000 Rp/325,845 Rp, assuming the effect on income lasts only one quarter.

The longer the benefits persist, the more we can amortize away the upfront procurement costs. Within our study period, our estimates suggest largely positive effects for each round of survey post-treatment (but the standard errors are large if we do not pool the post treatment surveys). Moreover, the persistently high repayment rates (even when there were widespread harvest failures) suggest that the credit program can be sustainable over multiple years. If we make the conservative assumption that our programs' benefits persist for two years and we use annualized procurement costs in the denominator, the benefit-to-cost ratios are 75% for storage and 80% for credit.[32]

We benchmark these estimates against those for Raskin and other transfer programs. Tabor (2005) estimates that the transfer benefit per unit cost for Raskin is 52% for targeted beneficiaries.[33] Hoddinott et al. (2000) report consumption effects from the Mexican Opportunidades program

[31] The ITT estimate of the treatment effect on quarterly household income is 151,000 Rp.

[32] We calculated this by annuitizing the procurement costs reported above using a discount rate of 10% (a standard assumption in the literature). The annuitized procurement costs for storage and for credit were 77,528 Rp and 187,749 Rp per eligible household, respectively.

[33] This assumes a leakage rate of 16%. However, World Bank (2005) estimates that only 18% of the Raskin budget translates into a subsidy for poor households, suggesting a much higher leakage rate.

implying a benefit-to-cost ratio of 77%.[34] Importantly, rice subsidies, cash and in-kind transfers are financed by per-period transfers while our programs are financed from one-time costs.

In summary, our benefit-to-cost estimates for storage and credit are 43% and 46% respectively. Amortizing procurement costs over 2 years increases our benefit-to-cost ratios to 75% for storage and 80% for credit. These calculations have the advantage of being comparable to other papers but ignore other effects (such as food shortages, health and seasonal smoothing effects) that are harder to monetize without estimating household preferences. For example, for credit, these benefits will have to weighed against the negative health effects in the harvest season. Another caveat is that these calculations ignore implementation costs. We discuss this in the appendix.

7.5. Limitations and Lessons for Future Work

We discuss several limitations of our research design and lessons for future work on seasonality. In particular, we are concerned about implications for consumption in scaled-up credit and storage programs, and how new data could better unpack the channels through which each program operates.

Timeliness and harvest risks in a finite study period

Timing is important in a seasonal study because even slight delays could be costly. For example, we had initially planned to distribute storage equipment in the first harvest season (April 2009), which would allow households to store over two harvest seasons. The equipment arrived four months late, but we had to wait till the following maize harvest (April 2010) for households to start storing staples. This was also the only harvest season where we had data for the full agricultural cycle (which we need to construct absolute seasonal differences within a cycle). This example illustrates how a seemingly short delay of 4 months resulted in us losing two rounds of post treatment data. Also, delays in seasonal surveys meant we were likely measuring some seasonal outcomes with recall error, which may make it harder to measure seasonal differences.

Harvest risks further exacerbated the problems above. These harvest failures tend to be related to weather patterns that are widespread, covering entire districts. Since we focus on rain-fed, staple subsistence farmers who only have one harvest a year, this means we only observe three harvest seasons in our three-year study, and any widespread harvest failures would reduce the statistical power of the study substantially (since each harvest failure will also have implications for the following lean season survey). This suggests it would be useful to stratify by regions (so that results are internally valid within regions), across multiple regions (to insure against widespread harvest risk) and have a longer study period.

General equilibrium price effects

We do not find statistically significant general equilibrium price effects because we only treat 18 villages in each district and the program is of limited duration. A sufficiently large expansion of the programs should ultimately reduce the staple supply in the harvest season and raise the staple supply in the lean season. This will translate into a drop in lean season staple prices and a rise in harvest season staple prices.

While these general equilibrium effects arise out of improved storage or credit markets, welfare effects for some households will be ambiguous. For example, consider a household that had access

[34] Calculated using benefits valued at 197 pesos per month and consumption effects of 151 pesos.

to a high-returns storage technology prior to the program and therefore did not experience a direct expansion of its budget set through food credit or food storage. In the short run, such a household will be unaffected by the programs. However, as a result of general equilibrium effects, since staples are expected to get cheaper in the lean season, lean season non-food consumption will get more expensive (relative to staples). If the household has a preference for lean season non-food consumption (that it funds through saved staples), it will be made worse off.

Measurement issues

As discussed above, inventory was hard to measure precisely due to the nature of maize storage, especially in control villages. Also, whether inventory was measured before or after consumption and sales mattered crucially. More frequent and precisely timed measures of inventory would help. Second, it would have been useful to collect more data on the price at which staples were sold. This would help us decompose the result that each program raised income from staple sales, so we could learn to what extent this was driven by changes in the quantity of staples sold rather than variation in prices. Third, as discussed earlier, this study would benefit from more detailed data on the consumption of other food and non-food items.

Finally, we lack statistical power in variables related to seasonality. By definition, seasonal differences are defined for each agricultural cycle instead of by season. For example, for the storage treatment, we only had one post treatment cycle (rounds 4 and 5), which limited the sample size. Due to our budget constraint, we faced a significant trade-off between spatial and time-series variation. Ultimately, we chose to have a larger cross-section (to insure against regional harvest risks) instead of a longer time series (to have more post treatment cycles). In the future, it would be useful to have a larger sample or to collect data on other seasonal outcomes that are measured with less noise. This would also aid in precision for other outcomes, since consumption and income are known to be measured with error. Having more power would allow us to trace out dynamic effects by rounds.

8. Conclusion

This paper focuses on staple farmers in West Timor who use low-MRT technologies to transfer assets between harvest and lean seasons. The seasonal storage program increased the retention rate of stored staples and the seasonal credit program allowed households to borrow cheaply in the lean season. By introducing new technologies to raise the harvest-to-lean season MRT for staple farmers, these programs implicitly subsidized the relative price of lean season consumption.

The storage program increased non-food consumption in the harvest and lean seasons, measured over a relatively short span of time. But storage had no effects on health or outcomes related to seasonal fluctuations. Overall, benefits of the storage program derived from both higher returns to savings and reduced social pressures.

The credit program increased reported income with no decreases in consumption. Credit also included more tools for insuring against risk. Participants showed reduced gaps in seasonal differences, especially in YAO villages. However, credit led to some deterioration in health in the harvest season. Repayment rates were consistently high except during harvest failures and there was no evidence of over-borrowing. For each program, we find some evidence of increased staple sales, but no evidence of changes in staple inventory. This is likely due to a combination of theoretically ambiguous predictions and data limitations.

Both storage and credit led to increases in non-food consumption or reported income but had null effects on staple consumption. This is notable given both programs' focus on staple food, and transaction costs related to the remoteness of program villages. This suggests staple farmers in our study could be close to staple food satiation, but still benefit from the higher MRT through expanded budget sets.

Since the programs incur front-loaded costs and have recurring financial benefits, our cost-benefit analysis argues that they provide a cost-effective way to help farmers adapt to seasonality. Amortizing procurement costs over 2 years results in benefit-to-cost ratios of 75% for storage and 80% for credit. In future work, it would be interesting to see if a longer-term analysis would raise the implied cost-effectiveness of the programs.

The food storage and food credit programs, when modified with caution, could inform food policy elsewhere. Rudimentary food storage technologies are prevalent in several agrarian economies, and the introduction of improved storage (used directly for storage programs or indirectly for credit programs) could similarly expand budget sets for other poor households. Our research comes with some caveats and suggestions for ongoing investigation.

Unlike regular subsidies on staples, these programs are of less immediate value to non-farming households whose incomes are not seasonal and not in-kind. Unless such households could replicate the behavior of farming households by conducting basic transactions using staples, they cannot take advantage of the lean season subsidy implicit in food storage and food credit. This also highlights an inherent strength and weakness of in-kind seasonal programs targeted at staple farmers. By raising the MRT of staple crops, the programs target the underlying source of seasonal frictions in our setting (high depreciation rate of staples). However, this implies that treatment effects are conditional on output, which matters in an environment with significant harvest risks.

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