Evaluating Seasonal Food Security Programs in East Indonesia

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Abstract

Food programs are large and expensive components of social safety nets in developing countries. For agricultural households, hunger is more acute in annual lean seasons, but food policies typically do not adapt to seasonality. There is limited research on this because of a paucity of panel data that tracks households across seasons. In this paper, we analyze consumption and income seasonality in East Indonesia. We design a unique seasonal household panel, develop a model to explain how credit and saving constraints generate seasonality, and present results from a randomized experiment of food storage and food credit. In both programs, economic well-being increased substantially (a one standard deviation increase). Under credit, participants report a reduction in both seasonal consumption gaps and food shortage, health improvements when credit is disbursed but deterioration when repayments are due. Under storage, households with a high propensity to save report a strong reduction in food shortages.

Keywords: Seasonality, hunger, food, randomized evaluation

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1 Introduction

The Food and Agricultural Organization estimated that 1.02 billion individuals were undernourished in 2009 (FAO). Eradicating extreme poverty and hunger is the first of eight United Nations Millenium Development Goals. Much of this hunger is seasonal, especially for farmers who depend on rain-fed agriculture.[1] Khandker (2009) estimates that 93% of households in the Greater Rangpur region in Bangladesh were below the food poverty line during the lean season in 2000, compared to 80% during the rest of the year.[2] Incomes and prices can also vary greatly within the agricultural cycle. If households are unable to effectively borrow or save, market frictions can generate cyclical variation in food shortages.

In several developing countries, food security policies are central to social safety nets and are characterized by high fiscal costs. In the Philippines, the rice subsidy program accounts for 70% of public social protection expenditures (Jha and Ramaswami, 2010). In Indonesia, the food subsidy program, Raskin, cost 0.23% of GDP in 2009 (Trinugroho et al., 2011). The seasonality of hunger is a common topic in policy discussions but many food security programs do not adjust to the timing and severity of food shortages. A recent World Bank report advocates that India's food subsidy program be modified to allow households to roll over their monthly quota to deal with seasonal variation in prices (The World Bank, 2011). A 2005 report by the Government of Indonesia notes that seasonal food insecurity is perhaps the most common form of food insecurity (GOI, 2005). One reason seasonality is ignored in the design of food policy could be the lack of data that tracks households across seasons, making it impossible for many top-down food policies to vary household eligibility by season.

This paper studies food policy through the lens of seasonality. We make two contributions. First, we present the results from a unique, large-scale panel survey in West Timor. Second, we conduct a randomized evaluation of two market-based food security programs. The region is primarily dependent on rain-fed agriculture and suffers from predictable annual hunger periods known locally as *musim paceklik* (famine season).[3]

[1] See Vaitla et al. (2009) for a discussion.

[2] The food poverty line was calculated by estimating the cost of a food basket needed to maintain the per capita daily caloric requirement (2112 calories) recommended by FAO (Food and Agricultural Organization).

[3] Fox (1977) writes: "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. Given the nature of their economy, there is little – save husbanding of all food resources – that a Timorese can

Our goal is to analyze seasonal variation in not just food consumption but also other expenditure patterns. The programs are designed to facilitate credit and savings in turn, which could help households overcome market frictions by lowering the opportunity cost of lean season consumption. Each program is independently evaluated against a control group.

Motivated by the lack of data investigating seasonality, we designed a series of surveys that tracks 2,877 households. We look at consumption, expenditures, health, income, employment, and subjective predictions across seasons over three years. Most studies of seasonality have had to rely on aggregating repeated cross-sections of households to construct village level, seasonal panels. However, to study income and consumption seasonality, it is necessary to have *household* level seasonal panels (Khandker, 2009).[4] First, multiple seasonal visits for each household reduce the measurement error of a household's average consumption and income (Deaton and Grosh, 1998), two important measures of economic well-being. Second, panels using village means that aggregate across households mask rich, within household variation. For example, for quarterly income and weekly food expenditures, we find that the within household standard deviations were 1.6 times the between household standard deviations. To measure seasonality, it is important to compare harvest and lean season outcomes for the same household because there is so much within household variation. Two households in the same village, for example, could have different harvest and lean season outcomes in the same year that cancel each other out when we take village means.

Analysis of our seasonal household panel suggests that there is meaningful seasonal variation in objective and subjective measures of well-being, including income, non-food expenditures and self-reported food shortages, but less seasonality in weekly food consumption. First, households report anticipated food shortages that vary across seasons. More than 33% of households anticipate facing food shortages in the next lean season but only 12% anticipate facing food shortages in the next harvest season. Second, we find that reported measures of past food shortages are very dynamic. Estimates of transition probabilities using households in control villages suggest that only 40% of households that report lacking food in one period still report lacking food in the next period. Yet, 93% of households that report receiving Raskin rice in the last

do to stave off this famine."

[4] Household level seasonal panels are extremely rare. We know of only one other large-scale, seasonal household panel. This survey was conducted in 1986-1989 in rural Pakistan, tracking 800 households across seasons. See Alderman and Garcia (1993) for more details. They analyze seasonal patterns of consumption and expenditure but do not use the data to evaluate food policy.

period still report receiving it in the next period, suggesting that the food subsidy program does not adjust to seasonal food shortages. Third, absolute seasonal differences in weekly food expenditures, monthly non-food expenditures and quarterly household income are economically significant.[5] For example, the median absolute difference in weekly food expenditures is 22,000 Rupiahs (the median weekly food expenditure is 27,000 Rupiahs).

We develop a simple model that shows how predictable food shortages in the lean season cannot be explained by pure borrowing constraints (See, for a discussion, Deaton and Grosh (1998)). Unlike life-cycles, agricultural cycles are by their very nature repetitive. Hence, even if individuals cannot borrow against a future harvest, they may be able to save from a previous harvest. Our model incorporates both borrowing and saving constraints. The saving "constraint" emerges from two features: first, prices of agricultural output are low during the harvest and high during the lean season, and second, agricultural output depreciates rapidly when stored. Traditional maize storage methods, which involve drying over a fire and hanging from the ceiling, result in an annual depreciation rate of 30% to 50% (deRosari et al., 2001). Additionally, these methods leave the grain highly visible and subject to what might be termed "social depreciation," which emerges from community pressures to share.[6] The saving and borrowing constraints imply that individuals are unable to effectively transfer agricultural output from harvest to lean season, either in cash or in kind. In this setting, we find that access to credit and savings will narrow the gap of inter-seasonal marginal utilities. Each, in effect, provides households with a superior technology (through lower infestation and less visibility[7]) to transfer assets from the harvest to lean seasons.

Given that need is time-varying and households might not require constant assistance across the agricultural cycle, subsidies can be expensive. In this paper, we design and conduct a randomized evaluation of food credit and food storage programs designed to match seasonal patterns of farmers. Unlike subsidies, these are institutional innovations that, in principle, can be ultimately self-sustaining.

Under the credit treatment, women's microcredit groups were formed and offered loans of rice and maize (the primary staples in West Timor) during the lean season,

[5]These were calculated by taking the absolute difference between the harvest season and lean season outcomes within each agricultural cycle.

[6]We collected data on how much households spend in a season on own festival expenditures and festival expenditures for others. We find that festival expenditures constitute 16% of total annual non-food expenditures and on average, 53% of this is spent on others.

[7]Baland et al. (2011) show how credit is used to disguise assets in Cameroon.

which were to be repaid in kind (with interest) during the following harvest. The storage treatment introduced several storage technologies that can reduce depreciation significantly. This is equivalent to significantly raising the interest rate on savings. We use mean effects analysis to jointly test the effect of our treatments on related outcomes within 5 categories: objective measures of seasonal differences, subjective measures of food shortages, health, economic well-being and food consumption. Each outcome is standardized using the mean and standard deviation of the control group so that treatment effects are measured in standardized units.

Our results are broadly consistent with the predictions of the model. Compared to control villages, households in credit villages show a reduction of 0.28 to 0.69 units for seasonal differences, a reduction of 0.83 units for subjective food shortages, an improvement in health by 1.48 units in the lean season when credit was disbursed but a deterioration of 0.90 units in the harvest season when repayment was due. There is a large (one standard deviation) increase in economic well-being. We did not detect effects on food consumption. These mean effects are mostly driven by the following outcomes: a decrease of 21,000 Rp in the seasonal differences in weekly food expenditures for 2 districts managed by one NGO, a 12% reduction in anticipated food shortages in the lean season, a 69% increase in income during the harvest season, household heads reporting 15 fewer sick days in the lean season compared to 3 more sick days in the harvest season, and household heads who are 17% more likely to report some sickness during the harvest season compared to 10% less likely in the lean season.

In the storage program, most significant effects are restricted to households with a high propensity to save. There is a decrease of 1.33 units (2.11 units) in subjective food shortages for all (high propensity) households, and an increase of 0.97 (1.10) units in economic well-being for all (high propensity) households. Beside the improvement in the physical depreciation rate, storage participants can also circumvent the need to contribute to neighbors' festival expenditures by committing to store harvest for the lean season. Storage participants reported a 10% to 25% reduction in the share of festival expenditures spent on neighbors' festivities. These two appear to be the most important mechanisms behind the treatment effect of the storage program.

Our paper is closely related to the literature that studies food security policies but to our knowledge, we are the first randomized control trial that evaluates the impact of food policies.[8] In recent years, a number of food credit and storage policies have been instituted in developing countries. For example, grain banks in Bhutan (Gelay, 2008),

[8]See for example Jha and Ramaswami (2010); Besley and Kanbur (1990).

western Africa (Lines, 2011), and Madagascar (Zeller, 2001) engage in various forms of credit and storage. Our analysis of the programs is essentially an attempt to answer a policy, rather than behavioral, question. Since the two interventions vary in timing and structure, a direct comparison of the two would not be informative. Rather, we take two frequently discussed solutions to problems of seasonality–food credit and food storage–and examine where the impacts of each lie. Though our program generates wealth effects through the channels of food, these are not the most responsive margins. This is consistent with the literature (see for example Banerjee and Duflo (2007); Strauss and Thomas (1998); Subramanian and Deaton (1996), who show that caloric deficits among the poor are not as acute as earlier expected). This paper serves as a reminder that the primary benefits of food programs may be discernible on altogether different sets of outcomes.

Our paper is also related to the literature on consumption and income seasonality.[9] Using cross-sectional data from Thailand and a high frequency panel data from 3 villages in India, Paxson (1993) and Chaudhuri and Paxson (2002) find that consumption seasonality does not track income seasonality. However, Khandker (2009) finds that seasonal income greatly influences seasonal consumption in Bangladesh. Our paper sheds further light on this question by using a much larger seasonal panel that tracks the same households over multiple harvest and lean seasons. In an improvement over the previous literature, we are also able to control for household fixed effects, seasonal prices and proxies for seasonal expenditures, such as festivities. We find evidence of income and consumption seasonality. Comparison of maize and rice farmers who face different seasons show that they have different seasonal income patterns and also different seasonal food consumption patterns but no difference in monthly non-food expenditure and festival expenditures.

2 Theoretical Framework

In this section, we build a simple consumption-savings model that allows us to demonstrate seasonality and explore the implications of storage and credit programs, respectively. We show how inter-seasonal fluctuation in consumption emerges as a result of multiple factors: credit constraints (which prevent borrowing against future harvests)

[9] See for example Sahn (1989); Paxson (1993); Alderman and Garcia (1993); Handa and Mlay (2006); Chaudhuri and Paxson (2002); Khandker (2009); Alderman and Sahn (1989); Behrman (1988); Pinstrup-Anderson and Jaramillo (1989).

and saving constraints. Saving constraints are a significant factor – individuals have difficulty storing their harvest due to both physical depreciation (of the staple and the purchasing power of cash) and informal pressures to share (such as gift and festival expenditures).

We start by describing an infinitely-lived individual who makes consumption-savings decisions in each period. To isolate the mechanisms that generate variation within, rather than across, an agricultural cycle, we assume there is no harvest risk.[10] The stripped-down model has the advantage of explicitly illustrating both how budget constraints affect choices and how storage and credit programs modify budget constraints.

2.1 Assumptions

In any year, the individual faces consumption choices in the harvest period (denoted H) and the lean period (denoted L). In each period, utility is a function of staple consumption (m, which could be rice or maize) and consumption of a numeraire good (c). We assume an additively separable utility function. Utility in period t is given by $U_t = u_m(m_t) + u_c(c_t)$, where each u_i is twice differentiable and strictly concave everywhere. We also make the following restriction: for each good i, $u'(0) = \infty$ (no corner solutions). Across periods, the agent discounts utility by a factor of $\delta < 1$.

The individual has an initial endowment of the staple in period H, denoted e. She also has income in each period, y_H and y_L. We assume that income refers not just to labor income but also to returns to assets. What distinguishes this model from a standard consumption-savings problem is the nature of the budget constraint, which depends on how the individual chooses to transfer resources across periods. The decision about how to transfer resources depends in turn on prices and depreciation rates. We make the following assumptions. The price of the numeraire good is invariant across seasons: $p^c_H = p^c_L = 1$. The staple is relatively cheaper in the harvest period: $p_H < p_L$. Finally, the staple depreciates. Any staple stored in period H, s, becomes γs in period L.[11]

The storage treatment can be captured by a rise in γ. The credit treatment can be captured by the option of a loan, b, that is repaid as rb in the following period.

We interpret γ broadly to include physical depreciation as well as norms related to gifts, which apply to endowment that is saved in kind (consider norms that create

[10]We discuss the consequences of risk later in this section.

[11]It is possible that the problems associated with storage could be solved with more efficient trade. However, possibly due to transportation costs or a lack of infrastructure, inter-island trade is limited. As a result, harvest season prices are lower than lean season prices.

pressure on households to share visibly stored assets–households more vulnerable to these taxes face a lower γ). By this interpretation, less liquid forms of storage in both rice and maize can reduce a household's exposure to social pressures and thereby raise the retention rate on savings.

2.2 Seasonality

First, we show how seasonality emerges from a combination of borrowing constraints and saving constraints. In the absence of risk, the consumer essentially faces a two-period problem (there is never an incentive to transfer resources from one agricultural cycle to the next). Consider the problem faced by a maize farmer in the harvest period. She must allocate her income and endowment of the staple to consumption in both harvest and lean periods. Furthermore, her lean period allocation depends on her saving methods. If she saves cash, we assume it earns no interest. If she saves the staple, it depreciates but can be resold at a higher price. Clearly, in the absence of transaction costs, the agent will save entirely in the staple or entirely in cash.

The utility maximization problem is the following:

$$\max_{m_H, c_H, m_L, c_L} U_H + \delta U_L$$

$$\text{s.t.}$$

$$(1)\ y_H + p_H e - (p_H m_H + c_H) \geq 0$$

$$(2)\ p_L m_L + c_L \leq \max \left\{ \begin{array}{l} \text{(A) } y_L + [p_H e + y_H - (p_H m_H + c_H)] \\ \text{(B) } y_L + [p_H e + y_H - (p_H m_H + c_H)] \frac{p_L}{p_H} \gamma \end{array} \right\}$$

Condition (1) establishes a no-borrowing constraint. Condition (2) states that, given consumption in H, consumption in L is limited to the depreciated value of assets. If the agent saves in cash, condition (2A) applies. If she saves the staple, condition (2B) applies. Notice that the only difference between Conditions (2A) and (2B) is an additional term, $\frac{p_L}{p_H}\gamma$, applied to the assets saved in H. This term represents the loss due to depreciation combined with the gain from rising staple prices.

We make the assumption that Condition (1) remains slack. Given that harvest gains are realized in period H, this is reasonable as long as employment income in period L (y_L) is not inordinately high. The individual will choose to save in cash if $\gamma \leq \frac{p_H}{p_L}$. This is the case where staple depreciation is sufficiently high or price gap is sufficiently low. Otherwise, she will save the staple.

The results resemble those from a standard utility maximization problem with four goods.[12] When the agent chooses to save the staple, it must be the case that the marginal benefit of a dollar saved in kind is greater than 1 ($\frac{p_L^m \gamma_m}{p_H^m} > 1$). Therefore, relative to saving cash, the first-order conditions are skewed towards period L – period L consumption relative to period H consumption is greater than when saving cash.

This framework can also accommodate the possibility that marginal utilities of consumption vary across time. In particular, we might expect that the higher effort required during the lean season translates into a higher marginal utility of consumption. The mechanics of the maximization problem, as well as the tradeoff between saving in cash and kind, stay the same. In fact, the problems associated with storage and credit constraints assume greater significance when the agent has more reason to move consumption to the lean season.

2.3 Predicted Impacts of Programs

An improvement in staple storage technologies serves to increase γ to some $\bar{\gamma}$. Depending on the initial conditions, this can affect the individual's consumption-saving decisions in three ways. First, if the individual was initially saving in cash, and if $\bar{\gamma}$ is a sufficiently small improvement over γ (i.e. $\bar{\gamma} \leq \frac{p_H}{p_L}$), she will continue to save in cash. In this case, the storage technology will have no effect. Second, if the individual was initially saving in cash, and if $\bar{\gamma}$ is sufficiently high (i.e. $\bar{\gamma} > \frac{p_H}{p_L}$), she will switch to saving the staple instead. This can be viewed as an overall rise in wealth. Third, if the individual was initially saving the staple, she will continue to do so, and consume more in the lean season than before. This too can be viewed as an overall rise in wealth emerging from raised interest rates (since the no-borrowing constraint is slack).

With credit, the agent has the option to borrow some maize, b_m, in period L, which is repaid in period H with interest, at rb_m. We assume that r is sufficiently low that the agent has no incentive to continue saving in the lean season. The agent might wish to borrow not just for consumption but for purposes of arbitrage (to sell in the lean season and buy back in the harvest season). We assume, as explained in Section 3, that there are institutional limits to loan sizes that prevent this.

Credit impacts the consumer very similarly to storage. If, under storage, a dollar saved in kind was worth $\frac{p_L^m}{p_H^m}\bar{\gamma}$, now a dollar consumed in kind is worth $\frac{p_L^m}{p_H^m}\frac{1}{r}$ in terms of

[12] First-order conditions and intermediate steps are available in an appendix (http://maisy.wharton.upenn.edu/research).

next period repayment.

In order to explicitly derive predictions of impacts from storage and credit programs, we assume a CRRA utility function: $u_m(x) = u_c(x) = \frac{x^{1-\frac{1}{a}}}{1-\frac{1}{a}}$, where $a > 1$. First-order conditions are in the online appendix.

We define the two types of agents above in the following way: "low storage" refers to types who, in the absence of a program, save little or none of their endowment in staple form, while "high storage" refers to types who ordinarily prefer to save a large percentage of their endowment in staple rather than cash. Low storage types might not respond substantially to a storage program (if they continue saving in cash). However, we expect that high storage types will – we are offering them a better return on an asset they already store.

Consider the impact of the storage technology on high storage types: a rise in γ leads to a reduction in m_H, a reduction in c_H, a rise in m_L, a rise in c_L. The rise in lean season consumption is a natural consequence of improved interest rates, which brings marginal utilities of lean and harvest season consumption closer to each other. The reduction in harvest season consumption comes from the fact that income effects are smaller than substitution effects. Next, we find that there are ambiguous changes in $m_H + m_L$ and $c_H + c_L$. This is because an improved storage technology has two effects – quantities already being saved now amount to more in the lean season, but additional amounts being saved as a result of improved technologies still face some loss. Therefore, despite positive wealth effects, total annual consumption could drop. Finally, there should be a reduction in $\frac{m_H}{m_L}$ (bringing the ratio down towards 1, resulting in a narrowing of the seasonal gap) and and a reduction in $\frac{c_H}{c_L}$ (in this case, bringing the ratio further below 1).[13]

Credit can be analyzed in exactly the same manner. A loan at an interest rate of r can be interpreted as raising retention from γ to $\frac{1}{r}$ (see the first-order conditions). This serves to make lean season consumption relatively cheaper than before. Additionally, since decisions are made in the lean season, the discount factor is applied to the harvest season instead of the lean season. This further raises the attractiveness of the lean season relative to the harvest season. Under the assumption that r is low enough that all types will choose to borrow, the impacts of credit are qualitatively similar to the impacts of storage.

[13] These results are robust to CARA and log utilities. In all these cases, substitution effects from storage (which make lean season consumption cheaper) are larger than income effects (which loosen the overall budget constraint and raise all consumption).

The predictions are summarized in the table below (using non-food per-capita expenditure as a proxy for non-food consumption):[14]

Predictions of the model:	**Credit & High Storage**
H staple consumption & non-food PCE	fall
L staple consumption & non-food PCE	rise
$\frac{H \text{ staple consumption}}{L \text{ staple consumption}}$ & $\frac{H \text{ non-food PCE}}{L \text{ non-food PCE}}$	fall
Total staple consumption & total PCE	ambiguous: rise or fall

2.4 Risk

Up to this point, we have assumed a fixed harvest. However, we might be concerned about heterogeneous treatment effects based on harvest size and harvest risk. In particular, what is the average impact on households that face high cross-cycle variation in harvests? To get a first-order approximation of how risk affects program impacts, we consider mean-preservisng spreads around the originally assumed harvest quantity.

First, consider the case of storage, and the impact on lean season staple consumption, $I \equiv \frac{m_L(\bar{\gamma})}{m_L(\gamma)} = \left(\frac{\bar{\gamma}^a}{\gamma^a}\right) \frac{y_L + p_L \bar{\gamma} e + \frac{p_L}{p_H} \bar{\gamma} y_H}{y_L + p_L \gamma e + \frac{p_L}{p_H} \gamma y_H} \left(\frac{\gamma^a}{\bar{\gamma}^a}\right)$. Since this ratio is strictly concave in e, we know that (a) impacts of storage are rising in the size of the endowment, and (b) riskier harvests will serve to reduce the average impact of storage on lean season staple consumption. Following the approach above, we find qualitatively identical results for harvest season staple consumption, and both lean and harvest season non-food consumption.

We can also look at the impact of risk on seasonal gaps, $G \equiv \frac{\frac{m_H(\bar{\gamma})}{m_L(\bar{\gamma})}}{\frac{m_H(\gamma)}{m_L(\gamma)}} = \left(\frac{\gamma}{\bar{\gamma}}\right)^a$. Since this is invariant in e, harvest risk should not affect the impact of storage on seasonal gaps.

For credit, risk lowers average impacts of the program for a more basic reason – if there is non-monetary punishment for default (that increases in the size of the default),

[14] It is important to note that, under more general utility functions, magnitudes of changes depend on rates of change of marginal utilities (u'_m, u'_c). If individuals are close to food satiation, most changes will be captured by non-food PCE. In other words, if u'_m is initially steep but drops off rapidly (in comparison to u'_c), storage or credit could have greater sustained impacts on non-food consumption. A quasilinear utility function helps demonstrate this point. Under such a utility function, in each period, the first tranches of income will be allocated to food. If there are rises in income, those rises will be directed towards non-food consumption.

individuals will borrow less in anticipation of a risky harvest. This reduced borrowing will directly reduce the impact of credit on lean and harvest season consumption and, unlike with storage, also reduce the impact of credit on the seasonal gap.This is because the quantity borrowed cannot be adjusted based on the next season's realized harvest.

Since maize is inherently subject to greater harvest failure than rice, we expect relatively smaller effects of the programs for households that are predominantly maize-producing.

2.5 Additional Hypotheses

We present some predictions that are beyond the scope of the model, but will be useful for interpreting the data.

Beyond the scope of the model:	**Storage**	**Credit**
Employment	ambiguous	ambiguous
Health	H: ambiguous L: rise	H: ambiguous L: rise
Anticipated & realized food shortage	fall	L: fall H: ambiguous

Possible drivers of employment and income are the following: (1) need, (2) health / productivity, (3) time available. In the lean season, storage reduces need while raising productivity and available time (less time spent on food search). In the harvest season, storage raises available time (less time gathering firewood and preparing for traditional storage), but possibly also raises need and reduces health. We expect lean season health to improve, with a possible worsening in harvest if reduced harvest season consumption has marginal impacts on health. Anticipated shortages depend on how far into the future individuals plan. If they do not actively plan for consumption beyond the current agricultural cycle, it is unlikely that the storage program will have an impact on predictions for distant seasons.

Under credit, drivers of employment and income move in the same qualitative directions as under storage. Health consequences in the harvest season could be exacerbated if the individual overborrowed or if harvest failed. Potential lean season gains from credit could be counterbalanced (or even outweighed) by worsened harvest season outcomes, especially in the event of overborrowing (if agents are time-inconsistent) or harvest failures.

Finally, as discussed above, it is reasonable to expect that households facing greater social pressures to share will experience stronger program impacts. This could happen from reduced visibility and reduced liquidity of assets, as well as other non-tangible impacts that NGO presence could have on savings behavior. In particular, households that spend significantly on gifts and non-household festivals might be particularly vulnerable to these social pressures. If so, such households face particularly acute saving constraints and therefore stand to benefit more from the credit and storage programs.

3 Program Design

The treatments were implemented in September 2008 and lasted 3 years. The project covers 96 rural villages in all 4 districts, or *kabupaten*s, in West Timor. There are unlikely to be contamination effects as the villages we cover are extremely rural– the average distance to the closest market is 20.44 km and the average distance to the closest subdistrict is 10 km. The objective of the pilot is to evaluate the impacts of three scaleable programs – credit, storage, and contract storage (described below) – relative to having no program at all.

Programs were randomly assigned in the following manner. First, 24 villages in each of 4 districts were selected for the study. Within each district, 6 villages were randomly selected to form the control group, while the remaining 18 were randomly assigned to one of the three treatment groups. The treatment programs were implemented by two NGOs, Yayasan Alfa Omega and Yayasan Tanaoba Lais Manekat (TLM), each of which operated independently in two districts. To be eligible for credit and storage programs, the NGOs required participants to be married (or once-married) women farmers.

Under the credit treatment, women's microcredit groups of up to 108 women were formed. Each member was offered loans of rice and maize during the lean season, which were to be repaid in kind (with interest) during the following harvest. Repaid grains were locally stored by the microcredit group and again distributed as loans during the next lean season. An externally imposed loan ceiling ensured that participants did not borrow unlimited amounts for the purposes of arbitrage. The program grant is used as seed money to provide the first round of loans and repaid food (with interest) is expected to sustain future loans. By participating in the credit program, the members are effectively getting access to a superior storage technology, for the use of which they pay a fee in interest.

Like credit, the pure storage treatment is built on the hypothesis that the obstacle to saving is based on lack of access to the technology. There are several storage technologies which, when implemented correctly, protect against rodents and moisture to provide virtually loss-less storage of rice and maize. This is equivalent to significantly raising the interest rate on savings.[15] Individuals were offered storage materials (sacks and jerry cans for small quantities, drums for larger quantities). There were no restrictions or conditions associated with use – people were free to deposit and withdraw at any time.

The contract storage treatment used the same storage technology as the pure storage treatment. However, individuals who chose to join were asked to commit to certain aspects of a savings plan – in particular, that they would not withdraw their deposits until a specified date early in the lean season. Violation of this agreement resulted in denial of future access to the program. The goal of this treatment is to understand if the current patterns of consumption are due to a lack of access to commitment products as opposed to simply a lack of access to storage products. It is possible that individuals need commitment both from their own future selves and from their friends and neighbors. If the pure storage treatment is equivalent to a savings account with a high interest rate, the contract storage treatment is equivalent to a term fixed deposit during which savings are made illiquid.

If these programs were scaled up, we would expect lean season food prices to fall in the long run. As our programs were small relative to the island population, we abstract from these general equilibrium effects in our analysis.

We encountered a some obstacles during the early stages of implementation. First, there were delays in procuring storage materials as they had to be purchased from other islands. This meant that storage treatments in most areas started late in the third survey round. An implication is that only rounds 4, 5, and 6 will likely pick up storage treatment effects. Second, we found that the distinctions between pure and contract storage were not strictly adhered to during implementation. For these reasons, we do not distinguish the storage treatment from the contract treatment in this paper.[16] Third,

[15]It is worth discussing why the women did not adopt these storage technologies before. Storage equipment is not readily available in local markets. It took the NGOs some time before they could locate a local supplier to transport the storage equipment to the villages. For the first year, materials were purchased from other islands.

[16]We also repeated the empirical analysis treating pure and contract villages separately. There were

nine of the villages received a treatment that was different from the initial assignment. These failures are accounted for in the empirical analysis. Finally, it is useful to keep in mind that harvest failures in maize for an entire district (24 villages, or a quarter of the sample) would have reduced the perceived effectiveness of credit.

4 Data

We collected a unique, large-scale seasonal household level panel where we surveyed all 2,877 households twice each year for 3 years, once during the lean season and once during the harvest season. All respondents are adult females who are knowledgeable of household issues.

We collected four sets of statistics.[17] First, we collected demographics such as age, education and marital status. Second, we collected detailed recall data on food-related measures including yields, ratio of produce stored, consumption and expenditure of staple food items in the previous week.[18]

Third, we collected non-food measures of well-being including income in the past 3 months, annual and monthly per capita expenditures (PCE), recent employment, assets and liabilities, and health outcomes.[19] All of the survey questions for food-related measures, income, employment and non-food expenditure items were taken directly from Indonesia's annual household survey, Susenas. All recall variables (including income, PCE, consumption and expenditure) have been winsorized at the top 0.5% to minimize biases due to outliers.

For expenditures, we also collected data on seasonal festival expenditures and how much was spent on own and others' festivities. Festival expenditures are important and constitute 16% of total annual non-food expenditures. On average, 53% of festival

no differences between the two treatment groups.

[17]We also collected experimental and subjective measures of time-preferences. See Basu and Wong (2008) for a discussion of the time preference data.

[18]We use the term *consumption* to refer to the the number of kilograms of food eaten by the household in the past week. We also explored converting food intake into caloric intake. However, we decided to stay with kilograms because the conversion from kilograms to calories would add another source of measurement error. There is a wide variety of staples being consumed (different types of rice, maize, tuber), each type likely to be associated with different caloric content. Our survey does not collect very detailed information about these sub-categories of staples. We use the term *expenditures* to refer to the total amount spent in the past week to purchase food.

[19]Our health outcomes are mostly self-reported health outcomes. We also collected objective data such as arm circumference of pregnant women and children under the age of 5. but there were too few of these individuals to use these variables in our regressons.

expenditures is spent on festivities of others. Expenditures for own festivals include expenditures for weddings (35%), religion (37%)[20], and traditional ceremonies (11%) whereas expenditures for others' festivals include weddings (69%) and traditional ceremonies (25%). Fourth, we collected subjective data to understand how individuals view their own economic futures. Respondents were asked to predict future prices and anticipate imminent food shortages.

Figure 1 shows the timing of the surveys compared to the timing of the treatment implementations. Because many of the villages were extremely rural, each round of survey took approximately 2 months to complete. The first round was in the lean season and was conducted between September and November 2008. The first two harvest season surveys (rounds 2 and 4) were delayed by 3 months and only began in July. This is 3 months after the typical harvest season for maize (April) and 1-2 months after the harvest season for rice (May-June).

Due to the costs of household surveys, we only had enough funding to survey 30 households per village. In addition, hamlets within each village also tended to be far apart. Our survey team could only focus on surveying households in 2 hamlets per village. To increase the percent of surveyed households who would be offered treatment, we first instructed the survey team to select 30 eligible households randomly within 2 hamlets in both the treatment and control villages. Then, we instructed the facilitators to offer all survey respondents in each village the option to participate. Since the selection of survey respondents is still orthogonal to the selection of program participants, the respondents in the treatment and control villages are still comparable, on average. We test this using a large number of pre-treatment outcomes.

5 Seasonality patterns in the data

In this section, we analyze how a variety of household outcomes vary across seasons, using data from control villages and also pre-treatment data in treated villages.[21]

First, seasonality in food-related outcomes appears small, especially compared to seasonality in non-food expenditures and income. We take advantage of the household panel feature by estimating household fixed effect models. We regress household outcomes on a harvest season dummy and household fixed effects. The coefficient on the harvest season dummy tells us how much the harvest season differs from the lean

[20] This is most likely Christmas as a majority of respondents are either Protestant or Catholic.

[21] In this analysis, we only used control villages that had no treatment mis-assignment problem.

season. Weekly food intake is 5.9% higher in the harvest season, and weekly food expenditures are 5,000 Rupiahs lower during the harvest season (the median weekly food expenditure is 27,000 Rupiahs). Food expenditures are naturally lower during the harvest season because prices are lower and households can consume from their harvests. Monthly non-food expenditures are 22% higher during the harvest season and quarterly income is 130,000 Rupiahs higher (the median quarterly income is 700,000 Rupiahs). All the estimates are significant at the 1% level (standard errors are clustered at the household level).

Next, anxieties related to expected food shortages in the future and experiences of food shortages in the past month are themselves seasonal. We asked households whether they anticipate food shortage problems in the next November, January and April. During the harvest season surveys, when households are planning how to allocate their harvest across seasons, more than 33% of households anticipate facing food shortages during the lean season but only 12% anticipate facing food shortages during the harvest season. Moreover, during the harvest season, households are 11% less likely to report lacking food in the previous month. Reported measures of food shortages are also very dynamic. Estimates of transition probabilities suggest that only 43% of households that report lacking food in one period still report lacking food in the next period. By contrast, 93% of households that report receiving Raskin rice in the last period still report receiving Raskin rice in the next period, suggesting that the food subsidy program does not adjust to seasonal food shortages.

To examine the absolute magnitude of seasonal differences, for each household, we calculate the absolute difference between the harvest season and lean season outcomes within each agricultural cycle.[22] We do so for 3 measures of economic well-being: quarterly income, weekly food and monthly non-food expenditures. In all 3 instances, the absolute differences are at least 60% of the median levels. The median absolute differences in quarterly household income, weekly food expenditures and monthly non-food expenditures are 700,000 Rupiahs (median: 700,000 Rupiahs) , 22,000 Rupiahs (median: 27,000 Rupiahs) and 10,000 Rupiahs (median: 17,000 Rupiahs) respectively. While income, food and non-food expenditures vary considerably across seasons, income seasonality is higher than expenditures for more than 90% of households. Overall, there is strong evidence of seasonal patterns in objective and subjective measures of well-being, including income, non-food expenditures and self-reported food shortages but less seasonality in weekly food consumption.

[22] We could not have constructed this measure without a seasonal household panel.

Fourth, we ask households to predict what rice and maize prices would be in the harvest and lean seasons. We find that they expect prices to vary for maize but not so much for rice. The median expected price for maize in April (harvest) is 2500 Rp compared to the median expected price in January (lean), 4000 Rp. For rice, the median expected prices are 6000 Rp and 6500 Rp, respectively.

Finally, we replicated the analysis in Chaudhuri and Paxson (2002) using our seasonal household panel. Using a household panel for 3 villages, they regressed income shares, food and non-food expenditures on month fixed effects, and month fixed effects interacted with an indicator for household types (eg. farm and non-farm households), controlling for household characteristics that are constant in a year. The idea is to compare household types who face different income streams and see whether they have different consumption patterns. They find evidence of differences in income seasonality but no differences in consumption seasonality, suggesting that seasonality in expenditures (food and non-food) does not track income seasonality. They conjecture that other confounders they do not observe, such as seasonal preferences (festival expenditures) or seasonal prices could be driving consumption seasonality.

We estimate a similar equation, comparing maize and rice farmers who face different income streams due to the timing of the harvest seasons. Table 1 reports the results. Column 1 controls for village fixed effects, columns 2 to 3 control for household fixed effects and column 3 further controls for expected seasonal maize prices. All columns also control for year fixed effects.[23] The first 3 columns include all villages and the next 3 columns include control and pre-treatment villages only.

Our results on non-food expenditures are similar to Chaudhuri and Paxson (2002) but unlike them, we find seasonality in food related outcomes. Furthermore, proxies for confounders such as festival expenditures or expectations of seasonal maize prices cannot explain seasonality in food related outcomes. Panel A shows that maize and rice farmers have different seasonal income patterns. Panels B and C show that maize and rice farmers have different seasonal food consumption and expenditure patterns, but Panels D and E show that they have no differences in seasonality of non-food expenditures and festival expenditures. These effects are robust to controlling for expectations of seasonal prices (columns 3 and 6).

To motivate the importance of seasonal household panels as opposed to seasonal village panels, we compared the within household and within village time series vari-

[23] The years refer to agricultural years (beginning in the planting season and ending in the harvest season). This year fixed effect absorbs omitted factors correlated with harvest shocks.

ation in each. Using our household panel, we observe 6 estimates of quarterly income for each household. We can calculate the standard deviation in income for each household. This gives us a distribution of 2,877 standard deviations, a statistic that measures the amount of within household variation in income. The median of this statistic is 1,012,000 Rp. We then aggregated across households to construct a village panel that tracks median income in the village across the 6 survey rounds. The corresponding median standard deviation is only 425,000 Rupiah (42%). Therefore, village panels that aggregate across households mask rich within household variation.

6 Empirics

Our main specification is an instrumental variable, cross-sectional regression that compares treatment and control villages using post treatment data. We only compare credit or storage to control groups but do not compare credit with storage. As shown in the model, their effects on the budget constraints are different, making them harder to compare.

$$y_{ivd} = \delta_0 + \delta_1 TAKEUP_{ivd} + \theta_d + \varepsilon_{ivd} \tag{2}$$

where y_{ivd} is the outcome for household i, in village v in district d. We use the treatment assignments ($TREAT_{vd}$) to instrument for a dummy that is 1 if household i participated in the programs ($TAKEUP_{ivd}$). All specifications control for district fixed effects, θ_d, since treatment was assigned randomly across villages within each district.[24]

To address the issue of having many outcomes, we follow (Kling et al., 2007) and use mean effects analysis. We constructed a summary index for each category of outcomes. That is, for each category with $Y_1, ..., Y_K$ outcomes, we calculated the standardized outcomes, $y_1, ..., y_K$, by subtracting the outcome by the mean in the control group in period 1 and dividing by the standard deviation in the control group in period 1.

[24]We report reduced form OLS regressions of outcomes on treatment assignment in Appendix A. In Appendix B, we repeat IV regressions but control for the dependent variable in the baseline (round 1). This specification controls for any pre-period differences that arise due to sampling error. Most results were robust to adding round 1 controls (we will note if otherwise). We also tried estimating specifications with household fixed effects and testing for differences between treatment and control groups. The results were very noisy, possibly because panel data exacerbates the measurement error problem. Since treatment was randomly assigned at the village level, the household fixed effect specification that uses within household variation also loses much of the useful, between village variation.

Then, we totaled the standardized outcomes for all k standardized outcomes.

To avoid inconsistencies due to one NGO's mis-assignment of villages to treatment groups, we report all intent-to-treat and instrumental variable results using 2 samples.[25] The first sample includes all 4 districts managed by both NGO's, including villages where assigned treatment was not the same as actual treatment. We also tried dropping the 9 villages where assigned treatment was not the same as the implemented treatment and the results were similar. The second sample includes only the two districts (48 villages) managed by Alfa Omega where there was no mis-assignment of treatment.

How the results are reported

We have 5 categories of outcomes. Our main outcomes relate to seasonality and food shortage issues: seasonal differences (Panel A) and anticipated and reported shortages in food (Panel B). Under the standard utility functions such as CRRA, Cobb-Douglas and log utility, we expect the treatments to reduce these outcomes but the effect is ambiguous for more general utility functions, depending on the size of the substitution and income effects. If we think the utility function is sufficiently concave, we expect lower seasonal gaps to be associated with an improvement in welfare.[26] We also added 3 categories of outcomes that are commonly used in the literature on food policy as proxies for well-being: health (Panel C), economic well-being (Panel D) and food consumption and expenditures (Panel E).

It is also worth noting that the results using the 2 samples are quite different. In most specifications, we found stronger treatment effects using Alfa Omega districts only compared to estimates using the sample with both NGO's. To our knowledge, Alfa Omega experienced less of the implementation issues (such as harvest failures during floods, late delivery of storage equipment) that could bias against finding treatment effects. For completeness, we report and discuss estimates from both samples.

We report regressions that pool all post treatment data (rounds 2 to 6 for the Credit treatment and rounds 3 to 6 for the Storage treatment), or all post treatment data in lean seasons, or all post treatment data in harvest seasons.[27] As shown in the model, some treatment effects are expected for all seasons, and some treatment effects are expected for lean or harvest seasons only. To avoid reporting multiple estimates for each de-

[25] Based on our investigation, we believe the mis-assignment error is orthogonal to unobserved village characteristics. The treatment assignment was updated in the process of assigning treatments but one NGO appeared to have used the older version of the treatment assignment. Results using both samples are similar, suggesting that the misassignment error is not driving our results.

[26] We are careful not to make unambiguous welfare statements without estimating preferences.

[27] We also looked at treatment effects by rounds but this reduced the power significantly.

pendent variable, when we discuss the results in the text, we report the coefficient for all seasons when the treatment effects are robust across both harvest and lean seasons. We report the coefficient for lean or harvest seasons only, otherwise. In the next two sections, we report results for the credit treatment (Section 7) and the storage treatment (Section 8).

7 Results for Credit

7.1 Check random assignment

Table C1 reports the OLS regression results using the first survey round. All regressions include district fixed effects. Each cell in the table reports the coefficient on the *CREDIT* dummy for one regression. With random assignment, we expect the treatment and control villages to be similar on average, pre-treatment. The outcomes are organized into 5 panels: household characteristics (including education, age, ownership of durables and livestock), subjective measures of food shortages, health, economic well-being (including income, annual and monthly per capita expenditure), and food (consumption and expenditures), agricultural production and storage.

Using all districts (Column 1), we see that 6 of the 34 coefficients are statistically significant but are opposite sign from our results, so, these pre-characteristics tend to bias us against our findings. Households in villages randomly assigned the credit treatment are more likely to anticipate food shortages, report more days sick, have lower food consumption and consume and store less maize as a share of staples. Only anticipated food shortage in November is significant at the 5% level, the other coefficients are either insignificant or significant at the 10% level.

Using Alfa Omega districts only (Column 2), more coefficients are significant than using all districts, but the differences also bias against our results. Household heads in villages offered the credit treatment are less likely to have graduated primary school. Annual non-food PCE is 17% higher (10% sig.) and food expenditures are 23% more likely to be zero in the past week (1% sig.). However, our main results are robust to adding pre-treatment controls, suggesting that these pre-treatment differences cannot explain our findings (See Appendix B). If anything, controlling for pre-treatment differences strengthens our results but to be conservative, we only report estimates without these controls.

7.2 Take-up

The Credit take-up rate is 40% using all four districts and 47% for Alfa Omega districts only. The results from the first stage regression are reported in Appendix A. Correspondingly, the instrumental variable estimates are about twice the magnitude of the OLS estimates.

A low take up rate is not necessarily bad from a cost perspective. The main food security program in Indonesia, Raskin, is a subsidized rice program that is extremely costly because leakage is high. In our data, more than 90% of the households report having received Raskin rice. This seems to be too high given our data on food consumption. We calculated that as many as 40% of households consumed enough calories (just from staples) to meet their daily energy requirements as defined by the FAO, significantly lower than the share of households receiving Raskin rice.

7.3 Treatment effects by outcome categories

Objective measures of seasonal differences, $|Harvest - Lean|$

Panel A reports the seasonal gap in outcomes, calculated as absolute differences across seasons within each cycle ($|Harvest - Lean|$). The first row of Panel A reports the results using the summary index as a dependent variable. We calculated the seasonal gap in log of food consumption in the past week, food expenditure in the past week,[28] log of income in the past 3 months and log of monthly non-food per capita expenditures.[29]

Our main result suggests that the credit treatment reduced the seasonal gap, especially in Alfa Omega villages. Table C2 shows that the seasonal gap index is lower in credit villages by 0.28 units (not sig.) in all districts and by 0.67 units (5% sig.) in Alfa Omega districts, in spite of measurement error issues.[30]

[28]We did not use logs for weekly food expenditures to avoid censoring problems because 35% of weekly food expenditures was 0.

[29]Monthly expenditures include rent, household items (soap, phonecards), health expenditures and health insurance. Monthly expenditures make up 65% of total non-food expenditures. Annual expenditures include annualized monthly expenditures, education, taxes, purchase of durables and also expenditures on seasonal festivities.

[30]There are two sources of errors that would bias the estimates toward 0. First, we expect absolute differences in these outcomes to exacerbate attenuation bias. Secondly, the harvest surveys were delayed due to budget delays that were not related to field activities. The harvest season begins in April and ends by June but the first two harvest season surveys were only conducted between July and August. Therefore, some recall measures such as consumption in the past week would be an imperfect measure of consumption in the harvest season due to the delay.

The effect is strongest for weekly food expenditures for Alfa Omega districts (Table C2). The credit treatment reduced the seasonal gap in weekly food expenditures by 21,000 Rupiahs (5% sig.). The effects are also economically significant. In the baseline (round 1), the average weekly food expenditures is 37,000 Rupiahs (including 0 food expenditures) and 52,000 Rupiahs (conditional on positive food expenditures). These effects operate through the extensive margin of food expenditures. This alone does not lend itself to a direct welfare interpretation. However, note that the likelihood of households reporting zero food expenditures goes up in *both* seasons (Panel E) even though there are no significant changes to food consumption. Taken together, this points to the efficacy of credit in aiding a transfer of resources across seasons.

Finally, the coefficients on quarterly income and monthly non-food expenditure are also negative.

Anticipated and reported shortages in food

Panel B reports results for anticipated food shortage issues in January, November (lean seasons) and April (harvest for maize farmers, lean season for rice farmers) and also reported experiences of food shortages (1 if the households lacked food in the previous month).

Credit participants in all districts report a reduction of 0.83 units (not sig.) in the subjective food shortage index using harvest season surveys and credit participants in Alfa Omega districts report a reduction of 1.29 units (5% sig.). These anticipatory effects are strongest during the harvest season surveys because this is is exactly when the credit participants are making plans about how to allocate harvest (net of credit repayment) across the seasons. Credit participants are also less likely to anticipate food shortages in the harvest season (April), even though this is when repayment is typically due.

Health

Panel C reports results for health outcomes. We have three health outcomes: (i) an indicator for whether the household head reported any sickness, (ii) the number of days the household head could not work due to sickness (includes 0's if there were no days affected) and (iii) an indicator for whether the household faced any shortages in expenditures for health.

Health-related outcomes deteriorate during the harvest season, when repayment is due, and improves during the lean season, when credit is being disbursed. Credit participants in all districts report a reduction of 0.90 unit (5% sig.) in the health index using harvest season surveys and an improvement in health of 1.48 units (10% sig.) in the lean season.

Using all districts (columns 1-3), household heads in credit villages are 10% (1% sig.) more likely to report health expenditure shortages in the previous month and 17% (1% sig.) more likely to report some sickness during the harvest season compared to 10% (not sig.) less in the lean season . However, they also report 15 fewer sick days during the lean season (5% sig.) compared to 3 more sick days in the harvest season (not sig.).

Economic well-being

Panel D reports outcomes related to economic well-being: log of income in the past 3 months, log of annual non-food per capita expenditure, an indicator that is 1 if the household head reported any employment status in the past week.[31]

Credit participants in all districts report an improvement of 1.04 unit (1% sig.) in the household well-being index in all seasons. A 1.04 standard deviation improvement in household well-being is quite large. The results are significant for all, lean and harvest season surveys but are strongest for the lean season surveys. Most of the effects are due to income and reported employment. Income in credit villages are 69% higher (10% sig.) during the harvest season. Using data on the sources of income, we find that most of the increase in income is due to sale of harvest, rather than wages, remittances or gifts. Reported employment is higher by 16% in the lean season (5% sig.). We do not find any treatment effects on per capita expenditure.

Food consumption and expenditures

Panel E only reports estimates on the major food related measures: log of total staple food consumption last week (rice plus maize consumption),[32] log of total staple food expenditure*s* last week, an indicator that is 1 if food expenditures in the past week was 0, expenditures per unit of consumption (ratio of food expenditure last week in thousands of Rupiahs to food consumption last week),[33] share of staple consumption that is maize (calculated as maize consumption divided by maize+rice consumption).

[31]The question in the survey was "What was your employment status in the previous week? Choose self-employed, self-employed with employees, wage workers." We caution that this is not an exact measure of labor force participation and employment. We could not include a full module on employment as the annual Indonesian household survey has.

[32]Due to the nature of recall data, we only asked how much households consumed in the previous week. Since lean season surveys were conducted in December, and some credit disbursements were made in January, some of these households may not have received their disbursements yet. This timing could be one reason why there is no effect on food consumption.

[33]The unit for food consumption was kilogram. This ratio measures the thousands of Rupiahs spent per kilogram of food consumed.

There is no significant treatment effect on the food index, for all districts or Alfa Omega districts (Table C2). There is a higher incidence of 0 food expenditures in all seasons for Alfa Omega districts with no effect on consumption, leading to a reduction in rupiahs spent per unit of food consumption.

7.4 Mechanisms

We examine two mechanisms that could explain the effects above.

Credit propensity

First, we show that the effects on seasonal differences (Panel A), health (Panel C), and income (Panel D) are related to the propensity to have credit (Table C3). We calculate the average amount of debt a household had in the past 6 months divided by the average income (both debt and income are averaged across rounds 1 and 2). *High credit* households are households whose debt-to-income ratio are strictly above the median debt-to-income.[34]

High credit households in Alfa Omega districts report a 1.10 unit (1% sig.) reduction in the seasonal gap index compared to a reduction of 0.55 units (10% sig.) for low credit households. While both types of households experience a reduction in the seasonal gap, not surprisingly, it is households with a higher propensity to use credit in the baseline who are able to use credit to reduce seasonal differences. This differential impact is robust to controlling for proxies of wealth such as assets (livestock, motorcycle) and quarterly income.

Both types of households report higher quarterly income but high credit households report between 32% to 55% higher income (mostly from sales of harvest) than low credit households. These could be households who have high returns to capital. With the credit program, they do not have to save their harvest for consumption in the lean season anymore. Instead, they can use the sales revenue for other investments. This could explain why income is higher for these households in all seasons but income is only higher for low credit households during the harvest season.

The perverse effects on health in the harvest season also appears to be related to

[34]Debt-to-income is commonly used to measure credit exposure. High debt-to-income households could be households who have access to credit (eg. entrepreneurs) or poor households who are debt-laden. Only 20% of households report positive debt-to-income and debt-to-income does not seem prohibitively high for these households (the median debt-to-income for households with positive debt is only 12%). Using data from control villages and village fixed effect regressions, we find that high credit households within a village have higher per capita expenditures, quarterly income and weekly food consumption. We conclude that these high credit households are more likely to be entrepreneurs.

credit exposure. High debt-to-income households in Alfa Omega districts are more likely to report some sickness and report shortages in health expenditures, but only during the harvest season. This is consistent with the theory that credit could lead to worse effects on reported health in the harvest season due to the burden of having to repay during the harvest season. The differential impact on the health of high credit households only operates in the harvest season because this burden is more pronounced during the harvest season and for households with higher debt-to-income ratios. In the lean season, when health improves, high credit households do not report better health outcomes than low credit households. There is no differential treatment effect on high credit households for subjective shortages (Panel B).

Harvest risk

We also find that the effects on seasonal gap (Panel A) and subjective shortages (Panel B) are related to differences in harvest risk (Table C4). We compared maize farmers (high harvest risk) to rice farmers (low harvest risk).

As discussed in the model, the treatment effects on seasonal differences would be weaker for credit participants facing more harvest risk because they may borrow less. Indeed, we find that rice farmers report a 0.80 unit (1% sig.) reduction in the seasonal gap index but maize farmers report a smaller reduction (0.11 unit, 1% sig.).

The effect on subjective measures of food shortage also shows that the treatment effect on lean season consumption is larger if the harvest risk is smaller. Accordingly, rice farmers in all districts report a reduction of 1.08 unit (5% sig.) of the subjective shortage index in the harvest season but maize farmers only report a reduction of 0.09 units (10% sig.). These differential impacts appear to be due to differences in harvest risks, and not differences in wealth. In the baseline survey, maize farmers do not report higher quarterly income, more livestock nor motorcycles than rice farmers.

It is surprising that maize farmers in all districts are 10.3% *more* likely to report lacking food in the previous month during harvest season surveys (1% sig.). However, maize farmers in Alfa Omega districts are 4.4% *less* likely to report lacking food in the previous month using harvest season surveys (1% sig.), indicating that the 10.3% effect is more likely due to the other two districts where maize farmers experienced harvest failures. There is no differential treatment effect on maize versus rice farmers for other categories of outcomes.

8 Results for Storage

8.1 Check random assignment

Table S1 reports the regression results using the first survey round. Using all districts (Column 1), we find that 5 of the 34 coefficients are significant. Households in villages randomly assigned the storage treatment own 0.54 more motorcycles (5% sig.), report 3 more sick days (1% sig.), are 2.8% less likely to be employed (5% sig.), consume 9.8% less food in the past week (5% sig.) and consume less maize (5% sig.). These results are opposite sign than our findings, so, bias us against our results.

Using Alfa Omega districts only (Column 2), households in storage villages are less likely to have completed primary school (5% sig.) are more likely to report zero food expenditures in the past week (5% sig.), produce 91kg more rice (10% sig.). All our results are robust to adding pre-treatment controls (see Appendix B).

8.2 Take up

The storage take-up rate is 42% for all districts and 49% for Alfa Omega districts. We report these results in Appendix A (Table S1.A).

8.3 Treatment effects by outcome categories

As discussed in Section 3, the storage equipment only arrived in round 3. Therefore, we only report results using 3 post-treatment rounds (rounds 4 to 6) here. We present results for regressions using all post-treatment rounds in Appendix C. Table S2 reports overall IV results for the storage treatment and Table S3 reports the results for high versus low storage households. We first calculate the average amount of maize and rice produced and stored (averaged over rounds 1 and 2), and calculate storage propensity as (average rice stored + average maize stored)/(average rice produced + average maize produced). High storage households are households with above-median storage propensity. As discussed in Section 2, we expect stronger treatment effects for households who save in-kind.

Seasonal gap

We did not find treatment effects on the seasonal gap index, but the gap in seasonal food expenditures did fall by 20,000 Rupiahs (5% sig.) for Alfa Omega districts. This could be because we only had 1 observation of seasonal gap, $|Round4 - Round5|$.

Anticipated and reported shortages in food

All households report a reduction in the subjective food shortage index by 1.33 units (10% sig.) and high storage households report a reduction in the subjective food shortage index by 2.11 units (1% sig.) in the lean season. Unlike the credit treatment, these effects on subjective shortages are stronger in the lean season for storage because households have to wait till the lean season to observe benefits from the storage equipment. Moreover, for high storage households, we find a statistically significant reduction in each component of the subjective shortage index: anticipation of food shortages in January, April and November as well as likelihood to report lacking food in the previous month. These effects are statistically and economically more significant than the effects for the credit treatment.

Health

There is a slight deterioration of health outcomes in the harvest season for Alfa Omega villages. Households are 6.5% more likely to report health expenditure shortages in the harvest season (10% sig.). High storage households in Alfa Omega districts are 8% less likely to report health expenditure shortages in the lean season (10% sig.) and high storage households in Alfa Omega report 1.3 fewer sick days (5% sig.) in the lean season.

Economic well-being

High and low storage households in all districts report higher economic well-being in the harvest season (0.97 unit for all households, significant at 5%). These effects appear to be driven by higher annual non-food expenditure for storage participants. The results are similar for Alfa Omega districts. For the credit treatment, economic well-being also increased about the same magnitude, but the effects were mostly driven by higher quarterly income and reported employment and there was no effect on non-food expenditure.

Food consumption and expenditures

We do not find treatment effects for the food index.

8.4 Mechanisms

Reduction in social gifts

The need to contribute to neighbors' festival expenditures could be a source of savings constraint. Storage participants could circumvent this savings 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 their neighbors' festivities. We find that storage participants report an 10.2% reduction in this share for all districts (not sig.) and a 25.1% reduction in Alfa Omega districts (1% sig.).

Harvest risk

Table S4 shows that maize and rice farmers have differential treatment effects for seasonal differences (Panel A), subjective shortages (Panel B) and economic well-being (Panel D). The seasonal gap is 0.76 units lower for rice farmers in Alfa Omega districts (5% sig.) but the effect is small and only slightly negative for maize farmers. For all districts, the gap is 0.87 units *larger* for maize farmers (1% sig.). This larger gap is due to increases in food expenditure gaps and income gaps. The fact that it is only larger for maize farmers in all districts but not for maize farmers in Alfa Omega districts suggest that the increase in the seasonal differences could be due to differences between the implementation by the two NGO's. Differences in harvest risk also affect subjective shortages (Panel B) and economic well-being (Panel D), for the same reasons as the credit treatment. Rice farmers report a reduction in anticipated food shortages by 1.11 to 2.46 units but maize farmers only report a small reduction. The economic well-being index increases between 1.43 to 1.61 units for rice farmers but the effects are smaller for maize farmers.

9 Discussion of results

Tables C5 and S5 summarize the key results. We can be confident that the significant coefficients are not driven by hitches in implementation. As noted above, our results are not sensitive to the inclusion or exclusion of mis-assigned villages. Also, since we stratified by district while assigning treatments and control, harvest failures do not bias results. Our findings are broadly consistent with the predictions of the model, but warrant further scrutiny.

The most notable non-result is consumption of maize and rice. While this is interesting, it is not implausible for a combination of two reasons. First, the data on consumption recall are noisy and subject to measurement error. Second, it is possible that marginal utilities associated with the consumption of staples diminish more rapidly than marginial 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.

It is also noteworthy that credit participants do not report increases in non-food per-capita expenditure. Storage, if adopted, raises the size of the pie to be split across the year. This is not necessarily the case with credit. Finally, while we would expect stronger results for maize than rice (given that storage problems are more acute for maize), we observe the opposite pattern. This is possibly attributable to widespread harvest failures in maize-producing regions. With little maize available at harvest, storage improvements are unlikely to have an impact. Also, the fact that rice farmers also report a benefit from storage drums suggest that the benefit may not just be an improvement in the physical storage technology, but perhaps also a lower pressure to spend on neighbor's festivities. Similarly, harvest failures generate additional repayment pressures on maize-producing households, which could counteract the potential lean-season benefits of credit.

10 Cost benefit analysis

10.1 Credit

To measure the cost effectiveness of the credit program, we follow a standard approach that allows us to benchmark our program against other food policies.[35] We calculate the numerator of the benefits-to-program cost ratio as the cost savings (to the household), of consuming 1kg of maize in the lean season. The cost savings are the difference in cost that the household has to pay under the credit program versus a counterfactual (saving from the previous harvest[36]). Under the credit program, this cost is 2763 Rupiah.[37]

The counterfactual cost depends on the physical loss rates. The table below shows that at a 30% loss rate, the counterfactual cost is 3571 Rp.[38] At a 40% loss rate, it is more profitable to save in cash and buy maize in the lean season, so the coun-

[35]Another method would treat part of the program cost as transfers that are valued by the participants. The cost to the program, then, would be the deadweight cost from raising funds.

[36]Another counterfactual could involve informal credit. Anecdotal evidence suggests that interest rates from these forms of credit are high. Using this counterfactual would increase the cost savings due to our credit program.

[37]Borrowing 1 kg of maize in December must be repaid with interest (10.5% over four months) in the harvest season. At a harvest season price of 2,500 Rupiahs/kg, the repayment amount is valued at 2,763 Rupiah. This is the median expected price reported in Section 4.

[38]At a 30% loss rate, a household needs to store 1.43 kg of maize during harvest, which costs 1.43 kg * 2500 Rupiahs/kg = 3571 Rp in foregone revenue from sales.

terfactual cost is 4000 Rp.[39] Therefore, the cost savings are 808 Rp and 1237 Rp respectively.[40] The last row of the table takes into account the time value of money in that the credit program delays the cost (repayment is 4 months *after* December) and the counterfactual requires foregoing revenue in the previous harvest (8 months *before* December). We follow the literature and assume an annual discount rate of 10%.

In-kind depreciation rates		Notes	30%	40%
Maize needed in previous harvest to deliver 1kg in December	[1]	$\frac{1kg}{(1-loss)}$	1.43 kg	1.67 kg
Counterfactual cost	[2]	$min([1]*2500Rp/kg, 4000Rp)$	3571 Rp	4000 Rp
Cost to deliver 1kg under credit program	[3]	$2500Rp*1.105$	2763 Rp	2763 Rp
Cost savings	[4]	$[2]-[3]$	808 Rp	1,237 Rp
Cost savings (time value of money, 10% discount rate):	[5]		1,316 Rp	1,371 Rp

We calculate the denominator of the benefits-to-program cost ratio in 3 ways. Our first estimate is 3979 Rp, an average over 3 years.[41] Our second estimate is 1013 Rp, assuming the program lasts forever.[42] Our third estimate assumes the program lasted 5 or 10 years, so that the program cost is amortized (using a 10% discount rate). The annual program costs are 3149 Rp and 1943 Rp respectively. The table below summarizes the cost benefit analysis.

[39] With cash, the proceeds from selling 1 kg of maize in the harvest season (2500 Rupiahs) would buy 0.63 kg of maize in the lean season (at 4000 Rupiahs per kg). This represents an expected depreciation rate of 38% (less than the physical loss rates of 40%). Therefore, the counterfactual cost is just the price of maize in the lean season.

[40] Calculated as 3571 Rp - 2763 Rp = 808 Rp (at 30% loss rates) and 4000 Rp-2763 Rp=1237 Rp (at 40% loss rates).

[41] Over three years, the total cost of the program was 2.5 billion Rupiahs. This includes the cost of procuring and delivering the food and the cost to facilitate the program. Since a credit village typically represented 1/3 of the responsibility of each facilitator, we calculate the facilitation cost of credit by dividing the total facilitator cost by 3. This way, the facilitator cost for credit was 646,511,605 Rp over 3 years or 215,503,868 Rp per year. A total of 638,391 kg of food was delivered. 3979 Rp is calculated as 2.5 billion Rp/638391kg.

[42] This assumes that all the "fixed cost" is amortized away because the credit cycles are repeated. There is no need to procure food for the subsequent years. The only cost would be the facilitator's cost (215,503,868 Rp). In principle, part or all of the facilitator cost could also decrease over time, as the community members take over more of the responsibilities, but we wanted to be conservative. 1013 Rp is calculated as 215,503,868 Rp divided by 212,797 kg of food delivered per year.

	No discount rates		With discount rates	
	30%	40%	30%	40%
3 years (no amortization)	20%	35%	29%	45%
5 years	26%	45%	36%	57%
10 years	42%	72%	59%	92%
Forever	80%	139%	113%	176%

Our benefits-to-program cost ratio ranges from 20% to 176% depending on the assumptions above. As a benchmark, Tabor (2005) estimates that the transfer benefit per unit cost for Raskin is 61% for all beneficiaries and 52% for targeted beneficiaries. The second number assumes a leakage rate of 16% (a well-known problem of food subsidies is that not all transfers benefit eligible households). The 52% estimate could be an over-estimate (The World Bank (2005) estimates that only 18% of the Raskin budget translates into a subsidy for poor households).

There are a couple of caveats to this analysis. First, the cost of credit to the household is uncertain (if there was a harvest failure, the unpaid interest would accrue over time) whereas the subsidized price the household has to pay in Raskin is roughly constant. Adjusted for risk, the cost to the household from credit could be higher. However, we argue that this added risk does not constitute a high cost because most participants were allowed to stay in the program as long as there was no evidence of strategic default. Also, there could be general equilibrium effects. With a scale-up, prices in the lean season could fall. This reduces the cost to operate the program since a large part of the cost is incurred in the lean season but it also reduces the cost savings from credit. On net, the impact on the cost-effectiveness is unclear.

10.2 Storage

For the storage program, we calculate the returns to investment on storage drums. Consider a household that saves a portion of the harvest in April for consumption in December. This can be done with or without drums. If they stored their maize in drums, the value of the stored maize would be 648,000 Rp in December.[43] With drums, the participant invests 250,000 Rupiahs to purchase a drum to store 180 kg of maize. There

[43] Assuming a depreciation rate of 10%, in December, the value of the stored maize would be 648,000 Rp (Calculated as 180 kg * 4000 Rp/kg * (1-0.1)). Anecdotal evidence from participants suggest that the depreciation rates with storage drums were less than 10%.

is also an opportunity cost of this equity of 16,667 Rp.[44]

Without drums, the household could store in cash or in-kind. Assuming in-kind depreciation rates of 30%, the value of the maize stored in-kind in December would be 504,000 Rp.[45] Therefore, the "profit" from storing maize in drums would be 127,333 Rp.[46] This represents 51% returns to investment.

As above, this analysis ignores general equilibrium effects. As the program scales up, more households would store in maize, expanding the supply in the lean season, and in turn dampening the lean season price. This will lower, but not eliminate, relative benefits from storage (drums will still raise physical retention, but at a lower lean season Rupiah value).

11 Conclusion

In this paper, we analyze seasonal food consumption and expenditure patterns in West Timor. We develop a model that shows that food shortages in the lean season in Timor cannot be explained by pure borrowing constraints. Our model shows that access to credit and savings both narrow the gap of inter-seasonal marginal utilities.

We utilize a unique seasonal household panel to study seasonal patterns and to credibly evaluate the cost-effectiveness of two food programs that adjust according to seasons. Our paper contributes to the literature on food policy and also the literature on consumption and income seasonality. On the latter, we validate the findings of Chaudhuri and Paxson (2002), that seasonality of consumption in non-food expenditures does not appear to track seasonality of income. However, our household fixed effect regression shows that maize and rice farmers who face different income streams appear to have different seasonal patterns for food consumption and expenditure. Our findings cannot be explained by expected differences in seasonal prices or differences in seasonal festivities.

Under credit, participants report a reduction in both seasonal consumption gaps and food shortage, increases in economic well-being, and health improvements when credit is disbursed but deterioration when repayments are due. Under storage, households with a high propensity to save report a reduction in food shortages and an increase in

[44] We assume a return to equity of 10%, leading to an opportunity cost of 16,667 Rupiahs for the investment of 250,000 Rp to buy the drums.

[45] Calculated as 180kg*(1-loss rate)*4000 Rp/kg.

[46] Calculated as 648,000 Rp - 16,667 Rp - 504,000 Rp.

economic well-being.

In the future, we plan to combine time preference data with these program effects as we expect treatment effects would be heterogeneous depending on time preferences, as alluded to in the theoretical framework. There is an inherent problem with measurements of time preferences that rely solely on tradeoffs over money. We have measured preferences using both money (actual payouts) and perishable consumption goods (hypothetical). By comparing responses to both types of questions, we hope to disentangle true time inconsistency from other factors such as credit constraints and social pressures, and understand how each type of agent responds to our food security programs.

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Figure 1: Timeline of surveys and treatment by year and month

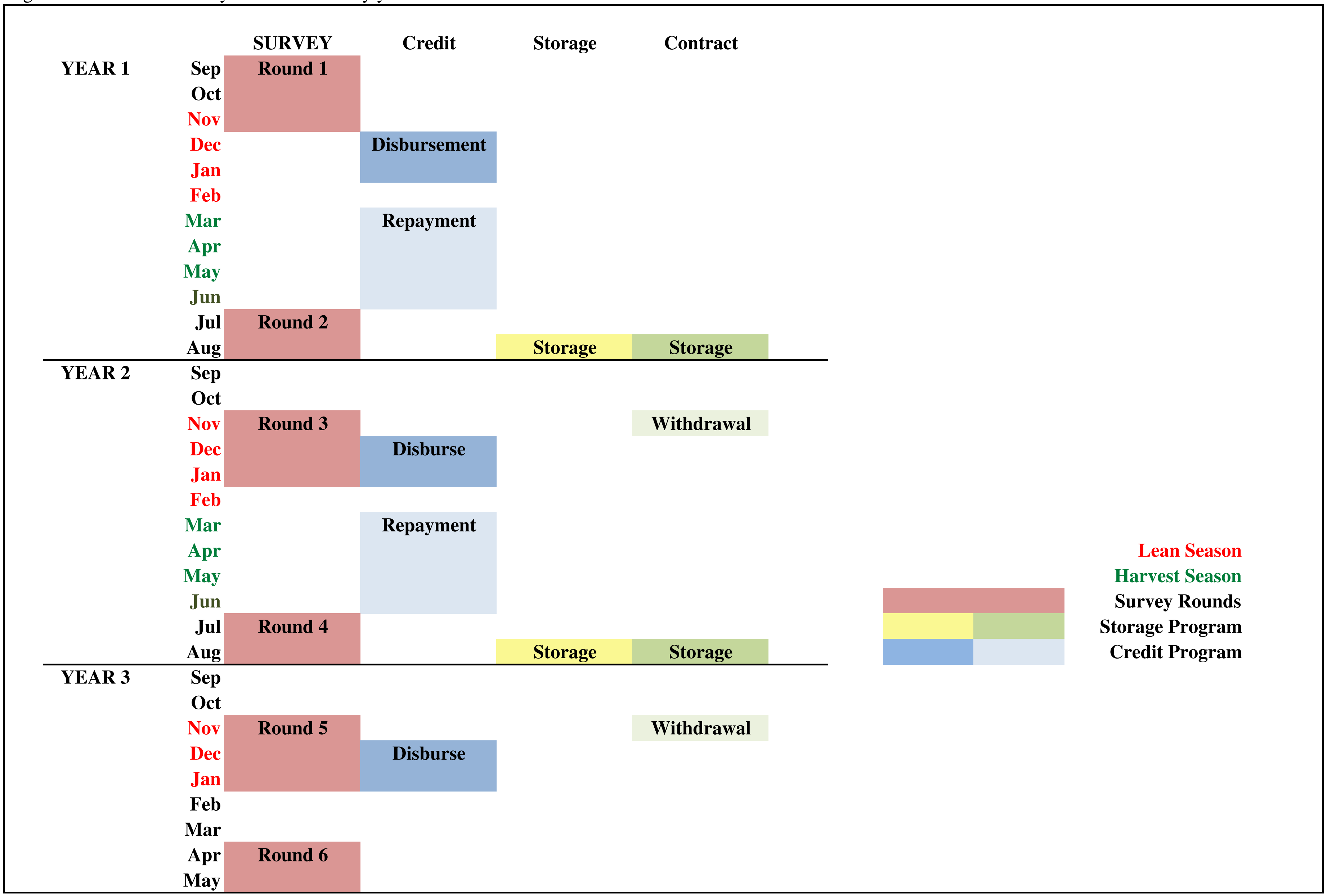

Table 1: Income and Consumption Seasonality Regressions

	All Villages			Controls Only		
	[1]	[2]	[3]	[4]	[5]	[6]
Panel A: ln(Income in the Past Quarter)						
Harvest	0.1762***	0.1568***	0.1842***	0.2608***	0.2791***	0.2112***
	(0.0277)	(0.0327)	(0.0370)	(0.0425)	(0.0611)	(0.0689)
Harvest*Maize Farmers	-0.2012***	-0.1781***	-0.1510***	-0.3170***	-0.3565***	-0.3130***
	(0.0330)	(0.0423)	(0.0421)	(0.0483)	(0.0800)	(0.0787)
ln(Expected Maize Price in a Season)			0.0955***			-0.0429
			(0.0337)			(0.0686)
N	15794	15794	15214	7871	7871	7546
R-squared	0.1013	0.2982	0.3096	0.1027	0.3588	0.3691
Panel B: ln(Food Consumption in the Past Week)						
Harvest	0.0439***	0.0044	-0.0114	-0.0167	-0.0502**	-0.0438
	(0.0149)	(0.0159)	(0.0208)	(0.0193)	(0.0251)	(0.0313)
Harvest*Maize Farmers	0.1084***	0.1631***	0.1737***	0.1225***	0.1707***	0.1974***
	(0.0203)	(0.0252)	(0.0254)	(0.0231)	(0.0318)	(0.0324)
ln(Expected Maize Price in a Season)			-0.0067			0.0620**
			(0.0251)			(0.0311)
N	16317	16317	15695	8347	8347	7976
R-squared	0.1343	0.2896	0.298	0.1777	0.4797	0.4798
Panel C: Food Expenditures in the Past Week (000's)						
Harvest	-8.5448***	-6.8078***	-7.6580***	-13.7481***	-11.9752***	-11.9681***
	(0.7867)	(0.9143)	(1.0833)	(1.1255)	(1.5547)	(1.8659)
Harvest*Maize Farmers	8.0693***	5.3682***	4.8818***	11.2286***	8.4774***	7.3622***
	(0.9734)	(1.1713)	(1.2469)	(1.3027)	(1.9014)	(1.9780)
ln(Expected Maize Price in a Season)			0.4477			-0.3965
			(1.0138)			(1.8046)
N	17262	17262	16047	8622	8622	8124
R-squared	0.1342	0.3228	0.3406	0.1519	0.4523	0.4615
Panel D: ln(Monthly Non-food Expenditures)						
Harvest	0.3050***	0.2602***	0.2643***	0.2012***	0.1481***	0.1269***
	(0.0172)	(0.0188)	(0.0217)	(0.0247)	(0.0309)	(0.0372)
Harvest*Maize Farmers	-0.0346	0.0345	0.0379	-0.0530*	0.0281	0.0342
	(0.0216)	(0.0231)	(0.0239)	(0.0302)	(0.0382)	(0.0401)
ln(Expected Maize Price in a Season)			0.015			-0.0231
			(0.0204)			(0.0380)
N	15609	15609	15025	7786	7786	7444
R-squared	0.2465	0.5207	0.5259	0.2007	0.6024	0.6007
Panel E: ln(Festival Expenditures)						
Harvest	-0.2646***	-0.2952***	-0.2882***	-0.1727***	-0.2074***	-0.2239**
	(0.0365)	(0.0486)	(0.0569)	(0.0500)	(0.0777)	(0.0963)
Harvest*Maize Farmers	-0.0761*	-0.0476	-0.0439	-0.1270**	-0.1215	-0.1093
	(0.0439)	(0.0624)	(0.0646)	(0.0591)	(0.1005)	(0.1050)
ln(Expected Maize Price in a Season)			0.0208			0.0086
			(0.0541)			(0.1073)
N	10840	10840	10448	6156	6156	5886
R-squared	0.0966	0.3578	0.3649	0.1175	0.53	0.5266
Year	Y	Y	Y	Y	Y	Y
Village	Y	N	N	Y	N	N
Household	N	Y	Y	N	Y	Y
Expected Maize Price	N	N	Y	N	N	Y

* p<0.10, ** p<0.05, *** p<0.01

All regressions are at the household-round level using surveys from round 1 to round 6. Coumns 1 to 3 include all villages and columns 4 to 6 only include control villages or storage villages before round 3 (pre-treatment). All regressions are of the form $y_{it} = \alpha + \beta H_t + \Upsilon H_t * Maize_i + FE + \varepsilon_{it}$, where y_{it} is outcome for household *i* in time *t*, H_t is an indicator for year *t*, $Maize_i$ is an indicator for maize farmers. The fixed effects are indicated in the table. Maize farmers are defined as farmers who produced more maize than rice (calculated using yields averaged from the first and second rounds of the survey).

Table C1: Testing random assignment (Credit treatment)

Sample	All Districts		Alfa Omega Districts	
	(1)		(2)	
Panel A: Household characteristics				
1(Graduated primary school)	-0.0091	(0.0307)	-0.0777*	(0.0379)
1(Graduated lower secondary school)	-0.0029	(0.0283)	-0.0008	(0.0407)
Age	-2.7425	(1.9284)	-2.0246	(2.6008)
Number of chickens owned	-0.1052	(0.3596)	-0.0187	(0.4894)
Number of cows owned	0.2431	(0.3271)	0.0218	(0.4719)
Number of pigs owned	0.0183	(0.1351)	-0.0403	(0.1591)
Number of motorcycles owned	0.335	(0.2050)	-0.0947	(0.2217)
Panel B: Anticipated and Reported Measures of Food Shortages				
1(Anticipate food shortage in January)	0.0951*	(0.0513)	0.0483	(0.0631)
1(Anticipate food shortage in April)	0.0894	(0.0535)	0.0397	(0.0694)
1(Anticipate food shortage in November)	0.0703**	(0.0341)	0.1019**	(0.0453)
1(Lacked food last month)	0.0552	(0.0554)	0.0687	(0.0778)
Panel C: Health				
1(Health expenditure shortages)	0.0048	(0.0292)	0.0041	(0.0439)
Number of days affected	2.7840*	(1.4520)	5.2198**	(2.4107)
Reported any sickness	0.021	(0.0376)	0.0532	(0.0491)
Panel D: Household Well-being				
Log(Income in the past 3 months)	0.2627	(0.3030)	0.56	(0.5908)
Log(Per-capita annual non-food expenditure)	0.0617	(0.0719)	0.1679*	(0.0962)
1 (any type of employment)	-0.0199	(0.0123)	-0.0318*	(0.0177)
Panel E: Food Consumption and Expenditures				
log(Food consumption last week, in mok)	-0.0771*	(0.0455)	-0.0604	(0.0689)
log(Food expenditure last week)	0.072	(0.0777)	0.0787	(0.1447)
1(Food expenditure was 0)	0.0623	(0.0536)	0.2281***	(0.0714)
Ratio of food expenditure to consumption	0.2182	(0.3461)	-0.4518	(0.5369)
Share of consumption that is maize last week	-0.0550*	(0.0274)	-0.0765*	(0.0427)
Share of food expenditure that is maize last week	-0.0093	(0.0295)	0.033	(0.0548)
Pan Panel F: Agricultural yields and storage				
Amount of maize produced (kg)	-4.4214	(29.0953)	-22.4436	(26.4347)
Amount of maize stored (kg)	-8.3823	(5.6075)	-15.1402**	(6.8477)
Amount of rice produced (kg)	-13.1704	(44.9455)	122.2978*	(68.5923)
Amount of rice stored (kg)	6.9815	(12.4893)	39.1369*	(21.8189)
Ratio of rice stored	-0.0247	(0.0388)	-0.0228	(0.0452)
Ratio of maize stored	-0.0525*	(0.0299)	-0.0221	(0.0343)

* p<0.10, ** p<0.05, *** p<0.01

Each cell corresponds to an OLS regression where the dependent variable is noted in the table. The estimate reported is the coefficient on the *treatment dummy*. All regressions include district (kabupaten) fixed effects because assignment of treatment was within each district. Standard errors reported in the parentheses. All standard errors are clustered at the village level. All regressions are at the household level.

Table C2: IV for Credit treatment

Sample:	All Districts			Alfa Omega		
Season:	All	Lean	Harvest	All	Lean	Harvest
	[1]	[2]	[3]	[4]	[5]	[6]
Panel A: Seasonal differences, |Harvest - Lean|						
Seasonal Gap Index	-0.279			-0.6733**		
	(0.2449)			(0.3122)		
log(Food consumption last week, in mok)	0.0206			0.0014		
	(0.1020)			(0.0649)		
Food expenditure last week, in 1,000 Rp.	-6.1679			-21.1662**		
	(7.9233)			(9.0463)		
log(Income in the past 3 months)	-0.0253			-0.1801		
	(0.1405)			(0.1493)		
log(Monthly non-food expenditure)	-0.1580*			-0.113		
	(0.0852)			(0.1087)		
Panel B: Anticipated and Reported Measures of Food Shortages						
Subjective Food Shortage Index	-0.5179	-0.0544	-0.8269	-1.0262*	-0.6311	-1.2896**
	(0.5059)	(0.6725)	(0.5425)	(0.5388)	(0.7783)	(0.5703)
1(Anticipate food shortage in January)	-0.0961	-0.0421	-0.1321*	-0.1071	-0.1091	-0.1057
	(0.0820)	(0.1120)	(0.0801)	(0.0978)	(0.1386)	(0.0923)
1(Anticipate food shortage in April)	-0.0216	0.0085	-0.0417	-0.0646**	-0.0212	-0.0935**
	(0.0299)	(0.0446)	(0.0385)	(0.0324)	(0.0478)	(0.0372)
1(Anticipate food shortage in November)	-0.0515	0.0553	-0.1226*	-0.1123	-0.0399	-0.1606**
	(0.0660)	(0.1074)	(0.0735)	(0.0713)	(0.1315)	(0.0807)
1(Lacked food last month)	-0.0392	-0.0787	-0.0129	-0.1308*	-0.0997	-0.1515
	(0.0672)	(0.0739)	(0.0834)	(0.0772)	(0.0854)	(0.0955)
Panel C: Health						
Health Index	0.0559	1.4835*	-0.8958**	0.0651	1.8685*	-1.1371***
	(0.4121)	(0.7983)	(0.4011)	(0.4865)	(0.9686)	(0.4356)
1(Health expenditure shortages)	0.0564*	-0.0144	0.1035***	0.0427	-0.0006	0.0715*
	(0.0317)	(0.0395)	(0.0372)	(0.0341)	(0.0388)	(0.0420)
Number of days affected	-4.3254	-14.9353**	2.7479	-3.4107	-18.7778**	6.8341*
	(3.2597)	(7.3830)	(3.3620)	(4.0060)	(8.9424)	(3.9112)
Reported any sickness	0.061	-0.1019	0.1697***	0.0411	-0.1503	0.1687***
	(0.0593)	(0.0930)	(0.0604)	(0.0670)	(0.1154)	(0.0628)
Panel D: Household Well-being						
Household Well-Being Index	1.0374***	1.0791**	1.0096**	1.0476**	0.9252	1.1292**
	(0.3713)	(0.4616)	(0.4174)	(0.5069)	(0.6157)	(0.4839)
Log(Income in the past 3 months)	0.5614**	0.385	0.6845*	0.4231**	0.3206	0.4923***
	(0.2672)	(0.2657)	(0.3593)	(0.1783)	(0.2529)	(0.1815)
Log(Annual non-food expenditure, 1,000 Rp)	0.1546	0.0125	0.2476	0.1356	-0.0444	0.257
	(0.1539)	(0.1834)	(0.1715)	(0.1489)	(0.2020)	(0.1682)
1 (any type of employment)	0.1339**	0.1614**	0.1081	0.1399	0.1371*	0.1426
	(0.0597)	(0.0689)	(0.0695)	(0.0851)	(0.0753)	(0.1002)
Panel E: Food Consumption and Expenditures						
Food Index	0.0362	-0.0704	0.1073	-0.0052	-0.4947	0.3211
	(0.4758)	(0.4882)	(0.6296)	(0.4626)	(0.5031)	(0.5619)
log(Food consumption last week, in mok)	0.2093	-0.0598	0.3869	0.0806	-0.0131	0.1428
	(0.1787)	(0.1304)	(0.2766)	(0.1249)	(0.1335)	(0.1370)
log(Food expenditure last week)	-0.3598	0.0177	-0.6104	-0.5033*	-0.6289	-0.4202
	(0.3698)	(0.3968)	(0.5269)	(0.2783)	(0.4423)	(0.2819)
1(Food expenditure was 0)	0.203	0.22	0.1917	0.5261***	0.5050***	0.5402***
	(0.1278)	(0.1388)	(0.1415)	(0.1771)	(0.1801)	(0.1993)
Ratio of food expenditure to consumption	-1.0416	-0.4072	-1.4736*	-2.9949***	-2.6950***	-3.1958***
	(0.8232)	(1.0341)	(0.8454)	(0.9925)	(1.0404)	(1.0918)
Share of consumption that is maize last week	-0.0403	-0.0456	-0.0375	-0.0956**	-0.1350***	-0.0692
	(0.0383)	(0.0392)	(0.0458)	(0.0479)	(0.0464)	(0.0549)
Share of food expenditure that is maize last week	-0.0543	-0.0924	-0.0314	0.0963	0.0579	0.1193
	(0.0582)	(0.0782)	(0.0585)	(0.0751)	(0.0583)	(0.1022)

* p<0.10, ** p<0.05, *** p<0.01

Each cell corresponds to an instrumental variable regression where the dependent variable is an outcome variable and the main independent variable is a take-up dummy instrumented with the treatment assignment. The estimate reported is the coefficient on the take-up dummy. The dependent variable for each regression is noted in the table. All regressions include district (kabupaten) fixed effects because assignment of treatment was within each district. Standard errors reported in the parentheses. All standard errors are clustered at the village level. Column 1 uses all the post treatment data (rounds 2 to 6). Column 2 only includes lean season data (rounds 3 and 5). Column 3 only includes harvest season data (rounds 2, 4 and 6).

Table C3: IV for Credit treatment, by credit propensity

Sample:	All Districts			Alfa Omega		
Season:	All	Lean	Harvest	All	Lean	Harvest
	[1]	[2]	[3]	[4]	[5]	[6]
Panel A: Seasonal differences, |Harvest - Lean|						
Seasonal Gap Index	-0.2308			-0.5538*		
	(0.2409)			(0.3177)		
Seasonal Gap Index_High Credit	-0.2251			-0.5490***		
	(0.3049)			(0.2046)		
log(Food consumption last week, in mok)	0.0291			0.0474		
	(0.1040)			(0.0644)		
log(Food consumption last week, in mok)_High Credit	-0.0405			-0.2135***		
	(0.1080)			(0.0361)		
Food expenditure last week, in 1,000 Rp.	-5.2801			-18.7330**		
	(7.8201)			(8.9430)		
Food expenditure last week, in 1,000 Rp._High Credit	-4.1483			-11.1806		
	(7.2958)			(7.0380)		
log(Income in the past 3 months)	-0.0178			-0.1661		
	(0.1425)			(0.1504)		
log(Income in the past 3 months)_High Credit	-0.0362			-0.0655		
	(0.1473)			(0.1648)		
log(Monthly non-food expenditure)	-0.1460*			-0.1054		
	(0.0856)			(0.1102)		
log(Monthly non-food expenditure)_High Credit	-0.0557			-0.035		
	(0.0876)			(0.0807)		
Panel B: Anticipated and Reported Measures of Food Shortages						
Subjective Food Shortage Index	-0.5144	0.0058	-0.8612	-0.9499*	-0.4565	-1.2789**
	(0.5112)	(0.6604)	(0.5555)	(0.5428)	(0.7332)	(0.5943)
Subjective Food Shortage Index_High Credit	-0.0164	-0.2814	0.1603	-0.3504	-0.8024	-0.049
	(0.3946)	(0.6075)	(0.3992)	(0.3518)	(0.6903)	(0.3321)
1(Anticipate food shortage in January)	-0.0875	-0.0283	-0.127	-0.0864	-0.0863	-0.0865
	(0.0842)	(0.1124)	(0.0821)	(0.1017)	(0.1391)	(0.0958)
1(Anticipate food shortage in January)_High Credit	-0.0402	-0.0647	-0.0239	-0.0949	-0.1047	-0.0884
	(0.0619)	(0.0926)	(0.0633)	(0.0735)	(0.1211)	(0.0695)
1(Anticipate food shortage in April)	-0.0209	0.0073	-0.0397	-0.0659**	-0.0125	-0.1015***
	(0.0303)	(0.0430)	(0.0405)	(0.0336)	(0.0488)	(0.0383)
1(Anticipate food shortage in April)_High Credit	-0.0032	0.0056	-0.0091	0.0058	-0.0401	0.0364
	(0.0220)	(0.0404)	(0.0319)	(0.0172)	(0.0332)	(0.0228)
1(Anticipate food shortage in November)	-0.0552	0.0645	-0.1351*	-0.108	-0.0099	-0.1734**
	(0.0668)	(0.1082)	(0.0761)	(0.0732)	(0.1283)	(0.0860)
1(Anticipate food shortage in November)_High Credit	0.0177	-0.0429	0.058	-0.02	-0.1377	0.0585
	(0.0589)	(0.0937)	(0.0623)	(0.0593)	(0.1082)	(0.0576)
1(Lacked food last month)	-0.0418	-0.0783	-0.0175	-0.1222	-0.0977	-0.1385
	(0.0677)	(0.0762)	(0.0820)	(0.0771)	(0.0880)	(0.0964)
1(Lacked food last month)_High Credit	0.0121	-0.002	0.0214	-0.0395	-0.009	-0.0599
	(0.0551)	(0.0828)	(0.0687)	(0.0390)	(0.0920)	(0.0402)
Panel C: Health						
Health Index	0.1798	1.4559*	-0.6710*	0.1445	1.8913*	-1.0200***
	(0.4016)	(0.7973)	(0.3435)	(0.4777)	(0.9711)	(0.3816)
Health Index_High Credit	-0.5788	0.1289	-1.0506	-0.3649	-0.105	-0.5383
	(0.5171)	(0.6080)	(0.7624)	(0.4160)	(0.2369)	(0.6065)
1(Health expenditure shortages)	0.044	-0.0048	0.0765**	0.0292	-0.0021	0.0501
	(0.0300)	(0.0400)	(0.0335)	(0.0325)	(0.0379)	(0.0379)
1(Health expenditure shortages)_High Credit	0.0577	-0.0452	0.1263*	0.0617*	0.0068	0.0983**
	(0.0357)	(0.0349)	(0.0655)	(0.0322)	(0.0322)	(0.0470)
Number of days affected	-5.3572	-15.1147**	1.1478	-3.2735	-18.6269**	6.9621*
	(3.3268)	(7.4555)	(3.0673)	(3.9915)	(8.9803)	(3.6625)
Number of days affected_High Credit	4.8214	0.8383	7.4767	-0.6303	-0.6933	-0.5883
	(5.3051)	(7.7930)	(7.5924)	(4.1217)	(1.8816)	(6.3536)
Reported any sickness	0.0582	-0.0951	0.1604***	0.0177	-0.1638	0.1387**
	(0.0598)	(0.0938)	(0.0601)	(0.0668)	(0.1116)	(0.0598)
Reported any sickness_High Credit	0.0133	-0.0318	0.0434	0.1076**	0.062	0.1380**
	(0.0494)	(0.0715)	(0.0646)	(0.0419)	(0.0694)	(0.0639)

Panel D: Household Well-being						
Household Well-Being Index	1.0113***	1.1141**	0.9428**	0.9384*	0.8936	0.9683**
	(0.3660)	(0.4632)	(0.4132)	(0.4983)	(0.6162)	(0.4699)
Household Well-Being Index_High Credit	0.122	-0.1636	0.3125	0.5018	0.1452	0.7395
	(0.3374)	(0.3799)	(0.3548)	(0.4764)	(0.5319)	(0.5118)
Log(Income in the past 3 months)	0.4936*	0.3131	0.6200*	0.3094*	0.2045	0.3808**
	(0.2718)	(0.2666)	(0.3679)	(0.1723)	(0.2416)	(0.1704)
Log(Income in the past 3 months)_High Credit	0.3234**	0.3457*	0.3059*	0.5319***	0.5470**	0.5192***
	(0.1514)	(0.2057)	(0.1846)	(0.1563)	(0.2537)	(0.1938)
Log(Annual non-food expenditure, 1,000 Rp)	0.1341	0.0099	0.2159	0.0998	-0.0265	0.1852
	(0.1624)	(0.1927)	(0.1777)	(0.1678)	(0.2163)	(0.1854)
Log(Annual non-food expenditure, 1,000 Rp)_High Credit	0.0953	0.0122	0.1464	0.1645	-0.0826	0.3291
	(0.1379)	(0.1525)	(0.1675)	(0.1817)	(0.1637)	(0.2402)
1 (any type of employment)	0.1396**	0.1720**	0.1087	0.136	0.1354*	0.1364
	(0.0603)	(0.0701)	(0.0710)	(0.0855)	(0.0751)	(0.1013)
1 (any type of employment)_High Credit	-0.0263	-0.0488	-0.0026	0.018	0.0074	0.0285
	(0.0458)	(0.0516)	(0.0445)	(0.0555)	(0.0559)	(0.0588)
Panel E: Food Consumption and Expenditures						
Food Index	-0.168	-0.2533	-0.1111	-0.0789	-0.5522	0.2366
	(0.4543)	(0.5048)	(0.6042)	(0.4631)	(0.5058)	(0.5641)
Food Index_High Credit	0.9541**	0.8546	1.0204*	0.3386**	0.2642	0.3883**
	(0.4109)	(0.6385)	(0.5428)	(0.1588)	(0.3065)	(0.1835)
log(Food consumption last week, in mok)	0.1654	-0.0608	0.3152	0.0472	-0.0346	0.1019
	(0.1592)	(0.1339)	(0.2404)	(0.1289)	(0.1422)	(0.1385)
log(Food consumption last week, in mok)_High Credit	0.2068	0.0045	0.3381	0.1551*	0.0993	0.1906**
	(0.1807)	(0.1129)	(0.2728)	(0.0933)	(0.1199)	(0.0895)
log(Food expenditure last week)	-0.3976	0.044	-0.69	-0.4333*	-0.5322	-0.3664
	(0.4044)	(0.3855)	(0.5888)	(0.2551)	(0.4119)	(0.2646)
log(Food expenditure last week)_High Credit	0.1742	-0.1244	0.3609	-0.3291	-0.4842	-0.243
	(0.2850)	(0.2365)	(0.3925)	(0.3026)	(0.5408)	(0.3421)
1(Food expenditure was 0)	0.2110*	0.2185	0.206	0.5318***	0.5019***	0.5518***
	(0.1257)	(0.1398)	(0.1400)	(0.1777)	(0.1847)	(0.1989)
1(Food expenditure was 0)_High Credit	-0.0372	0.0069	-0.0666	-0.0261	0.0145	-0.0532
	(0.0755)	(0.0863)	(0.0857)	(0.0880)	(0.1012)	(0.0985)
Ratio of food expenditure to consumption	-1.1804	-0.8183	-1.4296*	-2.8792***	-2.4819**	-3.1444***
	(0.7657)	(0.8653)	(0.8307)	(0.9660)	(1.0306)	(1.0689)
Ratio of food expenditure to consumption_High Credit	0.6539	1.9332	-0.2077	-0.5369	-0.9854	-0.2393
	(1.0757)	(2.3245)	(0.5195)	(0.4959)	(0.6730)	(0.5770)
Share of consumption that is maize last week	-0.0536	-0.0586	-0.0508	-0.1037**	-0.1448***	-0.0762
	(0.0384)	(0.0404)	(0.0461)	(0.0487)	(0.0478)	(0.0548)
Share of consumption that is maize last week_High Credit	0.0627**	0.0611**	0.0628**	0.0376	0.0452*	0.0325
	(0.0259)	(0.0285)	(0.0301)	(0.0254)	(0.0244)	(0.0297)
Share of food expenditure that is maize last week	-0.0582	-0.0958	-0.0356	0.0675	0.0154	0.1002
	(0.0559)	(0.0772)	(0.0546)	(0.0593)	(0.0544)	(0.0844)
Share of food expenditure that is maize last week_High Credit	0.0179	0.0163	0.0193	0.1352	0.2130*	0.0863
	(0.0556)	(0.0630)	(0.0661)	(0.1219)	(0.1272)	(0.1386)

* p<0.10, ** p<0.05, *** p<0.01

Heterogeneous treatment effect regressions by the debt-to-income ratio of each household. Each regression corresponds to an instrumental variable regression where the dependent variable is an outcome variable and the 2 main independent variables are (i) a take-up dummy instrumented with the treatment assignment (ii) the take-up dummy interacted with a dummy for high credit household. We calculated the average amount of debt divided by average income (averaged across rounds 1 and 2) . High credit households are households whose debt-to-income ratio are strictly above the median debt-to-income. The dependent variable for each regression is noted in the table. All regressions include district (kabupaten) fixed effects because assignment of treatment was within each district. Standard errors reported in the parentheses. All standard errors are clustered at the village level. Column 1 uses all the post treatment data (rounds 2 to 6). Column 2 only includes lean season data (rounds 3 and 5). Column 3 only includes harvest season data (rounds 2, 4 and 6).

Table C4: IV for Credit treatment, by main crop

Sample:	All Districts			Alfa Omega		
Season:	All	Lean	Harvest	All	Lean	Harvest
	[1]	[2]	[3]	[4]	[5]	[6]
Panel A: Seasonal differences, |Harvest - Lean|						
Seasonal Gap Index	-0.7968***			-0.9619***		
	(0.2348)			(0.2572)		
Seasonal Gap Index_Maize	0.9165***			0.8937***		
	(0.2863)			(0.3459)		
log(Food consumption last week, in mok)	-0.0552			-0.0328		
	(0.0801)			(0.0765)		
log(Food consumption last week, in mok)_Maize	0.1346			0.1047		
	(0.1155)			(0.0738)		
Food expenditure last week, in 1,000 Rp.	-21.9947***			-29.8180***		
	(7.3093)			(7.5189)		
Food expenditure last week, in 1,000 Rp._Maize	28.0093***			26.7884***		
	(8.2439)			(6.8592)		
log(Income in the past 3 months)	-0.1326			-0.2033		
	(0.1505)			(0.1608)		
log(Income in the past 3 months)_Maize	0.1908			0.0706		
	(0.1346)			(0.1392)		
log(Monthly non-food expenditure)	-0.1938*			-0.17		
	(0.1029)			(0.1097)		
log(Monthly non-food expenditure)_Maize	0.0644			0.1738		
	(0.1425)			(0.1575)		
Panel B: Anticipated and Reported Measures of Food Shortages						
Subjective Food Shortage Index	-1.0768**	-0.4705	-1.4810***	-1.2036**	-0.6662	-1.5619***
	(0.5177)	(0.7932)	(0.4962)	(0.5863)	(0.9007)	(0.5552)
Subjective Food Shortage Index_Maize	0.9891*	0.7364	1.1576**	0.5494	0.1085	0.8433**
	(0.5539)	(0.8640)	(0.5114)	(0.4153)	(0.7580)	(0.4020)
1(Anticipate food shortage in January)	-0.1191	-0.1053	-0.1283	-0.1117	-0.1258	-0.1023
	(0.1009)	(0.1484)	(0.0880)	(0.1147)	(0.1682)	(0.1008)
1(Anticipate food shortage in January)_Maize	0.0406	0.1119	-0.0068	0.0143	0.0519	-0.0108
	(0.0990)	(0.1524)	(0.0823)	(0.0914)	(0.1460)	(0.0680)
1(Anticipate food shortage in April)	-0.0455	-0.0009	-0.0752**	-0.0670*	-0.0217	-0.0973**
	(0.0324)	(0.0547)	(0.0344)	(0.0350)	(0.0558)	(0.0384)
1(Anticipate food shortage in April)_Maize	0.0423	0.0165	0.0594	0.0076	0.0017	0.0116
	(0.0348)	(0.0526)	(0.0423)	(0.0209)	(0.0420)	(0.0200)
1(Anticipate food shortage in November)	-0.1282*	-0.0088	-0.2077***	-0.1404*	-0.0337	-0.2115***
	(0.0661)	(0.1288)	(0.0665)	(0.0756)	(0.1487)	(0.0746)
1(Anticipate food shortage in November)_Maize	0.1358*	0.1135	0.1506*	0.0869	-0.0191	0.1576**
	(0.0712)	(0.1380)	(0.0799)	(0.0542)	(0.1180)	(0.0772)
1(Lacked food last month)	-0.1375*	-0.0977	-0.1639*	-0.1646**	-0.1075	-0.2026**
	(0.0728)	(0.0841)	(0.0858)	(0.0829)	(0.0931)	(0.0974)
1(Lacked food last month)_Maize	0.1738**	0.0336	0.2673***	0.1046**	0.0242	0.1582***
	(0.0739)	(0.0830)	(0.0897)	(0.0432)	(0.0602)	(0.0513)
Panel C: Health						
Health Index	0.3304	1.8197**	-0.6626*	0.185	1.9563*	-0.9959**
	(0.4846)	(0.8826)	(0.3685)	(0.5393)	(1.0090)	(0.3876)
Health Index_Maize	-0.4857	-0.5951	-0.4128	-0.3712	-0.272	-0.4373
	(0.4354)	(0.8205)	(0.5535)	(0.3862)	(0.7750)	(0.8338)
1(Health expenditure shortages)	0.0357	-0.0303	0.0796*	0.0488	-0.0052	0.0848*
	(0.0334)	(0.0387)	(0.0419)	(0.0366)	(0.0427)	(0.0459)
1(Health expenditure shortages)_Maize	0.0366	0.0281	0.0423	-0.019	0.0142	-0.0412
	(0.0384)	(0.0424)	(0.0510)	(0.0232)	(0.0277)	(0.0328)
Number of days affected	-6.3764	-17.1620**	0.814	-4.99	-19.3358**	4.5738
	(4.0509)	(8.1805)	(3.3495)	(4.4533)	(9.3190)	(3.5391)
Number of days affected_Maize	3.6297	3.9406	3.4225	4.89	1.7276	6.9982
	(3.8565)	(8.0661)	(4.8452)	(4.3401)	(7.3359)	(8.4979)
Reported any sickness	0.0385	-0.1508	0.1647***	0.0373	-0.1634	0.1711**
	(0.0656)	(0.1051)	(0.0635)	(0.0745)	(0.1222)	(0.0667)
Reported any sickness_Maize	0.0398	0.0865	0.0087	0.0118	0.0405	-0.0074
	(0.0610)	(0.0978)	(0.0707)	(0.0406)	(0.1028)	(0.0749)

Panel D: Household Well-being						
Household Well-Being Index	1.3666***	1.3047**	1.4079***	1.3764**	1.2341*	1.4713***
	(0.5138)	(0.6143)	(0.4964)	(0.5859)	(0.7034)	(0.5564)
Household Well-Being Index_Maize	-0.5826	-0.3993	-0.7048	-1.0182**	-0.9565*	-1.0592**
	(0.4843)	(0.5630)	(0.5227)	(0.4922)	(0.4986)	(0.5037)
Log(Income in the past 3 months)	0.6189***	0.4973*	0.7018***	0.5090**	0.3812	0.5940***
	(0.2242)	(0.2943)	(0.2477)	(0.2216)	(0.3105)	(0.2227)
Log(Income in the past 3 months)_Maize	-0.1021	-0.1991	-0.0308	-0.2646	-0.1835	-0.3171
	(0.2976)	(0.2963)	(0.3976)	(0.1862)	(0.2338)	(0.1949)
Log(Annual non-food expenditure, 1,000 Rp)	0.195	0.0041	0.3204*	0.1631	-0.0456	0.3036
	(0.1682)	(0.2077)	(0.1934)	(0.1810)	(0.2313)	(0.2074)
Log(Annual non-food expenditure, 1,000 Rp)_Maize	-0.0717	0.0149	-0.1294	-0.084	0.0037	-0.1423
	(0.1866)	(0.2021)	(0.2162)	(0.1433)	(0.1321)	(0.1878)
1 (any type of employment)	0.1858**	0.1922**	0.1800*	0.1944**	0.1870**	0.2015*
	(0.0836)	(0.0801)	(0.0950)	(0.0947)	(0.0869)	(0.1089)
1 (any type of employment)_Maize	-0.0918	-0.0541	-0.1281	-0.1671**	-0.1533**	-0.1810**
	(0.0756)	(0.0882)	(0.0801)	(0.0704)	(0.0717)	(0.0716)
Panel E: Food Consumption and Expenditures						
Food Index	0.0846	-0.3448	0.3709	0.0854	-0.4878	0.4676
	(0.4658)	(0.5273)	(0.5523)	(0.5168)	(0.5746)	(0.6145)
Food Index_Maize	-0.0856	0.4857	-0.4664	-0.2808	-0.0215	-0.4536
	(0.5221)	(0.5440)	(0.6886)	(0.3241)	(0.3880)	(0.3956)
log(Food consumption last week, in mok)	0.1536	-0.0644	0.2967*	0.1099	-0.0065	0.1866
	(0.1406)	(0.1401)	(0.1696)	(0.1432)	(0.1543)	(0.1546)
log(Food consumption last week, in mok)_Maize	0.0991	0.0081	0.1607	-0.09	-0.0201	-0.1355
	(0.2056)	(0.1605)	(0.3240)	(0.1165)	(0.1272)	(0.1254)
log(Food expenditure last week)	-0.6399	-0.4619	-0.7723	-0.8224**	-0.8743*	-0.7860*
	(0.4013)	(0.4502)	(0.5199)	(0.3801)	(0.4866)	(0.4632)
log(Food expenditure last week)_Maize	0.3853	0.6931*	0.2163	0.6328*	0.5335	0.6873
	(0.3847)	(0.3867)	(0.5210)	(0.3362)	(0.3550)	(0.4281)
1(Food expenditure was 0)	0.5956***	0.5236***	0.6436***	0.7292***	0.6580***	0.7767***
	(0.1241)	(0.1611)	(0.1209)	(0.1325)	(0.1781)	(0.1286)
1(Food expenditure was 0)_Maize	-0.6948***	-0.5374***	-0.7997***	-0.6289***	-0.4738***	-0.7324***
	(0.1388)	(0.1628)	(0.1462)	(0.1860)	(0.1475)	(0.2264)
Ratio of food expenditure to consumption	-3.3594***	-2.6910***	-3.8068***	-4.2495***	-3.8106***	-4.5417***
	(0.8376)	(1.0258)	(0.8752)	(0.8790)	(1.0448)	(0.9528)
Ratio of food expenditure to consumption_Maize	4.1199***	4.0491***	4.1547***	3.8630***	3.4096***	4.1652***
	(0.9494)	(1.2547)	(0.9564)	(0.8896)	(0.9699)	(0.9848)
Share of consumption that is maize last week	-0.1043**	-0.0987**	-0.1083**	-0.1229**	-0.1405**	-0.1113**
	(0.0454)	(0.0486)	(0.0486)	(0.0519)	(0.0566)	(0.0538)
Share of consumption that is maize last week_Maize	0.1137**	0.0941*	0.1261**	0.0843	0.0168	0.1302*
	(0.0521)	(0.0537)	(0.0633)	(0.0634)	(0.0554)	(0.0726)
Share of food expenditure that is maize last week	0.1262	0.0167	0.2102	0.2258*	0.102	0.3173*
	(0.1106)	(0.0726)	(0.1633)	(0.1254)	(0.0784)	(0.1808)
Share of food expenditure that is maize last week_Maize	-0.2482**	-0.1576*	-0.3224*	-0.2569**	-0.0959	-0.3719**
	(0.1156)	(0.0885)	(0.1665)	(0.1284)	(0.0697)	(0.1875)

* p<0.10, ** p<0.05, *** p<0.01

Heterogeneous treatment effect regressions by the main crop of the household (maize or rice farmers). Each regression corresponds to an instrumental variable regression where the dependent variable is an outcome variable and the 2 main independent variables are (i) a take-up dummy instrumented with the treatment assignment (ii) the take-up dummy interacted with a dummy for maize farmers. Maize farmers are defined as farmers who produced more maize than rice (calculated using yields averaged from the first and second rounds of the survey). The dependent variable for each regression is noted in the table. All regressions include district (kabupaten) fixed effects because assignment of treatment was within each district. Standard errors reported in the parentheses. All standard errors are clustered at the village level. Column 1 uses all the post treatment data (rounds 2 to 6). Column 2 only includes lean season data (rounds 3 and 5). Column 3 only includes harvest season data (rounds 2, 4 and 6).

Table C5: Summary of results for Credit treatment from instrumental variables regression

	All districts	Alfa Omega districts
Seasonal differences	Gap in monthly non-food expenditure lower by 16%*	Seasonal gap index lower by 0.67 ** Gap in food expenditure lower by 21,000 Rupiah **
Anticipated and reported measures of food shortages	13% less likely to anticipate food shortage in January (H) ** 12% less likely to anticipate food shortage in November (H) **	Food shortage index lower by 1.29 (H) ** 9% less likely to anticipate food shortage in April (H) *** 16% less likely to anticipate food shortage in November (H) ** 13% less likely to report lacking food in the last month (A) * (only sig. for A)
Health	Health index higher by 1.48 (L) * and lower by 0.90 (H) ** 11% more likely to report health expenditure shortages (H)*** Report 15 fewer sick days (L) ** 17% more likely to report any sickness (H) ***	Health index higher by 1.87 (L) * and lower by 1.14 (H) *** 7% more likely to anticipate health expenditure shortages (H) * Report 19 fewer sick days (L) ** Report 7 more sick days (H) * 17% more likely to report any sickness (H) ***
Household well-being	Household well-being index higher by 1.04 (A) *** Report 69% higher income in the past 3 months (H)* 16% more likely to report any employment (L)**	Household well-being index higher by 1.13 (H) ** Report 49% higher income in the past 3 months (H) *** 14% more likely to report any employment (L) *
Food consumption and expenditures	Spend 1500 Rp less per kg of staple consumed (H) *	50% lower food expenditure in the past week (A) * (only significant for A) 53% more likely to report no food expenditure in the past week (A) *** Spend 3000 Rp less per kg of staple consumed (A) *** 14% less maize as a share of staple consumption (L) ***

* p<0.10, ** p<0.05, *** p<0.01

This table summarizes the main results for the credit treatment (Table C3). Each summary index is defined so that higher is better. The estimates above are the coefficients on the TAKE UP dummy from an instrumental variables regression. (H) represent results using harvest season surveys only; (L) represent results using lean season surveys only; (A) represents estimates that are significant for all post-treatment surveys, harvest only and lean season only surveys and the reported estimate is the estimate using data from all post-treatment surveys. Seasonal differences always include both harvest and lean season surveys because seasonal differences are defined by the absolute difference between harvest and lean season outcomes, i.e., |Harvest - Lean|.

Table S1: Testing random assignment (Storage treatment)

Sample	All Districts		Alfa Omega Districts	
	(1)		(2)	
Panel A: Household characteristics				
1(Graduated primary school)	-0.0007	(0.0303)	-0.0809**	(0.0320)
1(Graduated lower secondary school)	0.0362	(0.0316)	0.0228	(0.0412)
Age	1.1763	(3.0626)	1.4096	(3.6757)
Number of chickens owned	0.1765	(0.3337)	0.11	(0.4622)
Number of cows owned	3148.2929	(3449.1864)	-0.3406	(0.2495)
Number of pigs owned	-0.1324	(0.1135)	-0.0597	(0.0922)
Number of motorcycles owned	0.5352**	(0.2245)	-0.0335	(0.2104)
Panel B: Anticipated and Reported Measures of Food Shortages				
1(Anticipate food shortage in January)	0.0415	(0.0487)	0.0273	(0.0612)
1(Anticipate food shortage in April)	0.0463	(0.0521)	0.0175	(0.0716)
1(Anticipate food shortage in November)	0.0134	(0.0261)	-0.0136	(0.0366)
1(Lacked food last month)	-0.0248	(0.0502)	-0.0316	(0.0679)
Panel C: Health				
1(Health expenditure shortages)	0.0075	(0.0260)	-0.0143	(0.0349)
Number of days affected	3.0808***	(1.1350)	3.3561***	(1.2221)
Reported any sickness	0.0417	(0.0342)	0.0893*	(0.0469)
Panel D: Household Well-being				
Log(Income in the past 3 months)	0.1733	(0.2959)	0.4921	(0.5588)
Log(Per-capita annual non-food expenditure)	0.0604	(0.0655)	0.0197	(0.0897)
1 (any type of employment)	-0.0280**	(0.0112)	-0.0282*	(0.0150)
Panel E: Food Consumption and Expenditures				
log(Food consumption last week, in mok)	-0.0976**	(0.0466)	-0.1337**	(0.0594)
log(Food expenditure last week)	0.0784	(0.0650)	0.0528	(0.0975)
1(Food expenditure was 0)	0.0368	(0.0465)	0.1213**	(0.0580)
Ratio of food expenditure to consumption	0.5458	(0.3398)	0.4136	(0.5423)
Share of consumption that is maize last week	-0.0574**	(0.0261)	-0.0894**	(0.0393)
Share of food expenditure that is maize last week	-0.031	(0.0247)	-0.0246	(0.0412)
Pan Panel F: Agricultural yields and storage				
Amount of maize produced (kg)	4.5254	(24.5730)	-6.5918	(25.0350)
Amount of maize stored (kg)	-1.7645	(5.6986)	-8.9804	(6.1302)
Amount of rice produced (kg)	-10.5889	(34.8907)	91.2188*	(46.5709)
Amount of rice stored (kg)	-1.4532	(7.3718)	13.8583	(11.4385)
Ratio of rice stored	-0.0321	(0.0414)	-0.0099	(0.0557)
Ratio of maize stored	-0.005	(0.0322)	0.0339	(0.0526)

* p<0.10, ** p<0.05, *** p<0.01

Each cell corresponds to an OLS regression where the dependent variable is noted in the table. The estimate reported is the coefficient on the *treatment dummy*. All regressions include district (kabupaten) fixed effects because assignment of treatment was within each district. Standard errors reported in the parentheses. All standard errors are clustered at the village level. All regressions are at the household level.

Table S2: IV for Storage treatment using rounds 4 to 6

Sample:	All Districts			Alfa Omega Districts		
Season:	All	Lean	Harvest	All	Lean	Harvest
	[1]	[2]	[3]	[4]	[5]	[6]
Panel A: Seasonal differences, |Harvest - Lean|						
Seasonal Gap Index	0.5107			-0.2852		
	(0.4289)			(0.2043)		
log(Food consumption last week, in mok)	0.7031			-0.0497		
	(0.4814)			(0.0760)		
Food expenditure last week, in 1,000 Rp.	-6.3445			-19.6372**		
	(8.7794)			(8.5609)		
log(Income in the past 3 months)	-0.0615			-0.1245		
	(0.1643)			(0.1541)		
log(Monthly non-food expenditure)	0.0942			0.1615		
	(0.1126)			(0.1775)		
Panel B: Anticipated and Reported Measures of Food Shortages						
Subjective Food Shortage Index	-0.5915	-1.3327*	-0.2209	-0.5931	-1.6279	-0.0757
	(0.3838)	(0.7805)	(0.4546)	(0.4055)	(1.1402)	(0.4343)
1(Anticipate food shortage in January)	-0.0507	-0.1888	0.0183	-0.0241	-0.2989	0.1133
	(0.0753)	(0.1374)	(0.0904)	(0.0855)	(0.1917)	(0.1061)
1(Anticipate food shortage in April)	-0.0118	-0.0603	0.0124	-0.0318	-0.0664	-0.0145
	(0.0311)	(0.0388)	(0.0315)	(0.0417)	(0.0512)	(0.0410)
1(Anticipate food shortage in November)	-0.0875*	-0.1228	-0.0698	-0.0539	-0.108	-0.0268
	(0.0481)	(0.1062)	(0.0623)	(0.0512)	(0.1607)	(0.0596)
1(Lacked food last month)	-0.0788	-0.1773*	-0.0295	-0.1422*	-0.216	-0.1052
	(0.0603)	(0.0985)	(0.0622)	(0.0762)	(0.1324)	(0.0687)
Panel C: Health						
Health Index	0.1207	0.417	-0.0274	-0.113	0.4354	-0.3871
	(0.2448)	(0.2957)	(0.2846)	(0.3092)	(0.4071)	(0.3282)
1(Health expenditure shortages)	0.0034	-0.052	0.0311	0.0288	-0.0435	0.0650*
	(0.0261)	(0.0376)	(0.0272)	(0.0355)	(0.0563)	(0.0342)
Number of days affected	-0.3545	-0.7172	-0.1732	0.4839	-2.2345	1.8431
	(1.5111)	(1.1376)	(2.2064)	(1.8678)	(1.5393)	(2.6838)
Reported any sickness	-0.044	-0.0943	-0.0189	-0.0021	-0.0589	0.0262
	(0.0501)	(0.0845)	(0.0518)	(0.0626)	(0.1025)	(0.0645)
Panel D: Household Well-being						
Household Well-Being Index	0.8070**	0.4752	0.9729**	0.6592	0.3965	0.7905
	(0.4029)	(0.4286)	(0.4614)	(0.4850)	(0.5452)	(0.5732)
Log(Income in the past 3 months)	0.5035	0.422	0.5475	0.138	0.224	0.0963
	(0.3578)	(0.2897)	(0.4723)	(0.2498)	(0.3354)	(0.2617)
Log(Annual non-food expenditure, 1,000 Rp)	0.3961**	0.3814*	0.4040***	0.3322**	0.3364	0.3308**
	(0.1606)	(0.2311)	(0.1555)	(0.1680)	(0.3063)	(0.1442)
1 (any type of employment)	0.032	-0.0201	0.0855	0.0412	-0.0283	0.1131
	(0.0568)	(0.0255)	(0.1017)	(0.0910)	(0.0317)	(0.1683)
Panel E: Food Consumption and Expenditures						
Food Index	0.0125	-0.0343	0.0359	-0.2686	-0.573	-0.1163
	(0.3374)	(0.4581)	(0.3772)	(0.4630)	(0.4549)	(0.5589)
log(Food consumption last week, in mok)	0.2181	-0.0957	0.3745	-0.0458	-0.1253	-0.0065
	(0.2002)	(0.1378)	(0.2707)	(0.1278)	(0.1534)	(0.1297)
log(Food expenditure last week)	-0.4709	0.1435	-0.7302	-0.254	-0.1821	-0.2899
	(0.3621)	(0.3599)	(0.4577)	(0.2336)	(0.2833)	(0.2624)
1(Food expenditure was 0)	0.1556	0.2180*	0.1244	0.2896**	0.2487	0.3101**
	(0.1009)	(0.1256)	(0.1139)	(0.1374)	(0.1720)	(0.1518)
Ratio of food expenditure to consumption	-0.6866	-0.7933	-0.6361	-1.7510**	-1.6104	-1.8211*
	(0.7531)	(0.9180)	(0.8370)	(0.8860)	(1.1252)	(1.0214)
Share of consumption that is maize last week	-0.0488	-0.0516	-0.0476	-0.0774*	-0.1056**	-0.0636
	(0.0345)	(0.0457)	(0.0361)	(0.0402)	(0.0523)	(0.0391)
Share of food expenditure that is maize last week	0.0111	-0.0017	0.0175	0.0892**	0.0908*	0.0908**
	(0.0392)	(0.0668)	(0.0366)	(0.0388)	(0.0519)	(0.0438)

* p<0.10, ** p<0.05, *** p<0.01

Each cell corresponds to an instrumental variable regression where the dependent variable is an outcome variable and the main independent variable is a take-up dummy instrumented with the treatment assignment. The estimate reported is the coefficient on the take-up dummy. The dependent variable for each regression is noted in the table. All regressions include district (kabupaten) fixed effects because assignment of treatment was within each district. Standard errors reported in the parentheses. All standard errors are clustered at the village level. Column 1 uses round 4 and 6 (post treatment) data. Column 2 only includes round 5 (lean season) data. Column 3 only includes round 4 and 6 (harvest season) data.

Table S3: IV for Storage treatment using rounds 4 to 6, by storage propensity

Sample:	All Districts			Alfa Omega Districts		
Season:	All	Lean	Harvest	All	Lean	Harvest
	[1]	[2]	[3]	[4]	[5]	[6]
Panel A: Seasonal differences, |Harvest - Lean|						
Seasonal Gap Index	0.2263			-0.2886		
	(0.3037)			(0.2030)		
Seasonal Gap Index_High Storage	0.5934			0.0072		
	(0.3626)			(0.1974)		
log(Food consumption last week, in mok)	0.3945			-0.0038		
	(0.3043)			(0.0759)		
log(Food consumption last week, in mok)_High Storage	0.6474			-0.0976		
	(0.4341)			(0.0642)		
Food expenditure last week, in 1,000 Rp.	-7.0248			-19.1614**		
	(9.0203)			(9.5827)		
Food expenditure last week, in 1,000 Rp._High Storage	1.4192			-1.0277		
	(5.4366)			(6.9960)		
log(Income in the past 3 months)	-0.0353			-0.0938		
	(0.1629)			(0.1603)		
log(Income in the past 3 months)_High Storage	-0.0558			-0.0671		
	(0.0929)			(0.1170)		
log(Monthly non-food expenditure)	0.0401			0.0714		
	(0.1006)			(0.1480)		
log(Monthly non-food expenditure)_High Storage	0.1127			0.1918		
	(0.1207)			(0.1757)		
Panel B: Anticipated and Reported Measures of Food Shortages						
Subjective Food Shortage Index	-0.2891	-0.6151	-0.1262	-0.2393	-0.6628	-0.0275
	(0.3949)	(0.7684)	(0.4609)	(0.4394)	(1.1321)	(0.4694)
Subjective Food Shortage Index_High Storage	-0.6308**	-1.4972***	-0.1976	-0.7642***	-2.0846***	-0.1041
	(0.2715)	(0.4284)	(0.3025)	(0.2909)	(0.5613)	(0.2570)
1(Anticipate food shortage in January)	0.0077	-0.0677	0.0454	0.0398	-0.1528	0.1361
	(0.0764)	(0.1381)	(0.0934)	(0.0930)	(0.1976)	(0.1152)
1(Anticipate food shortage in January)_High Storage	-0.1218**	-0.2525***	-0.0564	-0.1380**	-0.3156***	-0.0493
	(0.0527)	(0.0820)	(0.0578)	(0.0579)	(0.1137)	(0.0559)
1(Anticipate food shortage in April)	-0.0028	-0.0342	0.0129	-0.0139	-0.0251	-0.0083
	(0.0320)	(0.0425)	(0.0318)	(0.0446)	(0.0600)	(0.0421)
1(Anticipate food shortage in April)_High Storage	-0.0188	-0.0544*	-0.001	-0.0387*	-0.0893**	-0.0134
	(0.0181)	(0.0311)	(0.0176)	(0.0231)	(0.0444)	(0.0193)
1(Anticipate food shortage in November)	-0.0525	-0.0493	-0.054	-0.017	0.0059	-0.0284
	(0.0512)	(0.1044)	(0.0647)	(0.0590)	(0.1615)	(0.0699)
1(Anticipate food shortage in November)_High Storage	-0.0731**	-0.1534***	-0.0329	-0.0798**	-0.2460***	0.0034
	(0.0338)	(0.0552)	(0.0464)	(0.0380)	(0.0763)	(0.0456)
1(Lacked food last month)	-0.0625	-0.1086	-0.0395	-0.1198	-0.1363	-0.1115
	(0.0598)	(0.1018)	(0.0608)	(0.0755)	(0.1355)	(0.0696)
1(Lacked food last month)_High Storage	-0.0339	-0.1434**	0.0209	-0.0484	-0.1723**	0.0136
	(0.0428)	(0.0716)	(0.0454)	(0.0483)	(0.0812)	(0.0520)
Panel C: Health						
Health Index	-0.0681	0.3398	-0.272	-0.1895	0.3981	-0.4833
	(0.2850)	(0.2964)	(0.3510)	(0.3832)	(0.4209)	(0.4347)
Health Index_High Storage	0.3939	0.1611	0.5103	0.1653	0.0805	0.2077
	(0.2668)	(0.2276)	(0.3573)	(0.3904)	(0.2569)	(0.5174)
1(Health expenditure shortages)	0.0161	-0.0276	0.038	0.0386	-0.0146	0.0653*
	(0.0279)	(0.0396)	(0.0297)	(0.0386)	(0.0585)	(0.0387)
1(Health expenditure shortages)_High Storage	-0.0265	-0.0510**	-0.0143	-0.0213	-0.0625**	-0.0007
	(0.0196)	(0.0259)	(0.0234)	(0.0258)	(0.0312)	(0.0301)
Number of days affected	0.3907	-0.95	1.061	0.2605	-3.0018**	1.8916
	(1.9018)	(1.1018)	(2.7949)	(2.3320)	(1.4532)	(3.3981)
Number of days affected_High Storage	-1.5547	0.4856	-2.5749	0.4825	1.6573*	-0.1048
	(1.9773)	(0.8848)	(2.8997)	(2.7002)	(0.9220)	(3.9415)

Reported any sickness	-0.0033	-0.0815	0.0358	0.0273	-0.05	0.0659
	(0.0531)	(0.0866)	(0.0563)	(0.0742)	(0.1145)	(0.0738)
Reported any sickness_High Storage	-0.0850*	-0.0266	-0.1142**	-0.0636	-0.0191	-0.0858
	(0.0499)	(0.0619)	(0.0578)	(0.0693)	(0.0790)	(0.0784)
Panel D: Household Well-being						
Household Well-Being Index	0.6496*	0.2364	0.8562*	0.5264	0.0401	0.7695
	(0.3875)	(0.3950)	(0.4413)	(0.4859)	(0.4774)	(0.5787)
Household Well-Being Index_High Storage	0.3284	0.4983*	0.2434	0.2868	0.7699**	0.0453
	(0.2407)	(0.2769)	(0.2873)	(0.2892)	(0.3853)	(0.3590)
Log(Income in the past 3 months)	0.4219	0.2627	0.5049	0.1054	0.0243	0.1491
	(0.3154)	(0.2733)	(0.4105)	(0.2205)	(0.3115)	(0.2325)
Log(Income in the past 3 months)_High Storage	0.171	0.3340*	0.0892	0.0703	0.4295*	-0.114
	(0.1837)	(0.1926)	(0.2160)	(0.1897)	(0.2548)	(0.1912)
Log(Annual non-food expenditure, 1,000 Rp)	0.2666*	0.1486	0.3259**	0.2142	0.0427	0.3009**
	(0.1440)	(0.2063)	(0.1408)	(0.1546)	(0.2641)	(0.1415)
Log(Annual non-food expenditure, 1,000 Rp)_High Storage	0.2676*	0.4847**	0.1608	0.2503*	0.6250**	0.0633
	(0.1396)	(0.2026)	(0.1369)	(0.1516)	(0.2935)	(0.1250)
1 (any type of employment)	0.0413	-0.0029	0.086	0.0555	-0.0067	0.1185
	(0.0545)	(0.0246)	(0.0983)	(0.0875)	(0.0286)	(0.1642)
1 (any type of employment)_High Storage	-0.0191	-0.0354	-0.001	-0.0305	-0.0463	-0.0114
	(0.0387)	(0.0266)	(0.0626)	(0.0603)	(0.0340)	(0.1032)
Panel E: Food Consumption and Expenditures						
Food Index	0.0279	0.0529	0.0155	-0.0998	-0.2872	-0.0061
	(0.3306)	(0.4088)	(0.3762)	(0.4710)	(0.4379)	(0.5712)
Food Index_High Storage	-0.0322	-0.1819	0.0427	-0.3645	-0.6174*	-0.238
	(0.2084)	(0.3735)	(0.2229)	(0.2599)	(0.3713)	(0.2851)
log(Food consumption last week, in mok)	0.1098	-0.1105	0.2193	-0.0177	-0.1194	0.0324
	(0.1466)	(0.1390)	(0.1824)	(0.1266)	(0.1614)	(0.1267)
log(Food consumption last week, in mok)_High Storage	0.2253	0.0311	0.3216	-0.0599	-0.0127	-0.0827
	(0.1683)	(0.0930)	(0.2415)	(0.0777)	(0.1117)	(0.0717)
log(Food expenditure last week)	-0.2336	0.1786	-0.393	-0.1732	-0.0792	-0.2108
	(0.2417)	(0.3196)	(0.2845)	(0.2308)	(0.2659)	(0.2606)
log(Food expenditure last week)_High Storage	-0.4862	-0.0703	-0.6987	-0.1778	-0.2148	-0.178
	(0.3518)	(0.2531)	(0.4813)	(0.1935)	(0.2397)	(0.2151)
1(Food expenditure was 0)	0.1748	0.2621**	0.1311	0.2896*	0.2813	0.2938
	(0.1103)	(0.1335)	(0.1243)	(0.1566)	(0.1793)	(0.1793)
1(Food expenditure was 0)_High Storage	-0.04	-0.092	-0.014	0	-0.0705	0.0352
	(0.0710)	(0.0901)	(0.0814)	(0.1166)	(0.1247)	(0.1310)
Ratio of food expenditure to consumption	-0.8194	-1.1215	-0.6691	-1.7811*	-1.7147	-1.8146
	(0.7341)	(0.9219)	(0.8197)	(0.9468)	(1.1681)	(1.1103)
Ratio of food expenditure to consumption_High Storage	0.2763	0.6893	0.0685	0.0643	0.2241	-0.0138
	(0.5639)	(0.6849)	(0.6094)	(0.6963)	(0.7433)	(0.8020)
Share of consumption that is maize last week	-0.0361	-0.0318	-0.0386	-0.055	-0.0739	-0.0461
	(0.0357)	(0.0443)	(0.0366)	(0.0460)	(0.0550)	(0.0456)
Share of consumption that is maize last week_High Storage	-0.0264	-0.0416	-0.0188	-0.0478	-0.0682	-0.037
	(0.0273)	(0.0401)	(0.0317)	(0.0377)	(0.0478)	(0.0411)
Share of food expenditure that is maize last week	0.0038	0.009	0.0027	0.0655**	0.1081*	0.0498
	(0.0362)	(0.0687)	(0.0341)	(0.0326)	(0.0582)	(0.0371)
Share of food expenditure that is maize last week_High Storage	0.0149	-0.0214	0.0305	0.052	-0.0362	0.0924
	(0.0355)	(0.0480)	(0.0385)	(0.0517)	(0.0552)	(0.0586)

* p<0.10, ** p<0.05, *** p<0.01

Heterogeneous treatment effect regressions by the storage propensity of each household. Each regression corresponds to an instrumental variable regression where the dependent variable is an outcome variable and the 2 main independent variables are (i) a take-up dummy instrumented with the treatment assignment (ii) the take-up dummy interacted with a dummy for high storage household. We calculated the average amount of maize and rice produced and stored (averaged over rounds 1 and 2), and calculated storage propensity as (average rice stored + average maize stored)/(average rice produced + average maize produced). High storage households are defined as households whose storage propensity was strictly above the median. The dependent variable for each regression is noted in the table. All regressions include district (kabupaten) fixed effects because assignment of treatment was within each district. Standard errors reported in the parentheses. All standard errors are clustered at the village level. Column 1 uses round 4 and 6 (post treatment) data. Column 2 only includes round 5 (lean season) data. Column 3 only includes round 4 and 6 (harvest season) data.

Table S4: IV for Storage treatment using rounds 4 to 6, by main crop

Sample:	All Districts			Alfa Omega Districts		
Season:	All	Lean	Harvest	All	Lean	Harvest
	[1]	[2]	[3]	[4]	[5]	[6]
Panel A: Seasonal differences, |Harvest - Lean|						
Seasonal Gap Index	-0.2936			-0.7581**		
	(0.3835)			(0.2999)		
Seasonal Gap Index_Maize	1.1640***			0.8188***		
	(0.3714)			(0.2936)		
log(Food consumption last week, in mok)	0.3702			-0.1053		
	(0.3589)			(0.0927)		
log(Food consumption last week, in mok)_Maize	0.4805			0.0953		
	(0.2997)			(0.0736)		
Food expenditure last week, in 1,000 Rp.	-35.1738***			-40.8426***		
	(10.7778)			(10.2341)		
Food expenditure last week, in 1,000 Rp._Maize	41.7205***			36.7155***		
	(9.2156)			(8.5760)		
log(Income in the past 3 months)	-0.2784			-0.3481*		
	(0.2052)			(0.1954)		
log(Income in the past 3 months)_Maize	0.3125**			0.3868**		
	(0.1374)			(0.1617)		
log(Monthly non-food expenditure)	0.1016			0.1653		
	(0.2182)			(0.2763)		
log(Monthly non-food expenditure)_Maize	-0.0108			-0.0067		
	(0.1965)			(0.2325)		
Panel B: Anticipated and Reported Measures of Food Shortages						
Subjective Food Shortage Index	-1.5610***	-2.4644**	-1.1092**	-1.2356***	-2.9317**	-0.3875
	(0.4699)	(1.0194)	(0.5228)	(0.4545)	(1.2722)	(0.4875)
Subjective Food Shortage Index_Maize	1.4030***	1.6378**	1.2856***	1.1124***	2.2574***	0.54
	(0.4035)	(0.7029)	(0.4537)	(0.3792)	(0.8125)	(0.3641)
1(Anticipate food shortage in January)	-0.1558	-0.3742**	-0.0466	-0.0593	-0.4739**	0.1479
	(0.1000)	(0.1778)	(0.1248)	(0.1088)	(0.2106)	(0.1412)
1(Anticipate food shortage in January)_Maize	0.1521*	0.2683**	0.094	0.061	0.3030**	-0.06
	(0.0861)	(0.1351)	(0.1057)	(0.0859)	(0.1418)	(0.1094)
1(Anticipate food shortage in April)	-0.0416	-0.0711*	-0.0269	-0.0556	-0.0978**	-0.0344
	(0.0313)	(0.0421)	(0.0322)	(0.0398)	(0.0486)	(0.0399)
1(Anticipate food shortage in April)_Maize	0.0431**	0.0157	0.0568**	0.0411*	0.0544	0.0344
	(0.0218)	(0.0313)	(0.0274)	(0.0242)	(0.0339)	(0.0263)
1(Anticipate food shortage in November)	-0.2054***	-0.2182*	-0.1989***	-0.1624***	-0.2618	-0.1127*
	(0.0531)	(0.1307)	(0.0645)	(0.0505)	(0.1726)	(0.0602)
1(Anticipate food shortage in November)_Maize	0.1706***	0.1380*	0.1869***	0.1879***	0.2662***	0.1487***
	(0.0433)	(0.0806)	(0.0509)	(0.0458)	(0.0954)	(0.0435)
1(Lacked food last month)	-0.2131***	-0.3586***	-0.1404*	-0.2162**	-0.3762**	-0.1362*
	(0.0762)	(0.1295)	(0.0779)	(0.0856)	(0.1548)	(0.0798)
1(Lacked food last month)_Maize	0.1944***	0.2624***	0.1605**	0.1281**	0.2772**	0.0536
	(0.0585)	(0.1002)	(0.0629)	(0.0520)	(0.1120)	(0.0501)
Panel C: Health						
Health Index	0.2333	0.6447*	0.0276	-0.1164	0.4468	-0.3981
	(0.3240)	(0.3838)	(0.3697)	(0.3574)	(0.4416)	(0.3794)
Health Index_Maize	-0.163	-0.3295	-0.0797	0.006	-0.0198	0.0189
	(0.2532)	(0.2859)	(0.3268)	(0.2906)	(0.2325)	(0.3970)
1(Health expenditure shortages)	-0.0161	-0.0702	0.011	0.0222	-0.0491	0.0578
	(0.0333)	(0.0496)	(0.0336)	(0.0395)	(0.0613)	(0.0378)
1(Health expenditure shortages)_Maize	0.0282	0.0264	0.0291	0.0115	0.0096	0.0124
	(0.0221)	(0.0356)	(0.0253)	(0.0239)	(0.0393)	(0.0296)
Number of days affected	-0.3345	-0.5324	-0.2356	0.7322	-1.4994	1.848
	(2.0681)	(1.5824)	(3.0005)	(2.2451)	(1.8927)	(3.1723)
Number of days affected_Maize	-0.0289	-0.2675	0.0904	-0.4299	-1.2728	-0.0084
	(2.1135)	(1.2074)	(3.1034)	(2.6956)	(1.1423)	(3.9424)

Reported any sickness	-0.0706	-0.1781*	-0.0168	-0.0015	-0.0831	0.0393
	(0.0707)	(0.1081)	(0.0746)	(0.0706)	(0.1104)	(0.0738)
Reported any sickness_Maize	0.0384	0.1213	-0.0031	-0.0011	0.042	-0.0226
	(0.0536)	(0.0801)	(0.0573)	(0.0418)	(0.0661)	(0.0449)
Panel D: Household Well-being						
Household Well-Being Index	1.6125***	1.4330**	1.7022***	1.3865***	1.2840*	1.4377**
	(0.4984)	(0.5849)	(0.5991)	(0.5207)	(0.6683)	(0.6640)
Household Well-Being Index_Maize	-1.1656**	-1.3860**	-1.0555**	-1.2593**	-1.5366**	-1.1206**
	(0.4720)	(0.5690)	(0.5217)	(0.5104)	(0.6684)	(0.5570)
Log(Income in the past 3 months)	0.9251**	0.9995**	0.8900**	0.6506**	0.8198*	0.5667*
	(0.3632)	(0.3948)	(0.4201)	(0.3187)	(0.4329)	(0.3129)
Log(Income in the past 3 months)_Maize	-0.6086**	-0.8299**	-0.4956	-0.8844***	-1.0189***	-0.8154***
	(0.2761)	(0.3293)	(0.3032)	(0.2785)	(0.3795)	(0.2572)
Log(Annual non-food expenditure, 1,000 Rp)	0.7900***	0.9435**	0.7150***	0.6170**	0.8278*	0.5129***
	(0.2548)	(0.3846)	(0.2362)	(0.2434)	(0.4497)	(0.1939)
Log(Annual non-food expenditure, 1,000 Rp)_Maize	-0.5695**	-0.8126**	-0.4497**	-0.4957**	-0.8553**	-0.3171**
	(0.2387)	(0.3504)	(0.2128)	(0.2114)	(0.3915)	(0.1506)
1 (any type of employment)	0.0662	-0.0156	0.1498	0.0691	-0.0323	0.1738
	(0.0843)	(0.0319)	(0.1517)	(0.1120)	(0.0382)	(0.2062)
1 (any type of employment)_Maize	-0.0495	-0.0065	-0.093	-0.0489	0.007	-0.1058
	(0.0758)	(0.0369)	(0.1250)	(0.0971)	(0.0465)	(0.1596)
Panel E: Food Consumption and Expenditures						
Food Index	0.0182	-0.2685	0.1615	-0.2822	-0.7353	-0.0556
	(0.3900)	(0.4931)	(0.4588)	(0.4913)	(0.4897)	(0.5932)
Food Index_Maize	-0.0082	0.3389	-0.1818	0.0236	0.281	-0.1052
	(0.2740)	(0.4293)	(0.3004)	(0.2883)	(0.4579)	(0.3005)
log(Food consumption last week, in mok)	0.1782	-0.1148	0.3294	0.0179	-0.1236	0.0889
	(0.1832)	(0.1581)	(0.2328)	(0.1482)	(0.1757)	(0.1507)
log(Food consumption last week, in mok)_Maize	0.0575	0.0275	0.0651	-0.1096	-0.003	-0.1643*
	(0.1427)	(0.1096)	(0.1830)	(0.0889)	(0.1125)	(0.0986)
log(Food expenditure last week)	-0.7681**	-0.4226	-0.9276**	-0.7449**	-0.6168	-0.8180**
	(0.3863)	(0.5359)	(0.4533)	(0.3415)	(0.3848)	(0.4050)
log(Food expenditure last week)_Maize	0.365	0.6928	0.2429	0.6733***	0.6012**	0.7221**
	(0.2929)	(0.4390)	(0.3567)	(0.2428)	(0.2997)	(0.2846)
1(Food expenditure was 0)	0.5993***	0.6712***	0.5633***	0.6812***	0.6258***	0.7088***
	(0.1393)	(0.1515)	(0.1613)	(0.1584)	(0.1832)	(0.1767)
1(Food expenditure was 0)_Maize	-0.6421***	-0.6559***	-0.6352***	-0.6779***	-0.6530***	-0.6904***
	(0.1204)	(0.1350)	(0.1374)	(0.1325)	(0.1626)	(0.1447)
Ratio of food expenditure to consumption	-3.1811***	-3.2542***	-3.1473***	-4.2741***	-3.9302***	-4.4433***
	(1.0101)	(1.1227)	(1.1211)	(1.0184)	(1.2083)	(1.1677)
Ratio of food expenditure to consumption_Maize	3.5995***	3.5466***	3.6262***	4.3360***	3.9714***	4.5150***
	(0.8620)	(0.9836)	(0.9375)	(0.8937)	(1.1193)	(0.9337)
Share of consumption that is maize last week	-0.1449***	-0.1659***	-0.1345***	-0.1498***	-0.1888***	-0.1303***
	(0.0436)	(0.0536)	(0.0449)	(0.0485)	(0.0643)	(0.0460)
Share of consumption that is maize last week_Maize	0.1387***	0.1647***	0.1254***	0.1244***	0.1424***	0.1149***
	(0.0362)	(0.0447)	(0.0371)	(0.0358)	(0.0479)	(0.0350)
Share of food expenditure that is maize last week	0.2172**	0.2087	0.2205**	0.2664***	0.2541**	0.2717**
	(0.0938)	(0.1361)	(0.0964)	(0.0982)	(0.1099)	(0.1137)
Share of food expenditure that is maize last week_Maize	-0.2532***	-0.2576**	-0.2499***	-0.2431***	-0.2258**	-0.2473**
	(0.0856)	(0.1160)	(0.0894)	(0.0942)	(0.1003)	(0.1087)

* p<0.10, ** p<0.05, *** p<0.01

Heterogeneous treatment effect regressions by the main crop of the household (maize or rice farmers). Only post treatment data are included (round 3 to 6). Each regression corresponds to an instrumental variable regression where the dependent variable is an outcome variable and the 2 main independent variables are (i) a take-up dummy instrumented with the treatment assignment (ii) the take-up dummy interacted with a dummy for maize farmers. Maize farmers are defined as farmers who produced more maize than rice (calculated using yields averaged from the first and second rounds of the survey). The dependent variable for each regression is noted in the table. All regressions include district (kabupaten) fixed effects because assignment of treatment was within each district. Standard errors reported in the parentheses. All standard errors are clustered at the village level. Column 1 uses all the post treatment data (rounds 4 to 6). Column 2 only includes lean season data (round 5). Column 3 only includes harvest season data (round 4 and 6).

Table S5: Summary of results for Storage treatment from instrumental variables regression

	All districts	Alfa Omega districts
Seasonal differences	NA	All: Gap in food expenditure lower by 20,000 Rupiah ** High Storage: Gap in food expenditure lower by 20,000 Rupiah *
Anticipated and reported measures of food shortages	All: Food shortage index lower by 1.33 (L) * 18% less likely to report lack of food in the past month (L) * High Storage: Food shortage index lower by 2.11 (L) *** 32% less likely to anticipate food shortage in January (L) *** 9% less likely to anticipate food shortage in April (L) ** 21% less likely to anticipate food shortage in November (L) ** 25% less likely to report lack of food in the past month (L) **	All: 14% less likely to report lack of food in the past month (A) * (only sig. for A) High Storage: Food shortage index lower by 2.75 (L) *** 47% less likely to anticipate food shortage in January (L) *** 11% less likely to anticipate food shortage in April (L) ** 24% less likely to anticipate food shortage in November (L) *** 31% less likely to report lack of food in the past month (L) **
Health	High Storage: 8% less likely to anticipate health expenditure shortages (L) *	All: 7% more likely to anticipate health expenditure shortages (H) * High Storage: 8% less likely to anticipate health expenditure shortages (L) * Report 1.3 fewer sick days (L) **
Household well-being	All: Houhold well-being index improve by 0.97 (H)* Annual non-food expenditure higher by 40% (A) * High Storage: Household well-being index higher by 1.10 (H) * Annual non-food expenditure higher by 53% (A) **	All: Annual non-food expenditure higher by 33% (H) ** High Storage: Annual non-food expenditure higher by 47% (A) *
Food consumption and expenditures	All: 19% more likely to report no food expenditure in the past week (L) * High Storage: Spend 1400 Rp less per kg of staple consumed (L) *	All: 31% more likely to report no food expenditure in the past week (H) ** Spend 1800 Rp less per kg of staple consumed (H) ** 11% less maize as a share of staple consumption (L) ** 9% more maize as a share of staple expenditure (A) ** High Storage: 33% more likely to report no food expenditure in the past week (H) * Spend 1400 Rp less per kg of staple consumed (L) *

* p<0.10, ** p<0.05, *** p<0.01

This table summarizes the main results for the storage treatment (Tables S3 and S4). The estimates above are the coefficients on the TAKE UP dummy from an instrumental variables regression. (H) represent results using harvest season