Pre-Analysis Plan: Resilience

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1 Introduction

The number of households living in extreme poverty has declined by 72% since the 1990s. However, the pace of this reduction has slowed in recent years (World Bank, 2018). In many cases households are slipping back into poverty when hit by a natural, economic or political shock. Moreover, extreme levels of poverty are increasingly concentrated in places affected by shocks and conflict: more than 100 million 'acutely food-insecure people' lived in countries affected by conflict or extreme weather events in 2019 (FSIN, 2020). This figure is estimated to double in 2020 as a result of the COVID-19 pandemic. Recognizing these trends, institutions have focused on bolstering household *resilience* by ensuring that adverse shocks and stressors that befall households do not have long-lasting adverse development consequences (FSIN, 2020).

The concept of resilience has gained attention because it recognises the importance of addressing shorter-term humanitarian needs while simultaneously supporting communities in their efforts to cope with future crises induced by climate change, conflict, and other factors. Many institutions, including the World Food Programme (WFP), have increasingly used this concept of resilience as a basis for their programming. This pre-analysis plan focuses specifically on the household resilience impacts of WFP's Food Assistance for Assets (FFA) program, which has been delivered to 9.6 million people in 50 countries in 2020, targeting some of the most food insecure and conflict prone areas in the world. This intervention provides immediate cash or in-kind transfers to households and supports the creation of assets designed to benefit households and/or communities in the medium or long-run.[1]

A growing literature documents positive welfare gains from these types of livelihood programs at a single point in time (Banerjee et al., 2015; Haushofer and Shapiro, 2018; Macours, Premand, and Vakis, 2020). Much of this evidence focuses on only a single welfare measure and very few studies come from the most shock-prone and high-poverty countries. There is particularly a lack of evidence on whether these interventions can help households cope with seasonality and shocks, and transition more permanently out of poverty. To fill this gap, the World Food Programme and its partners will implement the same randomized control trial (RCT) across 4 countries (Mali, Niger, Rwanda, and South Sudan) to estimate the impact of FFA on welfare *dynamics*. We build on existing measurement approaches for resilience and develop a high-frequency survey to capture variations in food security due to seasonal

[1]FFA is typically delivered as part of WFP's integrated package of interventions, which aim to improve food security and nutrition by smoothing food consumption in the short-term, while supporting livelihoods and addressing barriers to development in the long-term (e.g., better climate information, access to markets, education, WASH, etc.). While all WFP program activities are potentially important for building resilience, livelihood activities are particularly appealing to study because they are connected to immediate and future wellbeing.

changes or other covariates (e.g., extreme weather events, conflicts, or economic downturns that affect larger populations simultaneously) and idiosyncratic shocks (e.g., death in the family, or loss of livestock that affect specific individuals or households) (Barrett and Constas, 2014; Cissé and Barrett, 2018; Phadera et al., 2019). This approach to measurement allows the evaluation to separately estimate effects of livelihood programming on mean consumption over time, from impacts associated with improved capacity to smooth consumption across seasonality or shocks (i.e. standard deviation over time for a given household). Furthermore, this approach can be used to establish whether certain types of households can successfully transition out of poverty; and the times of the year they are most likely to do so. In addition to contributing to richer outcome measures for evaluating impacts, expanding the use of high frequency data may also contribute to the use of the resilience measures for targeting purposes. For example, if high frequency data allows the evaluations to separate the people, households, or communities who are food insecure only sometimes from those who are food insecure all the time, better targeting decisions could be made.

In each of our country contexts, we randomly assign villages to a treatment and control group. Random assignment is made after communities conduct their targeting exercise to identify eligible participants. This ensures that all of our outcomes are measured on households who would have been selected for participation regardless of their treatment status. Villages in the treatment group invite targeted beneficiaries to work on an asset for 3-6 months and receive cash or in-kind transfers as compensation.[2] Villages in the control group receive FFA at the end of the study period where project funds allow. We collect data at regular intervals from the entire sample for at least one year. By comparing FFA recipients to the control group throughout the year we can identify the impact of these programs on welfare dynamics.

We also aim to benchmark this conditional cash transfer (CCT) program against a pure cash transfer, and isolate the impacts of this livelihood program beyond the direct income benefits of cash transfers alone. In some countries (South Sudan) we do this by introducing a pure cash treatment arm (UCT), which delivers the same monetary value to households as the CCT arm without requiring any additional work. In countries where this is not fea-

[2]In most country contexts, WFP and its partners implement cash transfers and associated livelihood activities alongside other interventions in the spheres of health and education. In three out of four countries, these other non-livelihoods interventions will be delivered to both the treatment and control groups, so that the experimental design measures the additional contribution of cash + livelihoods beyond other activities. In one country (Niger), the additional activities will only be delivered together with the livelihood activity. This paper focuses on the impact of FFA, and as such we will pool all treatment arms that include a livelihoods component through an approach similar to that typically followed in meta-analysis. We will also test the impact of FFA separately with the natural hypothesis that impacts may differ between Niger where FFA is implemented alongside other interventions and the other contexts where FFA is delivered by itself. We discuss the implications of this further in the Analysis section.

sible (Mali), we try to capture the value of cash alone by randomly selecting 1-2 households within each community to receive an unconditional cash transfer upon completing our high frequency survey. While we recognize that a one-time cash drop may not be directly comparable to a longer-run UCT or CCT program, this smaller experiment is designed to provide a framework for estimating the marginal value of a dollar transferred by WFP. Moreover, by providing these cash drops throughout the year we can map whether households' marginal propensity to consume varies with the season. There are some countries where neither approach to estimating the value of an unconditional transfer is possible (Niger, Rwanda).

Finally, beyond testing the overall impact of livelihood activities on wellbeing, a key ambition of this paper is to investigate whether activities themselves can be timed to accommodate households' vulnerability to seasonal fluctuations and shocks that are often connected to weather patterns and agricultural cycles. We identify one such mechanism: adjusting the timing of cash transfers and labor requirements. The WFP's FFA activities currently couple cash and labor requirements. Adjusting the timing of cash transfers and asset building activities to match seasonal fluctuations in household consumption and labor could accommodate this inherent variability throughout the year and further improve wellbeing. To test this hypothesis, we conduct a pilot to randomize existing CCT villages in South Sudan into two groups based on the timing of transfers and livelihood activities: a "Coupled CCT," and a "Decoupled CCT."[3] The coupled CCT provides cash transfers and work requirements at the same time (in the pre-harvest season). The "de-coupled CCT" provides cash in the pre-harvest season when the Marginal Propensity to Consume (MPC) and Marginal Product of Labour (MPL) are high: households are busy cultivating their crops and have few other sources of income to rely on. Work requirements are introduced in the post-harvest season when the MPC and MPL are low: households have sold their crops and are no longer busy tending to their fields.[4] If households lack a technology to substitute consumption and labor inter-temporally – as seasonality in MPC and MPL suggests – decoupling the two can enhance wellbeing.

This study makes three primary contributions. A growing literature has relied on measuring the impacts of livelihood programs at a single point in time, and documents positive gains in wellbeing (Banerjee et al., 2015; Haushofer and Shapiro, 2018; Macours, Premand, and Vakis, 2020). Yet, rural households are systematically exposed to seasonal fluctuations and shocks such as changes in precipitation or agricultural productivity, which means that

[3]We use the term "existing CCT" to refer to villages that had already been enrolled in FFA prior to the beginning of the study.

[4]This means that participants will not receive transfers in the same months they work on assets. To the extent that households benefit from these assets, and the opportunity cost of engaging in this work is low, we would not expect this de-coupling to affect households' investment in the asset

higher wellbeing at one point during the year does not necessarily imply levels of persistently high or improving wellbeing. Given the dynamic environments under which people make constrained decisions over labor, productivity, and consumption, we know the people who are poor today may not be the people who are poor tomorrow. This means that evaluating these programs, and especially evaluating the modalities by which programs can be optimized requires measuring wellbeing repeatedly throughout the year both across seasons and before and after shocks. Building on the proposals of Barrett and Constas (2014); Cissé and Barrett (2018) to conceptualize resilience as avoidance of poverty in the face of shocks and stressors, we propose to directly measure core parameters of an underlying structural equation of motion for welfare dynamics. These measures are calculated from a minimum set of food security indicators collected at higher frequency than is typical of most impact evaluations which often only include one baseline and one endline survey in the same season of the year. Our proposed measurement framework allows the evaluation to separately estimate program effects on reference levels of consumption associated with changes in permanent income (i.e., mean consumption) from impacts associated with improved capacity to smooth consumption across seasonality or shocks (i.e., standard deviation over time for a given household).

Our experiment also contributes to the literature by studying the impact of a livelihoods activities above and beyond the impact of cash transfers alone. We complement a growing literature on the impacts of multi-faceted programs that aim to generate long-term changes in household wellbeing (Banerjee et al., 2015). In most cases, these studies do not test which of the program's dimensions are individually necessary. Recent work by (Macours, Premand, and Vakis, 2020) isolates the benefits of adding capital grants, and a skills training component to a standard conditional cash transfer program. They find that both of these interventions improve households' ability to smooth consumption by diversifying their income streams. Our approach complements this work by trying to identify the marginal contribution of asset activities beyond unconditional cash transfers.

Our experiment also explores how changing the timing of a livelihood program improves welfare. Literature on cash-for-work programs have long recognized that their impact depends on participants' outside option (Jalan and Ravallion, 2003; Datt and Ravallion, 1994; Bertrand et al., 2017). Given that earning opportunities vary substantially across locations and seasons, it follows that impact of these programs could vary significantly as well – as explored in Beegle, Galasso, and Goldberg (2015) who shift a cash-for-work program from the harvest to the lean season. We expand on this work by explicitly separating the timing of the cash and labor components from a similar livelihood activity.

This approach builds on a recent literature that investigates different ways to overcome the negative consequences of seasonal fluctuations. Burke, Bergquist, and Miguel (2019) observe large seasonal price fluctuations in Kenyan grain markets and offer farmers loans to take advantage of these unexploited arbitrage opportunities. They find farmer revenues increase significantly as farmers start to buy when prices are low, and sell with they are high. Bryan, Chowdhury, and Mobarak (2014) observe large decreases in consumption during the yearly seasonal famine in Bangladesh and offer travel subsidies to farmers to find work. They document large increases in migrant households' consumption. Moreover, Fink, Jack, and Masiye (2020) find that liquidity-constrained households often sell too much labor off the farm during the lean season, to meet short-term cash need, at the cost of future production and consumption. Finally, Casaburi and Willis (2018) observe that very few people purchase insurance when the premiums must be paid up-front. By shifting this payment to the post-harvest season, they dramatically improve the share of households that buy insurance. We complement this existing work by studying how a major international assistance program can be designed to account for seasonality. Unlike previous work, this type of program does not build on an existing market structure (e.g. grains or insurance). Rather, we focus on a standard form of aid and re-optimize the timing of its component parts.

2 Research Context

The World Food Program was established in 1961 as a vehicle to provide food assistance through the United Nations system. WFP operates along the humanitarian-development nexus, supporting people to move from a situation where they need humanitarian assistance to sustained development. WFP's Strategic Plan for 2017-2021 aligns with the broader 2030 Agenda and the Sustainable Development Goals, particularly, SDG 2 on ending hunger and all forms of malnutrition. With almost two-thirds of the extreme poor in the world now living in countries affected by conflict, climate shocks and economic downturns, meeting these goals will be a challenge.

The concept of 'resilience' has become increasingly prominent in WFP operations. This is reflected in WFP's policies that advocate for the use of innovative tools and approaches to strengthen resilience of individuals and communities (WFP, 2015). Many WFP country offices have streamlined the provision of an integrated 'resilience' package where communities and households receive a bundle of activities over several years. The entry point for many of these programs are FFA activities. WFP uses "Vulnerability Analysis and Mapping (VAM)" and "Essential Needs Assessments" to understand which populations require which types of support. The selection of specific beneficiaries among those who are eligible takes place at the community level through a Community-based Participatory Planning (CBPP) approach.

The CBPP ranks households from most vulnerable to least vulnerable. Depending on the country context, different shares of the population are then targeted for FFA (see country specific designs).

The organization works with local governments and stakeholders to select the type of assets they will work on based on Seasonal Livelihood Planning. The assets mainly fall into 5 categories: water source development (dams, weirs, and water points) for productive purposes; natural resources development and management; improving crop and livestock productivity; improving market linkage and access to social services and infrastructure; and income generation (feedlots, market stalls). The asset creation activities take place for 3-6 months during a year. While households work on the assets, they receive monthly cash/vouchers/food transfers to cover their immediate food needs. As they rehabilitate or create assets, they contribute to improving their long-term food security and resilience. Additional activities under the integrated programme, such as delivering nutrition, WASH or school-based programming services, are delivered in the villages around the sites where the assets are created.

3 Experimental Design

3.1 Program Details and Sampling

The livelihood activities in this study align with similar programs that provide cash payments tied to the condition of undertaking some form of work (CALP, 2020). While the nature of the work differs substantially across programs, it typically involves an activity that is designed to generate positive returns for the household, or the community they live in. WFP introduced a livelihood program called Food Assistance for Assets (FFA) in the 1990s to meet the short-term food needs of vulnerable populations (through cash transfers), while promoting long-term resilience through the production of assets (WFP, 2019).

We design an RCT that measures the impact of the WFP livelihood program on welfare dynamics. To this end, villages in all countries are randomly allocated to a treatment and control group (Figure 1). In the treatment arm (CCT), WFP provides their cash-for asset program to selected beneficiaries. We compare CCT beneficiaries to the control group to isolate the benefits of a livelihood program on welfare dynamics. Note, communities are informed of the support they will receive or not (their randomized treatment status) after the CBPP process is completed to enable a comparison of similar populations across treatment and control.

In some countries (South Sudan), we introduce a second treatment arm (UCT), where

WFP provides unconditional cash transfers of the same monetary value as the cash transfer provided under CCT to households.[5] We compare CCT to UCT recipients to understand whether the positive returns from the asset outweigh the costs from having to invest additional labor over time. The CCT activities do not typically produce measurable income gains in Year 1, which makes the comparison between the UCT and CCT possible.[6]

Where this is not feasible (Mali), we introduce randomized cash drops to one respondent per village in the treatment and control groups during each round of the high frequency surveys (as an incentive for participating). By randomizing at the individual level within village, we are powered to estimate the impact of unconditional cash transfers (in the short run). We recognize that a one-time transfer is not directly comparable to a longer term program. Nevertheless, the cash drop provides a framework for bounding the marginal value of an additional dollar that WFP transfers in a given month.[7] Taken together these experiments are designed to isolate the additional benefit of assets on their own. This complements existing research on graduation programs, which were designed to understand the effect of a package of interventions that includes assets combined with other forms of assistance (namely cash and training) (Banerjee et al., 2015).

Finally, we hypothesize that the welfare gains associated with these programs could increase if the timing of their own activities were adjusted to accommodate seasonality and shocks. These fluctuations are especially relevant in agricultural economies where households' marginal utility of consumption and opportunity cost of labor are positively correlated, as in the context of all cases enrolled in the study so far. During the pre-harvest season, households have less disposable income and less time to devote to non-farm activities. In the post-harvest season, households have additional income from selling their crops and fewer demands on their time. It follows that cash transfers should be provided in the pre-harvest season when the marginal utility of consumption is high, and work requirements should be reserved for the post-harvest season when the returns to alternative labor allocations are low. To test this hypothesis, we pilot an experiment with existing CCT villages in South Sudan, dividing them into two groups. In the first group, villages receive the "Coupled" WFP cash for asset program - households are invited to work on the asset while they receive cash payments. In the second group, villages receive a "De-coupled" WFP cash for asset program, whereby the cash transfers are provided when the marginal utility of consumption is highest

[5]We do not include the value of the materials provided for asset construction in the CCT.

[6]In most cases the activities that beneficiaries engage in can be broadly categorized in two groups: small scale vegetable plots – whose yields we can capture in one agricultural cycle; and larger scale projects (i.e. irrigation ditches) that do not generate income gains to the household specifically.

[7]Given that this is a one-time surprise transfer to 1 person within a village, we believe the spillover effects are negligible.

(the pre-harvest season), but work requirements are limited to when the marginal cost of labor is low (the post-harvest season). Comparing the de-coupled CCT to the coupled CCT isolates the welfare gains associated with providing cash and labor at times when the MPC is high and the MPL are low, respectively. Importantly, this tests the value of changing the timing of programs to account for seasonal variation in labor calendars and consumption patterns.

3.2 Countries

In what follows we provide details of each country program.[8]

3.2.1 Mali

Table 1: Experimental Design: Mali

Control	2764 (46)
FFA	2651 (45)
Cash drop	851 (91)

The comparison of FFA versus of control is restricted to households that are above the 30% threshold poverty status. The bottom 30% received FFA (CCT) and an additional cash transfer (UCT) in treatment, and cash (UCT) in control villages. In addition, 851 households (9-10 households per village) are randomly selected to receive a separate UCT of $30 USD at one point throughout the year. Please note that additional activities take place across FFA and control locations (these are balanced). These activities include (i) nutrition and WASH services, and potentially (ii) education; (iii) facilitation of market access for smallholder farmers. To verify that work on FFA takes place, participants sign a log book during each work day, which is cross checked with the FFA beneficiary list before payments. Attendance is nearly universal. Assets include and vegetable garden development, irrigation, water retention dykes, compost pits, and other agricultural work.

3.2.2 Niger

Table 2: Niger Experimental Design

Control	2335 (45)
FFA+	2379 (46)

[8]See Appendix Table for additional detail

WFP Niger implements an integrated resilience program including a package of interventions: Food for Assets (FFA), seasonal cash transfers (lean season support), preventive and curative nutrition/health measures, school feeding, facilitation of market access for smallholder farmers (SAMS). As part of the FFA intervention, WFP provides cash for individuals from 3-4 villages surrounding the site to work on assets during the agricultural off-season (February-May). Most assets involve the recuperation of communal plots, which are managed by a committee. The sample of targeted beneficiaries include the poor and very poor, where the very poor also receive seasonal cash transfers. This varies by region but average target rate per village across program areas is 69%.

3.2.3 Rwanda

Table 3: Experimental Design: Rwanda[9]

Control	387 (18)
FFA	783 (34)

The Food-for-Asset (FFA) program targets households from the poor and very poor socio-economic classification categories who are not already benefiting from a public works program, and they comprise 30% of villages on average. The program includes a cash transfer conditional on working in community projects. Beneficiaries receive $30 per month over a period of 2-3 months while working on community assets, the most common of which are land terracing and marshland reclamation. Work compliance is done by an on-site supervisor who collects attendance records with household identifiers.

3.2.4 South Sudan

Table 4: South Sudan Experimental Design

Control	595 (29)
FFA	540 (24)
UCT	505 (23)
De-coupled FFA	224 (8)
Coupled FFA	224 (8)

In South Sudan, the program targets households in the bottom 30% of the poverty distribution as defined by the CBPP. The FFA includes a cash transfer of $45 per month for 6 months during the lean (pre-harvest) season, conditional on participating in a public works program. Assets include land clearing and plantation, vegetable gardening, community road, dyke, and pond construction, and tree seedling production. The work on the community assets takes place during the same 6 months, and is verified using attendance lists at each work site. Please note that additional activities may be implemented across treatment and control communities including: a) educational services and b) access to quality health and nutrition services for women and children under five years. The "pure cash" UCT treatment arm includes the same cash transfer ($45), but without the work requirement. Control communities receive some form of WFP assistance once the study ends, where funds allow. The targeting was the same across UCT and CCT and control.

The De-coupled FFA group will continue to receive the cash transfer in the lean season, but work requirements will shift to the post-harvest season.

4 Measurement Framework

4.1 Defining Resilience

Measurement of resilience has mostly taken one of three approaches in the literature. The first is to define ex ante characteristics of households that are expected to be associated with lower resilience, and construct a “resilience index.” This is the approach of FAO’s RIMA index or the TANGO resilience index, as well as examples of resilience evaluations that use characteristics like diversification of livelihood strategies as a proxy for resilience Macours, Premand, and Vakis (2020). The second is to regress outcomes on measures of shocks in order to isolate the contribution of shocks on food security. The third is to use measurement of different households’ food security at different times to impute a given household’s food security path and then measure parameters of the imputed distribution as in Cissé and Barrett (2018) or Christian and Dillon (2018).

Our measurement framework extends these existing imputation-based measures of food security dynamics by allowing idiosyncratic shocks that are not shared across households. The measures of interest are closely related to proposed measures of vulnerability (Ligon and Schechter, 2003), but we aim to measure underlying consumption smoothing behavior rather than the welfare consequences of such behavior. We argue that resilience is best described not by a single index, but by the following simple structural equation for household welfare:

$$y_{it} = \alpha_i + f_i\left(d\right) + \delta_i t + \epsilon_{it}$$

Where y_{it} is a measure of wellbeing such as aggregate consumer expenditure, food security, or poverty status, for an observation unit i at time t. Since the programmes included in the study primarily focus on improving food security and nutrition outcomes, selected food security indicators will be used as measures of wellbeing.[10] The four components of this equation determine a household’s ability to avoid food insecurity over time, and can be estimated as a regression of household food security on time and survey dates. To understand this equation, imagine using this framework to estimate a household’s level of resilience. Specifically α_i, the household specific fixed effect, measures a household’s reference level of food security. The second term is a function of the calendar date on which food security is measured, and measures seasonality. The third term is a trend measuring how quickly a household is improving food security over time t. Finally, ϵ_{it} measures exposure to shocks

[10] The model is flexible and allows for the observation unit to be an individual, a household, or a village/community, etc, with analysis for each main specification planned for the household level. Similarly, the length of the interval defined by the time t could be defined as daily, monthly, semiannually, yearly, etc., as is relevant.

not systematically correlated with survey dates. Figure 3 shows how this looks in a plot, where we measure a household's consumption or food security status in ever period from t = 0 to some period t = T.

Impact evaluations typically focus on measuring a household's consumption at one point in time, with the view that a single observation is a sufficient statistic for that household's reference level of well-being for a given year. In panel A, the red and blue households differ only in their value of α. The household whose consumption is depicted by the red line is always "more food insecure" than the household whose consumption trajectory is shown by the blue line, meaning that for any given food security threshold, the blue household will be food insecure if and only if the red household is also food insecure.

However, the average food security of the household over the period (α_i) only captures one feature of the consumption function that is important for welfare analysis. The blue household in panel B has a steeper δ, indicating a steeper trend in food security, meaning that this household will move above the poverty line and/or farther away from it. The blue household in panel C has a seasonal pattern with greater variability than the household with a red line. Seasonality could lead to households falling below a food security threshold in the lean season. In panel D, both the red and blue household experience a shock at the same point.

Given the structure of the equation of motion for consumption above, each component could be estimated if data were collected every day from t=0 to T. However, such data is virtually impossible to collect and may not be necessary to distinguish impacts arising from influencing different components of the wellbeing equation. We propose to operationalize resilience measurement by repeated sampling of the same household on different dates within a pre-defined period, and estimating key household-specific parameters of the structural consumption equation from this sample of consumption at different dates.

4.2 Operationalizing Feasible Measures of Resilience

These impact evaluations will estimate welfare trajectories within a one year period following the start of a program. Figure 3 shows a hypothetical consumption path for a household in a period t = 0...T. The dynamics shown could represent either a seasonal consumption path with one lean season and one peak season, or a household who experiences one positive and one negative shock.

The first measure of the consumption equation we are concerned with is the **household's intra-annual reference** level of consumption – this is α_i in the structural equation. If we observed a household's value of consumption on every day, this would be measured as a household's average food security status over the period – as shown by m in Figure 3 – Panel A. Next we consider the household's **intra-annual standard deviation**, the average of the household's deviations from the reference mean (Figure 3 – Panel B). The standard deviation captures the combined influence of both $f(d)$ and (ϵ) on household welfare trajectories. This single indicator summarizes the variability associated with both seasonality and shocks within the period. The third measure, is the time trend. However, by limiting the comparison within a year, we do not consider a year-on-year trend in welfare. The final measure we consider is the **share of the period the household spends below a poverty** line or food security range. This is the number of days covered below the poverty line divided by the total number of days in the period of interest (Figure 3 – Panel C). Resilience is then defined as the ability of a household to avoid poverty over time, which we operationalize in the following way:

- A household with a higher m is on average higher above or less below the food security threshold. So households with higher m are more resilient than households with lower m. The intra-annual reference mean of food security is measured by: $\hat{m}_i = \frac{1}{n_i}\sum_{t=0}^{T} y_{it}$
- Conditional on m, having a higher standard deviation will increase the likelihood of falling below a food security threshold, the share of time spent below the poverty threshold, and/or the number of days that are relatively far below the food security threshold. Conditional on m, households with a higher standard deviation are less resilient. The intra-annual reference standard deviation of food security is measured by: $\hat{s} = \frac{1}{\sqrt{n_i}}\sqrt{\sum_{t=0}^{T}(y_{it} - m_i)^2}$
- Households who spend more time below the threshold are less resilient than households who spend less time above the line. The share of observations below a poverty line is measured by: $\hat{share}_i = \frac{1}{n_i}\sum_{t=1}^{T} \mathbb{1}(y_{it} < \bar{y})$

where n_i is the number of times community, household, or individual i is surveyed; T is the length of the period over which resilience is measured, y_{it} is a measure of household food security status, and $\bar{y}$ is a threshold below which a unit is considered poor or food insecure. These three measures, defined for a selected set of food security indicators, will be our main welfare outcomes. Below we consider power and describe how frequently we need to measure outcomes to detect changes on these outcomes associated with interventions.

Figure 4 shows what how the measures look like for the household with the hypothetical sinosoid function shown so far, assuming a quarterly data collection schedule in which food security status is observed at 3 month intervals. For this household, the reference level of consumption m (shown by the red dashed line) is simply the average of the 4 points. The intra-annual standard deviation estimated by calculating the standard deviation of the four points, the average of the solid red lines. The range is the difference between the highest of the four values and the lowest, the difference between the dashed black lines. And the share of the period spent below the poverty line is the number of observations that fall below the poverty line (the grey dashed line) divided that by the total number of observations (number of grey dots divided by number of blue dots).

5 Data Collection and Survey Instruments

5.1 Timeline and Survey Instruments

Data will be collected through baseline, midline and endline surveys. We will administer the baseline survey in Year 1 before beneficiaries receive any one of the treatments listed above. Typically, baselines will take place at the same time beneficiaries are registered with WFP – a few months or a few weeks prior to the first cash transfer. A midline will take place the following year, after Year 1's harvest, but before Year 2 of the program. Finally, we will implement the endline survey before Year 3 of the program. Comparing outcomes at midline and endline will be particularly valuable for documenting how the impact of FFA changes over time since the benefits of FFA programs typically take more than 1 year to materalize.[11] We complement these yearly rounds of data-collection with high-frequencies surveys that ask a smaller set of questions at more regular intervals (Table 6). Further details of these shorter surveys, including timing, is discussed in 7 below on power calculations.

At baseline, we conduct a household roster by asking the primary household head to list each member of their household, their age, gender, highest level of education, whether they have a disability, primary activity. The following outcomes variables will be defined according to that roster.

5.2 Primary Outcomes

Consumption and Food Security Our primary measure of consumption and food security is WFP's *Food Consumption Score:* which catalogues the number of days in the past

[11]For example, in South Sudan this timeline will look as follows. Targeting will take place in October 2020, and beneficiaries will be officially enrolled in the program in February 2021. The baseline will be rolled-out alongside the registration of beneficiaries. Transfers will be made starting March 2021, and work requirements will begin March 2021 for the Coupled CCT beneficiaries, and in September 2021 for the De-Coupled CCT beneficiaries. The re-targeting exercise and the midline survey will take place between November-Jan 2021 – after Year 1 harvest but before Year 2 transfers. We conclude field operations with an endline survey in February 2023.

week the household consumed major food categories (e.g. maize, tubers, fish, eggs, vegetables, etc). The final score is the sum of these counts.

We also use several additional measures of household consumption and food security for robustness:

- *Food Insecurity Experience Scale:* The Food Insecurity Experience Scale captures respondents' overall food insecurity levels over the past 12 months. It consists of eight questions capturing a range of food insecurity severity, with yes/no responses.

- *Consumption Expenditure:* Expenditures over a standard reference period for a comprehensive list of food and non-food goods are asked.

5.3 Secondary Outcomes as Mediators

Our secondary outcomes are intermediate outcomes that influence the primary outcomes at the end of the theory of change.

Income Generating Activities We ask respondents which types of income generating activities they currently pursue, including: 1) non-farm business, 2) agriculture and livestock, 3) wage employment. For non-farm business, we ask for revenue and profits from the two largest businesses managed by the household. For agriculture and livestock, we ask for all plots cultivated by the household in the previous year, including input use, labor, and quantity of each crop harvested and sold. We also ask respondents about the current stock of livestock, and profits from livestock over the previous 12 months.

Reservation Wages In high frequency surveys, we will ask respondents a series of questions designed to capture their reservation wage, including the minimum hourly wage they would be willing to accept for jobs that take various amounts of time, how often they would be willing to work, and how likely they think it is that they would be able to find work.

High frequency surveys will include a hypothetical question asking a member of the household would be willing to accept a job for a day helping to track down community members to remind them to participate in the survey and the minimum wage they would accept to take such a job. We ask this question both allowing the to select any member to accept to accept the job, and restricting to the person the household identified as most likely to work on WFP assets. This allows us to measure the opportunity cost of labor for the person in the household with the lowest opportunity cost.

Time-Use At baseline/endline the primary beneficiary is asked what activities they were doing at various points during the previous day, followed by questions about the amount of time spent on a set of activities. As most of WFP's beneficiaries will be engaged in agricultural activities through the year, a standard agricultural module will collect information about how households allocate their labor investments across the agricultural cycle.

It is very important to capture the amount of time WFP beneficiaries, or another member of their household, invest in WFP programming and whether this displaces other activities they would normally engage in. To this end, we develop a dedicated module on WFP activities, which asks which member of the household has spent time WFP assets, how much time they have devoted to this, and what this person would have been doing otherwise. Time use is important to measure in addition to income and reservation wages, because households may substitute away from uncompensated activities to work on WFP assets (which we would not pick up through our income measures alone).

In our high-frequency surveys we will again ask a set of questions asking for the number of hours respondents spent on specific activities (working outside the home; working inside the home; on leisure; and WFP activities). Finally, and only where possible, we intend to monitor work on the asset.[12]

Assets We ask about a comprehensive list households assets owned by the household. At baseline we ask about the amount and value of these assets. In our high frequency surveys and endline, we ask about the same set of assets (how many they own and their value). We want to make sure we cover assets that are correlated with wealth, as well as productive assets (to be used in income generating activities).

Shocks and Coping Mechanisms We ask households what shocks (drought, flood, family death, asset loss, job loss, etc.) households have suffered over the previous 12 months and the severity of each shock. In response to any of the shocks identified, we ask which coping mechanisms the household used over the previous 12 months to help manage. Examples of coping mechanisms are selling assets for cash, reducing consumption,increasing labor supply, and access to safety nets.

Migration We ask which household members have migrated over the previous six months (or since the last survey), and whether they send money back home.

[12]Nominate a 'collector' who maintains an attendance sheet.

Financial Outcomes We ask each household about about four financial outcomes: their current savings levels, whether they have taken a loan and their current outstanding debt, and if they receive any cash transfers (from NGOs, friends, or family members) over the past month.

5.4 Tertiary Outcomes

Our tertiary outcomes are outcomes at the end of the theory of change - but they are not the primary motivation for doing the study.

Conflict We measures two outcomes of conflict: 1) whether the household experienced conflict in the last year; 2) conflict outcomes (at the village level) measured by the Armed Conflict Location & Event Data Project (ACLED).

Psycho-social well-being We create a psycho-social well-being index from the following measures:

- *Stress (Cohen)*: We measure stress using 10 questions from Cohen's Perceived Stress Scale (the most widely used tool for measuring the perception of stress).
- *Well-being*: We measure well-being by asking the Cantril Self-Anchoring Striving Scale for both the present and future. The tool instructs households to imagine a ladder with steps numbered from 0 (bottom) to 10 (top). The top of the ladder represents the best possible life for the respondent, while the bottom of the ladder represents the worst possible life for them. Respondents are asked to think about where on the ladder they feel now, and where they think they will feel 5 years from now.
- *CESD*: We measure depression using the ten-question Center for Epidemiologic Studies Depression Scale (CESD), a standardized screening tool that assesses mental and emotional health disorders.
- *Life Satisfaction*: Life satisfaction is measured with an adapted version of Diener's Satisfaction With Life Scale.
- *Self-efficacy*: We measure ability to cope with challenges using a 10-question General Self-Efficacy Scale (GSE).
- *Aspirations*: We measure aspirations for the future by asking beneficiaries about their hopes for the educational attainment, employment, and income for the youngest male and female child of the household.

Women's Empowerment We ask about perceptions around gendered decision-making, drawn from the Demographic Health Surveys. We measure how strongly people believe they have control over the situations and experiences that affect their lives using Rotter's locus of control questionnaire. We also ask about women's time-use, wage, and labor outcomes specifically.

Social Capital We ask 3 indices related to social capital: a social cohesion closeness of community index, a financial support index, and a collective action index. We also ask for trust of various community members and institutions.

6 Hypothesis and Analysis

The sampling frame will be the list of eligible households, where eligibility is determined by each country's targeting process. Village level treatment assignment will be stratified by geographic area in each country. As a randomization check we perform a balance test on basic demographic data as well as on outcome variables that are collected at baseline (FCS, FIES, psychosocial and subjective wellbeing, livelihood sources, and asset index).

Across all specifications, we use double-selection LASSO to select controls for precision and we control for baseline measures of our outcomes when they are available through an ANCOVA specification.[13] We cluster standard errors at the community level whenever the treatment of interest is assigned at the community level. We will also report randomization inference significance levels for all hypothesis tests. Finally, within each outcome category we will report multiple hypothesis corrected p-values for all hypothesis tests.

6.1 Primary Analysis

For our primary analyses, we focus on the mean and standard deviation of the FCS.

6.1.1 Specification 1a

To determine the additional contribution of assets to resilience, as measured by improvements in food security, we run the following specification:

$$Y_{hct} = \beta_0 + \beta_1 \text{UCT} + \beta_2 \text{CCT} + \varepsilon_{hct} \tag{1}$$

[13] As a robustness check, we also run all specifications without any controls. This is not our preferred approach because in expectation it is lowered powered.

where Y_{hct} is the mean or intra-annual standard deviation, UCT is an indicator for receiving cash in the pre-harvest season, and CCT is an indicator for whether a village was assigned to a CCT treatment arm. We test whether $\beta_1 \neq \beta_2$, which is a comparison of the average outcome Y in the UCT and CCT groups. A priori we might expect $\beta_2 > \beta_1$ if the productive asset confers additional benefits to the household. There may be time horizons, under which $\beta_1 > \beta_2$ if the productive asset requires labor that diverts from other productive activities in the short term, but additional income from the asset takes time to materialize.

We take the meta-analysis approach where interventions with common core treatments are pooled despite differences their implementation and other complementary treatments. For the purposes of specification 1, the UCT dummy will include any treatment arm that includes a cash transfer but does not impose a conditional requirement to provide labor. Please note that any country that does not have a UCT will not contribute to the estimation of β_1. Currently only South Sudan will contribute to the estimation of β_1. The CCT arm includes any treatment arm where both a cash transfer and a requirement for the household to provide labor to be eligible for the transfer are present. For our primary outcomes, we will report a single pooled regression for all countries, including country fixed effects. We will also report the same regression separately for each country in the window.[14]

In most contexts additional WFP interventions focused on health, education and other activities will be delivered in both the treatment and control groups, such that any difference between the two groups can be interpreted as the impact of FFA. In Niger, the additional activities will only be included in the CCT areas (which is often referred to as FFA+). We acknowledge that the impact of the FFA program could be different in Niger as a result, and we propose to separately estimate this regression equation for each country to identify such differences. A finding that Niger has greater impacts than the others country contexts would not be sufficient to quantify benefits of FFA delivered it's own. The cases that randomize only FFA against a control group remain the cleanest test of the impact of FFA by itself. Where other WFP interventions are implemented in groups that are not part of the FFA experiment, specification 1a can be used with other programs as treatments. When other interventions do not perfectly with FFA treatment arms, access to other interventions will be treated as a heterogeneity variable for interaction with treatment as described below.

We also note that in an ideal world all complementary interventions would be cross randomized, allowing for the marginal impact of each program to be evaluated separately. Unfortunately, due to constraints in programmatic implementation and statistical power,

[14]The definition of period within which the primary are calculated will be based on the minimum duration of data collection across countries. Each country's separate regression will include the outcome calculated on both the cross-country minimum duration of high frequency and that country's maximum horizon for high frequency.

this type of design is infeasible. .

6.1.2 Specification 1b

A feature of FFA, especially relative to a UCT is that it may take time for impacts to develop if assets divert labor from other productive activities in the short term but produce income gains in the longer term.

$$Y_{hctr} = \beta_0 + \beta_1 \text{round} + \beta_2 \text{UCT} + \beta_3 \text{CCT} + \beta_4 \text{UCT} * \text{round} + \beta_5 \text{CCT} * \text{round} + \varepsilon_{hct} \quad (2)$$

'where y is mean of FCS, intra-annual standard deviation of FCS and assets and income measured at baseline and endline; and round is a high frequency data round of collection. In countries that include both a midline and endline, we also estimate this specification where y is annual income and round is baseline, midline, or endline. This specification allows us to test whether the difference in average outcomes change by round. For example if the difference between β_4 and β_5 is greater for the midline interactions than for the endline interactions, we infer that UCT groups are more advantaged relative to CCT groups at midline than they are at endline when the CCT group has had more time to realize the returns to assets or better re-adjust their labor decisions to CCT conditions.

6.1.3 Specification 1c

Within a country, UCT and CCT transfers are delivered at the same time and in the same amounts for all recipients. In order to more finely assess the marginal contribution of an additional dollar, we will assign individual households in both control and UCT/CCT treatment arms to receive a small transfer we call a cash drop (in countries where this is feasible and agreed by WFP partners).[15] This cash drop is a lottery to win $30 in the month before each round and will come as a surprise. These transfers will allow us to test whether expanding the transfers in a given month would have increased food security relative to the control or the fixed transfer amounts in UCT/CCT using the following specification where Y_{hcrt} is FCS measured in high frequency round r at time t:

$$Y_{hct} = \beta_0 + \beta_1 \text{cashdrop} + \beta_2 \text{UCT} + \beta_3 \text{UCT} * \text{cashdrop} + \beta_4 \text{CCT} + \beta_5 \text{CCT} * \text{cashdrop} + \varepsilon_{hct} \quad (3)$$

The interaction terms with the cash drop in the above specification tell us the marginal

[15] This cash drop also provides compensation for the time of answering repeated surveys, which will hopefully improve survey response compliance.

impact on Y of an additional increase in cash in the previous period. For example, if $\beta_5 > 0$ for a particular round t, we conclude that additional cash in that round increases the outcome beyond the usual CCT program.

We also investigate whether cash drops are more effective in certain parts of the year over others. A further test of the role of seasonality will be the interactions of the cash drops with the months in which a household is selected to receive the drop. We will implement this test by interacting the cash drop and its interactions with treatment arms with a full vector $\mathbf{R}$ of dummies indicating the round in which the household received a cash drop.

$$\begin{aligned} Y_{hctr} = \beta_{0r} * \mathbf{R}\,1 \; + \beta_{1r}\text{cashdrop} * \mathbf{R} \; + \beta_{2r}\text{UCT} * \mathbf{R} \; + \beta_{3r}\text{UCT} * \text{cashdrop} * \mathbf{R} \\ + \beta_{4r}\text{CCT} * \mathbf{R} \; + \beta_{5r}\text{CCT} * \text{cashdrop} * \mathbf{R} \; + \varepsilon_{hct} \end{aligned} \tag{4}$$

The test of whether the MPC varies throughout the year is a test of whether $\beta_r = \beta_s$ for $s \neq r$, with the natural hypothesis that beta will be highest in the round before the primary agricultural harvest in a given country, which is the lean season and food security is typically lowest.

6.1.4 Specification 2a

Do the impacts of a CCT program depend on the timing of the cash and work requirement? We can answer this research question in South Sudan by running the following specification:

$$Y_{hct} = \beta_0 + \beta_1\text{UCT} + \beta_2\text{CoupledCCT} + \beta_3\text{De-coupledCCT} + \varepsilon_{hct} \tag{5}$$

where "De-coupled CCT" is an indicator for whether the household is assigned to a CCT treatment arm where the asset and cash are provided in different periods. We test whether $\beta_2 \neq \beta_3$. We hypothesize that $\beta_3 > \beta_2$ as households in the de-coupled CCT can spend more time working on their primary income generating activities rather than the asset during the pre-harvest season.

6.1.5 Specification 2b

Above we estimate the reduced form impact of the de-coupled CCT. A natural hypothesis is that de-coupling a CCT is important because household welfare depends on the timing and amount of income they receive throughout the year. We explore this proposed mechanism by running the following specification:

$$Y_{hct} = \beta_0 + \beta_1 \text{Pre-Harvest Season Income} + \beta_2 \text{Post-Harvest Season Income} + \varepsilon_{hct} \tag{6}$$

Where we instrument:

$$\text{Pre-Harvest Season Income} = \eta_0 \text{UCT} + \eta_1 \text{De-coupledCCT} + \eta_2 \text{CoupledCCT}$$
$$\text{Post-Harvest Season Income} = \gamma_0 \text{UCT} + \gamma_1 \text{De-coupledCCT} + \gamma_2 \text{CoupledCCT}$$

We test whether $\eta_1, \eta_2 \neq \eta_0$ ($\gamma_1, \gamma_2 \neq \gamma_0$) to determine whether the conditionality of an asset affects income. Moreover, we investigate whether $\eta_1 \neq \eta_2$ ($\gamma_1 \neq \gamma_2$) to determine whether the income effects from a CCT depend on timing of work requirements. Finally, if any of these inequalities hold – such that we get a strong instrument for both post and pre harvest season income – we want to test whether $\beta_1 \neq \beta_2$.[16]

It is important to note that this IV specification can be difficult to interpret if the decoupling changes household outcomes though other channels than seasonal income. Therefore, we view this analysis as a mechanism test rather than a primary outcome.

6.2 Secondary Analyses - Mediation

6.2.1 All other mediators

To identify the underlying reasons why FCS might shift, we run the following specification on all the mediator outcomes we list in the outcomes section above:

$$Y_{hct} = \beta_0 + \beta_1 \text{UCT} + \beta_2 \text{CCT} + \varepsilon_{hct} \tag{7}$$

These outcomes include: revenue/profits earned from income generating activities (non-farm business, agriculture and livestock, wage employment), reservation wages, time-use and assets. The interpretation of this specification is the same as specification 1a. Taking each one in turn, we hypothesize that households who receive UCTs will earn higher revenue by investing some of the cash transfers they receive into new income-generating opportunities. Recipients of CCT may earn less revenue from income generating activities in year 1 if they devote less time to other activities they were previously engaged in. As CCT beneficiaries start to earn revenue from the assets they are working on in subsequent years, their revenue

[16] An alternative specification would be to estimate the total annual income separately from the ratio of income earned in the pre-harvest relative to the post-harvest season.

should increase. As household revenue increases for UCT recipients in year 1, and CCT recipients in subsequent years, we expect FCS to rise. Similarly, we expect both UCTs and CCTs to help households develop their asset base, which should boost FCS. Next, we hypothesize that receiving transfers through a UCT or CCT will increase reservation wages in the short run, which may discourage households from finding alternate jobs. The subsequent impact on FCS depends on whether the transfers they receive and invest offset any forgone income from jobs they turned down. Finally, we expect labor allocations to shift with a CCT as households re-allocate their time to working on the WFP asset.

6.2.2 Shocks

In addition to seasonality, and trends, the other feature underlying household resilience is their ability to avoid shocks. Many programs are designed to help households mitigate the impacts of shocks, but evaluating the ability to smooth shocks can be difficult. Typically, assessing the ability of a program to buffer against shocks is done by interacting a treatment effect with a variable measuring exposure to a shock (Gunnsteinsson et al., 2019; Macours, Premand, and Vakis, 2020). Evaluations measuring the interactions between shocks and program effects ex post at single suffer from two problems. First, evaluations that measure post-treatment welfare only once capture a single period of the recovery trajectory, meaning that they can either fail to measure the full depth of welfare costs associated with the shocks if the endline is conducted too late after the shock, or the full recovery associated with the program if the endline is conducted too soon, or both. We solve this problem with the high frequency data collection, which allows us to directly observe recovery trajectories. Moreover, the shocks are rarely pre-specified in experiments, meaning that the literature on shock mitigation may be vulnerable to publication bias. To determine the differential impact of the programs based on whether a household was exposed to a shock (from a pre-determined list of shocks):

$$Y_{hct} = \beta_0 + \beta_1 \text{UCT} + \beta_2 \text{CCT} + \beta_3 \text{UCT} \times Shock + \beta_4 \text{CCT} \times Shock + \beta_5 Shock + \varepsilon_{hct} \quad (8)$$

The test of interest for each treatment arms is the interaction of shock, which tells us whether shocked or unshocked households have a larger response to treatment. For example if

$$\beta_3 > 0$$

, the treatment effect of the UCT is larger for households who experienced a shock. The list of shocks pre-specified for each country will include both natural events (eg droughts as defined by rainfall during main cultivation months falling below a defined threshold) and conflict (eg as defined by a recorded conflict in standardized data such as ACLED) and economic shocks. The pre-analysis plan will be updated before each country begins implementation of main treatment arms to include shock definitions for that country.

6.3 Tertiary analyses- non pre-specified analyses

6.3.1 Additional Outcomes

We examine the effect of the UCT and CCT program on four additional outcomes using primary specification (1).

Conflict and Social Cohesion: We are motivated by previous research showing that aid programs may have the negative side effect of promoting or pro-longing local conflict (Crost, Felter, and Johnston, 2016; Nunn and Qian, 2014) and having unanticipated impacts on social cohesion (Roy et al., 2015).

Psycho-Social: We are motivated by a recent meta-analysis (Ridley et al., 2020), that shows how anti-poverty programs such as cash transfers reduce the incidence of adverse mental health conditions such as depression. As adequate mental health can itself facilitate escape from an avoidance of poverty, these measures are important outcomes to measure in the evaluation of CCT and UCT programs.

Women's Empowerment: We are motivated by a complementary stream of work that investigates whether women's participation in public works contributes to closing the gender gap in autonomy. We anticipate that women's participation in the labor market through a public works program will boost women's empowerment. Indeed, we expect women's agency within the household to increase, and norms around women's labor market participation to improve (Christian et al., 2021)[17].This in turn can generated sustained decreases in gender gaps in labor force participation and autonomy in the long-run.

6.3.2 Socio-Economic Determinants

We are interested in two social and demographic characteristics that could influence the impact of the treatments.

[17]The climate and resilience window of evaluations described in this concept note are linked to a second window of evaluations exploring the impacts of of programming decisions directly on gender equality and women's empowerment. One country, Rwanda, is contributing to both windows. This analysis is described in full detail in (Christian et al., 2021)

Gender The first are differences based on the gender of the main beneficiary, as gender is increasingly recognized as a vital mediator of the impacts of poverty interventions. Ex-ante it is unclear whether women would be expected to benefit more or less from the interventions. On the one hand, women may face larger constraints than men in their local environments, making the potential impact of assistance more powerful. Other the other hand, these same constrains may limit the usefulness of the interventions if they prevent women from taking advantage of profitable opportunities (e.g. starting a business in a male dominated area).

Wealth We will also investigate differential effects by baseline levels of wealth (defined by above/below median asset count). Similarly to above, it is again ex-ante ambiguous whether the ex-ante most poor households in the sample will react most or least to the intervention. While the poorest households may have the most to gain from assistance, they may also lack the financial foundations necessary to leverage the additional assets to build lasting resilience.

We will estimate the heterogeneous effects using the following specification:

$$Y_{hct} = \beta_0 + \beta_1 \text{UCT} + \beta_2 \text{CCT} + \beta_3 \text{UCT} \times \text{Het. Var} + \beta_4 \text{CCT} \times \text{Het. Var} + \beta_5 \text{Het. Var} + \varepsilon_{hct} \tag{9}$$

The coefficient of interest for a given treatment arm and heterogeneity variable is the coefficient of the interaction term. For example, if $\beta_4 > 0$ and the heterogeneity variable is gender of the household head is female, the treatment effect of the CCT is larger for female headed households.

6.3.3 Re-Targeting

While the timing of program implementation is one dimension on which programs account for dynamic adjustments, a second dimension can involve updating targeting and beneficiary selection to reflect changes over time in the welfare rankings of households. Indeed, given that livelihood strategies, income, food security etc are imperfectly correlated over time due to shocks and stressors, the ranking of households by vulnerability status changes over time. In the presence of these stochastic shocks, the next most vulnerable household that communities choose to include in period t may not perfectly overlap with the poorest households considered highest priority for inclusion in period t+s.

To study the implications of these decisions in South Sudan, we ask all the villages in our sample at the first stage of targeting to draw up a list of beneficiaries, where the 5 last households will be kept in 'reserve'. These reserve households represent those who would have been selected by the community if budget had been slightly more permissive. After the harvest season (at least 6 months after initial targeting, but no more than one year) – during which time shocks associated with the main agricultural harvest may have shifted new households into poverty – we ask communities to identify the next 5 households who would be included. We call these the post-harvest 'additional' households who represent the next five households the community would want to enroll if budget constraints allow. They may be the same or different from the households named during initial targeting 6-12 months before.

We then subdivide CCT villages into two groups (Figure 1). In non-retargeted villages, the 5 'reserve' households will be enrolled right away in the pre-harvest season. In re-targeted villages, the post-harvest 'additional' beneficiaries will receive the program instead. We return the following season and collect our main outcomes from both reserve and post harvest samples in both communities. We then apply a difference-in-difference specification to determine the relative treatment effect of the CCT for post-harvest beneficiaries relative to the 'reserve' households in re-targeted vs. non-retargeted villages. This will reveal whether communities take into account shocks and variability of income when they select which households to target with WFP assistance. Specifically, we restrict our sample to the set of CCT recipients and run the following specification:

$$\begin{aligned} Y_{hct} = \beta_0 + \beta_1 \text{Reserve} + \beta_2 \text{Additional} + \beta_3 \text{Retargeted} + \\ \beta_4 \text{Reserve} \times \text{Retargeted} + \beta_5 \text{Additional} \times \text{Retargeted} + \varepsilon_{hct} \end{aligned} \tag{10}$$

Where

- β_0 = Outcome for standard beneficiaries households in non-retargeted villages
- $\beta_0 + \beta_1$ = Outcome for reserve households in non-retargeted villages
- $\beta_0 + \beta_2$ = Outcome for additional beneficiaries in non-retargeted villages
- $\beta_0 + \beta_3$ = Outcome for standard beneficiaries in retargeted villages
- $\beta_0 + \beta_1 + \beta_3 + \beta_4$ = Outcome for reserve households in retargeted villages
- $\beta_0 + \beta_1 + \beta_3 + \beta_5$ = Outcome for additional beneficiaries in retargeted villages

This specification tells us the welfare consequences of changing the set of beneficiaries based on revealed shocks. We test the following hypotheses:

- $\beta_3 + \beta_5 > 0$: additional beneficiaries in retargeted villages will see larger impacts then reserve households in non-retargeted villages.

- $\beta_1 < 0$: the last people to be included in the beneficiary list (reserve households) will experience lower benefits than the standard beneficiaries (who are selected first).
- $\beta_3 + \beta_4 < 0$: reserve households that receives benefits are better off than reserve households that do not.

Specification 3b We can also test whether communities choose to enroll a different set of beneficiaries after they observe shocks than they would have chosen if the choice was made prior to the revelation of shocks. We restrict our sample to the set of cash-for-asset recipients and run the following specification:

$$X_{hct} = \beta_0 + \beta_1 \text{Reserve} + \beta_2 \text{Additional} \tag{11}$$

where X represents a set of socio-demographic characteristics collected at baseline including reserve status, gender of household head, FCS, and asset index. In particular we are interested to see whether the communities provide cash to those with higher variance or lower mean in food security. In particular:

- $\beta_2 \neq \beta_1$ if the socio-demographics of reserve households differ from those of additional beneficiaries.
- $\beta_2 \neq 0$ if the socio-demographics of additional households differ from those of standard beneficiaries.
- $\beta_1 \geq 0$ if the socio-demographics of reserve households will reflect a poorer status relative to the standard beneficiaries. It could however be zero if everyone in a particular context is equally poor.

Specification 3c Finally, we can apply the ML techniques developed by Chernozhukov et al. (2018) to predict who benefits from each program based on observable characteristics, and determine the quality of targeting under each treatment arm – comparing whether the beneficiaries selected under each program match those we predict would derive the highest returns.

To this end, we construct a training sample and estimate separate LASSO regressions for the treatment and control groups to pick which of the observed covariates predict measures of income and consumption. Next, we run OLS regressions for the treatment and control groups with the covariates selected by the two LASSO procedures, and recover the beta coefficients from these regressions. We then turn to the validation dataset and calculate the conditional expectation functions under treatment and control status, applying the beta coefficients estimated with the training dataset. We take the difference between the two, which serves as the predicted benefit index. We compute this predicted benefit index for households that were not selected for WFP assistance and compare it to the predicted benefit index for those who were selected.

7 Statistical Power

7.1 Power for Low Frequency Measures

For our power calculations on low frequency measures (those collected only at baseline, midline, and endline), we focus on the ability to detect the reduced form effect of treatment on overall household income and consumption. We use the standard minimum detectable effect formula $MDE = \sigma_\varepsilon(z_{0.8} + z_{0.975})\sqrt{\frac{1+\rho(m-1)}{NP(1-P)}}$, where σ_ε is the standard deviation of the outcome, $z_{0.8} + z_{0.975} = 2.80$, ρ is the intracluster correlation which we assume is equal to 0.05, m the number of observations per cluster, N is the number of observations, and P is the proportion of treated observations.

The main unknown in the formula above is σ_ε, which we estimate via the following process. First, we select the five consumption goods that best predict the outcome of interest (household income and household consumption respectively) controlling for household demographics and village fixed effects. We then take the standard deviation of the predicted outcome and scale it by $1/R^2$, where the R^2 is drawn from the regression of the residualized predicted outcome on the residualized actual outcome. This yields the final σ_ε which we use in the MDE formula above.

7.2 High Frequency Data and Resilience Outcomes

In section 4, we describe how we conceptualize resilience by a household, individual, or community's welfare dynamics. In this section, we describe how we we will determine the sample size needed to identify program impacts on two parameters of the welfare function, the mean and standard deviation of food security status over a year. Because high frequency measurement is expected to be more expensive, we plan to collect these measures for only a subset of households surveyed at baseline, midline, and endline.

To make recommendations for sample size and power, we used data collected by 601 households from 32 communities surveyed every month for a period of 18 months in the setting of a humanitarian program.[18] We use the first twelve of these 18 months so that we

[18] As this data source is not currently publicly available the location of the data collection is not disclosed

are consistent in using one full year as the relevant period. This data is unique, because it collects three common food security indicators: Household Hunger Scale, Food Consumption Score, and Household Dietary Diversity Score. We take this as our starting point and assess the role of survey frequency on power to compute changes in these measures over time. We model through simulations a hypothetical experiment that assigns half of the 32 communities to treatment. All households in treated communities experience one of three treatment effects:

1. increases the mean of high frequency measures by X% of the control mean holding other parameters constant

2. decreases the standard deviation of food security measures for a household over time by X% of baseline control SD, keeping other parameters constant

3. decreases the share of the year spent in poverty by X% of the control proportion in poverty (as defined by standard thresholds for each indicator)

This allows us to estimate power for detecting effects of programs that may make households less food insecure on average but not change variability around that mean or vice versa.

For each of these effects, we replicate the hypothetical experiment with the assigned effect size for a given parameter 1,000 times, regress the measure on treatment, and calculate the proportion of the 1,000 hypothetical experiments in which we can reject the null hypothesis of no impact of treatment at the 10% level. This proportion is our estimate of the statistical power of an experiment with this sample size to estimate the effect. The goal of these simulations is to give guidance for how frequently countries need to collect food security data in order to identify impacts on these measures of household resilience.

Table 7 presents results of power calculations to detect a 15% effect size for each of the 3 outcome measures with varying frequencies of data. For a 15% effect on power gains in increasing frequency from bi-monthly to monthly frequency are small, but the power losses in going from a quarterly to semi-annual schedule are large. We therefore focus on comparisons with the bi-monthly and quarterly schedules and compare effect sizes needed to obtain 80% power to guide the decisions on whether to plan for quarterly or bi-monthly data collection.

Table 8 repeats the power exercise for different effect sizes for bimonthly and quarterly schedules. By default, each country aims for bimonthly data collection for 30 communities, 600 households, which is sufficient to detect a 20% a change in either mean or standard deviation of food security at 80% power for all three measures. However, the frequency will

here.

be allowed to adjust by country context. If additional rounds are more expensive, for example because of a low cell phone penetration requiring in person visits, quarterly schedules may be used this frequency is sufficient to detect impacts on both means and standard deviations of 20% of control averages with 80% power for 2 of these three food security measures. In such cases, additional calculations will be performed to determine whether adding additional households or clusters (eg villages, communities) is necessary to increase power for expected effects, and these adjustments to the default frequency will be added to the pre-analysis plan prior to the start of high frequency data collection.

Changes in proportion of the year below the food insecurity threshold are lower powered for feasible frequencies of data collection and sample sizes, so these will be considered a secondary outcome.

8 Ethics and Institutional Review

All WFP evaluations conform to 2020 United Nations Evaluation Group (UNEG) ethical guidelines. CBT and Gender window impact evaluations are also subjected to institutional review board (IRB) approvals. Each impact evaluation ensures informed consent, privacy, confidentiality, cultural sensitivity, fair recruitment of participants, and that evaluation activities and results do not cause harm.

Tables

Table 5: Outcome Variable Descriptions and Respondents

Consumption	Description	Primary Respondent
Food Consumption Score	Comprised of the number of days in the past week the household consumed major food categories (e.g. maize, tubers, fish, eggs, vegetables, etc). The final score is the sum of these counts.	Household Head
Food Insecurity Experience Scale	The Food Insecurity Experience Scale (FIES) asks respondents eight questions capturing a range of food insecurity severity, with yes/no responses over the past 12 months (e.g. "In the past 12 months, Was there a time when you or others in your household worried about not having enough food to eat because of a lack of money or other resources?"). The index is then the sum of these values across all eight questions.	Household Head
Consumption Expenditure	For a comprehensive list of items under major consumption categories (food, clothes, hygiene, transport, etc.), we ask the total amount the household has spent on each item during the relevant reference period (week/month/year). We then aggregate these amounts together for the households total consumption.	Household Head
Mental Health		
Well-Being	Comprised of one Cantril Ladder question for the respondent's present state, and one Cantril Ladder question for the future. The respondent is asked to imagine a ladder with steps numbered from zero at the bottom to 10 at the top, with the top of the ladder represents the best possible life for themselves and the bottom of the ladder representing the worst. They are then asked to choose which step of the ladder they feel they stand on at the present moment, and which step they will be on in five years' time.	Household Head
Depression	We use the Center for Epidemiologic Studies Depression Scale Revised (CESD-R-10), which asks respondents to report how frequently in the past week they have experienced 10 statements on depression symptoms (e.g. "I was bothered by things that usually don't bother me").	Household Head
Stress	Index of responses to 10 questions regarding the respondent's current mental state and stress levels (e.g. "In the last month, how often have you felt that things were going your way?).	

General Self Efficacy	We use a a 10-item General Self Efficacy (GSE-10) psychometric scale that is designed to assess optimistic self-beliefs to cope with a variety of difficult demands in life (e.g. "I can successfully solve problems if I put in enough effort"). This scale explicitly refers to personal agency, i.e., the belief that one's actions are responsible for successful outcomes.	Household Head
Life Satisfaction	We ask respondents the extent to which they agree or disagree with 5 statements regarding their overall satisfaction with life, such as "In most ways, my life is close to my ideal."	
Aspirations	We ask respondents about their hopes for the educational attainment, job, and income for their youngest male and female children when they reach age 30.	Household Head
Financial		
Savings	At baseline, we ask households about their total current stock of savings. At endline, we ask about savings activity over the previous three months.	Household Head
Loans	At baseline, we ask households about the number of loans they have received or given, and the total amounts outstanding. At endline, we ask about any new loans taken or given and total amounts outstanding.	
Insurance	We capture any insurance products that the household is currently covered by. Insurance products may be provided by private companies, NGOs, or the government.	Household Head
Cash Transfers	We capture all cash transfers made over the previous 12 months to or from other households or remittances from a migrant household member.	Household Head
Other Outcomes		
Assets	We ask about current ownership of a comprehensive list of households assets. At baseline we ask about the amount and value of these assets. At endline, we inform households about the number they said at baseline and inquire about a) whether these quantities changed, b) why (died, sold, damaged, destroyed), and the value lost/gained. The lists are generated from a shortened list of assets asked on LSMS or the nearest equivalent for the context. Each country will include a mix of productive assets like farm implements and household durable goods like furniture and basic electronics.	Household Head
Shocks	We ask households what shocks (drought, flood, family death, asset loss, job loss, etc.) households have suffered over the previous 12 months and the severity of each shock.	Household Head

Coping Mechanisms	We ask about which coping mechanisms the household used to help manage reported shocks. Examples of coping mechanisms are selling assets for cash, reducing consumption, or increasing labor supply.	Household Head
Income Activities	We ask respondents which types of income generating activities they currently pursue, including: 1) non-farm business, 2) agriculture and livestock, 3) wage employment. For non-farm business, we ask for revenue and profits from the two largest businesses managed by the household. For agriculture and livestock, we ask for all plots cultivated by the household in the previous year, including input use, labor, and quantity of each crop harvested and sold. We also ask respondents about the current stock of livestock, and profits from livestock over the previous 12 months.	Household Head
Time Use	At baseline/endline the primary beneficiary is asked what activities they were doing at various points during the previous day, followed by questions about the amount of time spent on a set of activities. As most of WFP's beneficiaries will be engaged in agricultural activities through the year, a standard agricultural module will collect information about how households allocate their labor investments across the agricultural cycle.	
Migration	The total number of household members who have migrated over the previous six months (or since the last survey), where they migrated, the activity they migrated to perform, and for how long they were away from home.	Household Head
Women's Empowerment	We ask about perceptions around gendered decision-making, drawn from the Demographic Health Surveys. We measure how strongly people believe they have control over the situations and experiences that affect their lives using Rotter's locus of control questionnaire.	Female Household Head
Social Capital	We ask 3 indices related to social capital: a social cohesion & closeness of community index, a financial support index, and a collective action index. We also ask for trust of various community members and institutions.	Household Head
Safety Nets	We ask households which government or NGO-provided programs and social safety nets they have benefited from in the previous 3 years, and the amount of cash and non-cash benefits from each.	Household Head

Reservation Wages	In high frequency surveys, we will ask respondents a series of questions designed to capture their reservation wage, including the minimum hourly wage they would be willing to accept for jobs that take various amounts of time, how often they would be willing to work, and how likely they think it is that they would be able to find work.	Household Head
Women's Dietary Diversity	We ask the female household head about her dietary diversity the previous day.	Female Household Head
Child health	We ask the caretaker of one randomly selected child between 6 and 23 months about the child's Minimum Meal Frequency, Dietary Diversity, prevalence of diarrhea, and vaccinations of measles and vitamin A.	Female Household Head

Table 6: Outcome Variable Collection Periods

	Baseline	**High Frequency**	**Endline**
Consumption			
Food Consumption Score	X	X	X
Food Insecurity Experience Scale	X	X	X
Consumption Expenditure	X		X
Financial Outcomes			
Savings	X		X
Borrowing	X		X
Cash Transfers	X		X
Insurance	X		X
Other Outcomes			
Assets	X	X	X
Income Activities	X	X	X
Shocks and Coping	X	X	X
Women's Empowerment	X		X
Migration	X		X
Time Use	X	X	X
Safety Nets	X		X
Social Capital	X		X
Reservation Wages		X	X
Dietary Diversity	X		X
Mental Health			
Subjective Well-Being	X		X
Depression	X		X
Stress	X		X
General Self Efficacy	X		X
Life Satisfaction	X		X
Aspirations	X		X

Notes: mental health or subjective well-being can be collected high frequency pending country office interest in these outcomes and length of the survey.

Table 7: Power Calculations with 32 clusters & 600 households - 15% effect size

FCS

Frequency	Mean	SD	Share of obs < threshold
Monthly	0.982	0.883	0.428
Bi-monthly	0.973	0.856	0.325
Quarterly	0.952	0.769	0.277
Semi-annually	0.873	0.360	0.234

HDDS

Frequency	Mean	SD	Share of obs < threshold
Monthly	0.958	0.869	0.773
Bi-monthly	0.943	0.752	0.681
Quarterly	0.904	0.742	0.517
Semi-annually	0.794	0.350	0.334

HHS

Frequency	Mean	SD	Share of obs < threshold
Monthly	0.290	0.657	0.251
Bi-monthly	0.258	0.553	0.231
Quarterly	0.247	0.352	0.214
Semi-annually	0.189	0.195	0.172

Table 8: Power Calculations with 32 clusters & 600 households - Varying Effect Sizes

FCS

Bimonthly				Quarterly			
Effect size	Mean	SD	Share of obs < threshold	Effect size	Mean	SD	Share of obs < threshold
15%	0.973	0.856	0.325	15%	0.952	0.769	0.277
20%	1.000	0.980	0.522	20%	0.999	0.958	0.415
25%	1.000	0.999	0.708	25%	1.000	0.998	0.572
30%	1.000	1.000	0.839	30%	1.000	1.000	0.733

HDDS

Bimonthly				Quarterly			
Effect size	Mean	SD	Share of obs < threshold	Effect size	Mean	SD	Share of obs < threshold
15%	0.943	0.752	0.681	15%	0.904	0.742	0.517
20%	0.999	0.948	0.899	20%	0.997	0.946	0.765
25%	1.000	0.995	0.984	25%	1.000	0.996	0.924
30%	1.000	1.000	0.999	30%	1.000	1.000	0.984

HHS

Bimonthly				Quarterly			
Effect size	Mean	SD	Share of obs < threshold	Effect size	Mean	SD	Share of obs < threshold
15%	0.258	0.553	0.231	15%	0.247	0.352	0.214
20%	0.400	0.813	0.351	20%	0.335	0.555	0.281
25%	0.514	0.941	0.448	25%	0.443	0.723	0.363
30%	0.643	0.991	0.577	30%	0.545	0.868	0.455

Table 9: Power Calculations with 90 clusters & 1600 households - Varying effect sizes

FCS

Bimonthly				Quarterly			
Effect size	Mean	SD	Share of obs < threshold	Effect size	Mean	SD	Share of obs < threshold
15%	0.996	0.884	0.420	15%	0.958	0.712	0.365
20%	1.000	0.990	0.600	20%	1.000	0.922	0.546
25%	1.000	1.000	0.777	25%	1.000	0.984	0.683
30%	1.000	1.000	0.881	30%	1.000	1.000	0.851

HDDS

Bimonthly				Quarterly			
Effect size	Mean	SD	Share of obs < threshold	Effect size	Mean	SD	Share of obs < threshold
15%	0.973	0.847	0.713	15%	0.972	0.700	0.802
20%	0.999	0.973	0.915	20%	1.000	0.892	0.968
25%	1.000	0.998	0.992	25%	1.000	0.971	0.997
30%	1.000	1.000	1.000	30%	1.000	0.996	1.000

HHS

Bimonthly				Quarterly			
Effect size	Mean	SD	Share of obs < threshold	Effect size	Mean	SD	Share of obs < threshold
15%	0.394	0.697	0.307	15%	0.372	0.537	0.285
20%	0.523	0.892	0.423	20%	0.480	0.752	0.362
25%	0.603	0.982	0.527	25%	0.548	0.859	0.436
30%	0.725	0.992	0.654	30%	0.653	0.940	0.563

Figures

Figure 1: Experimental Design

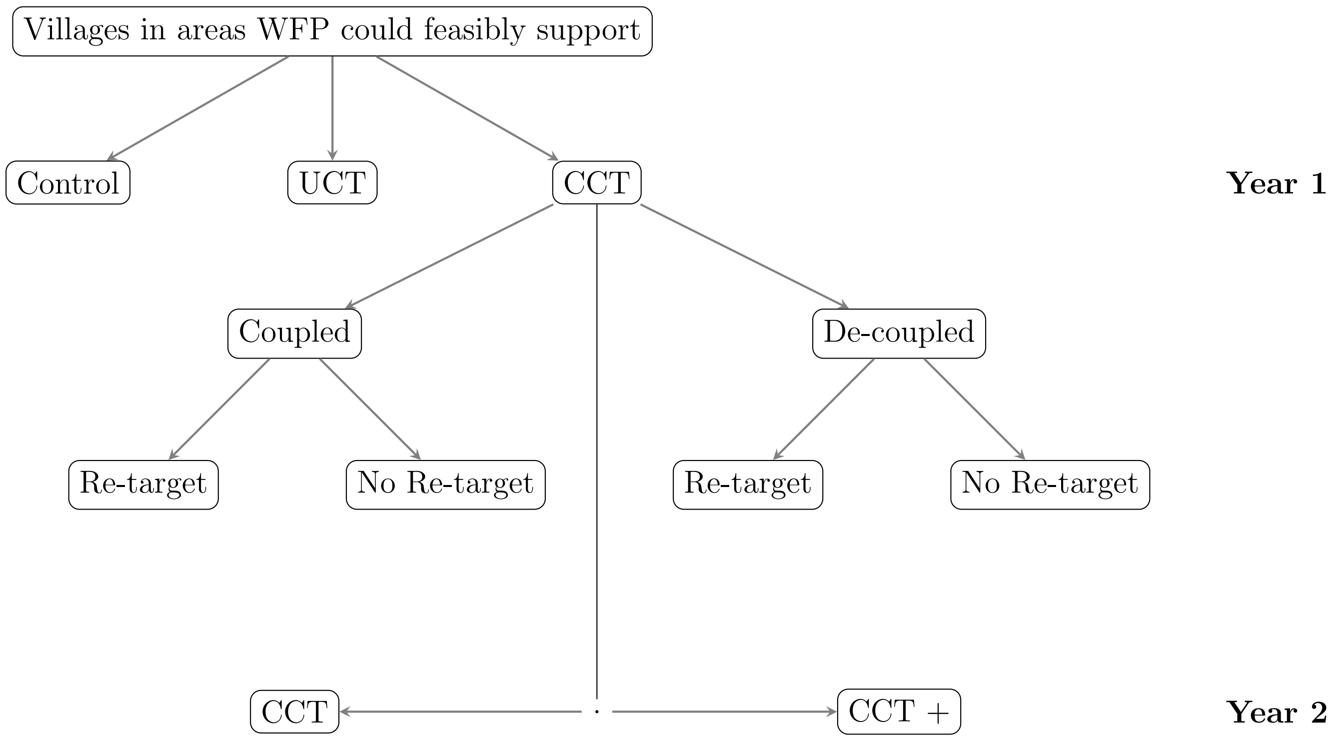
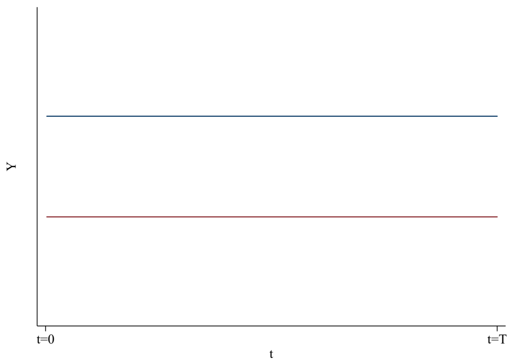
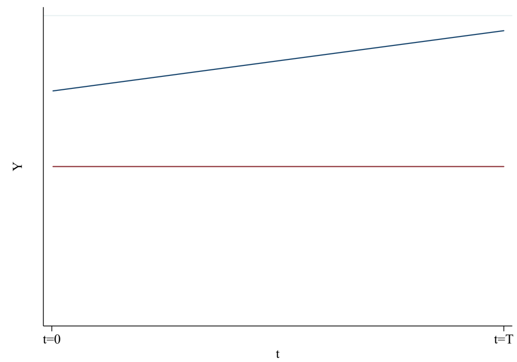


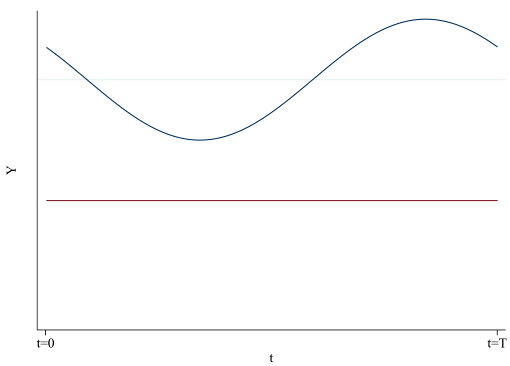
Figure 2: Examples of components of the structural welfare equation



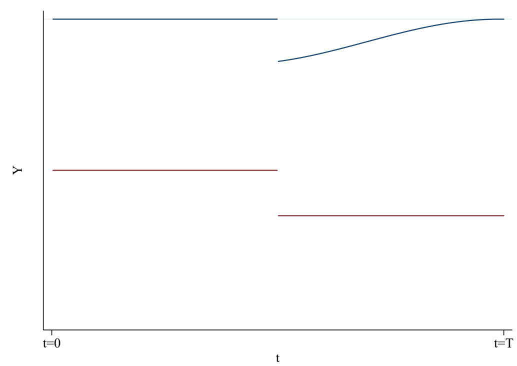
(a) High vs Low α



(b) High vs low δ

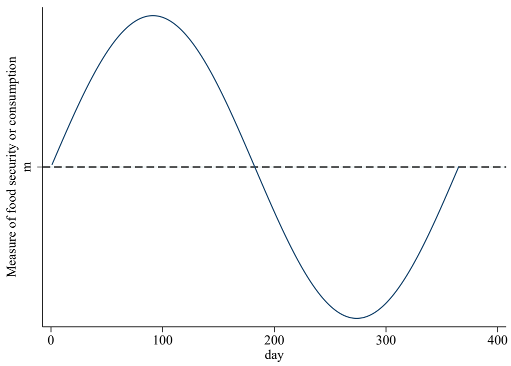


(c) Flat vs seasonal welfare

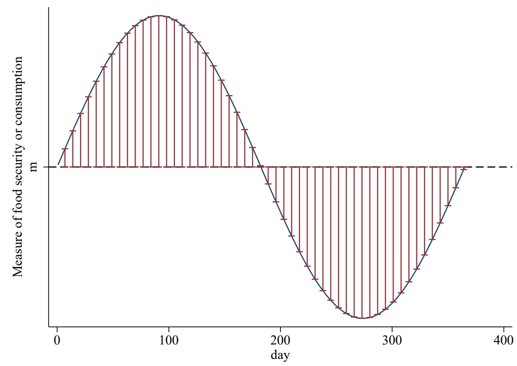


(d) Differential variance of ϵ due to shocks

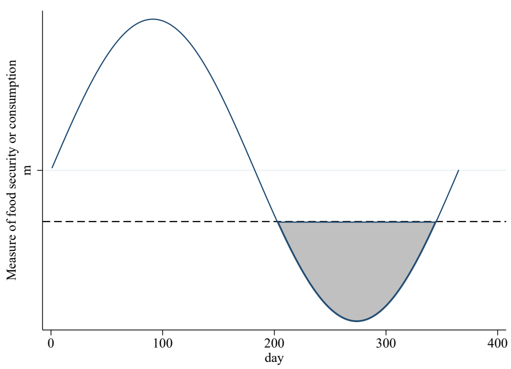
Figure 3: Examples of components of the structural welfare equation



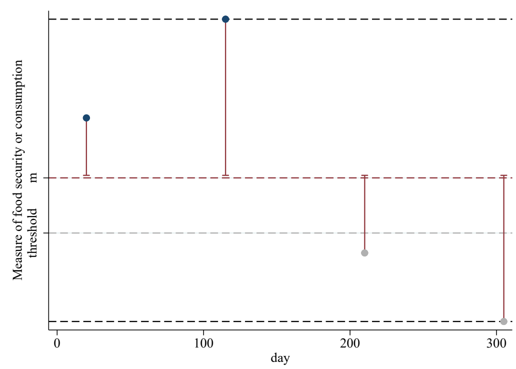
(a) Intra-annual mean



(b) Intra-annual SD



(c) Intra-annual share below a threshold



(d) Intra-annual share below a threshold

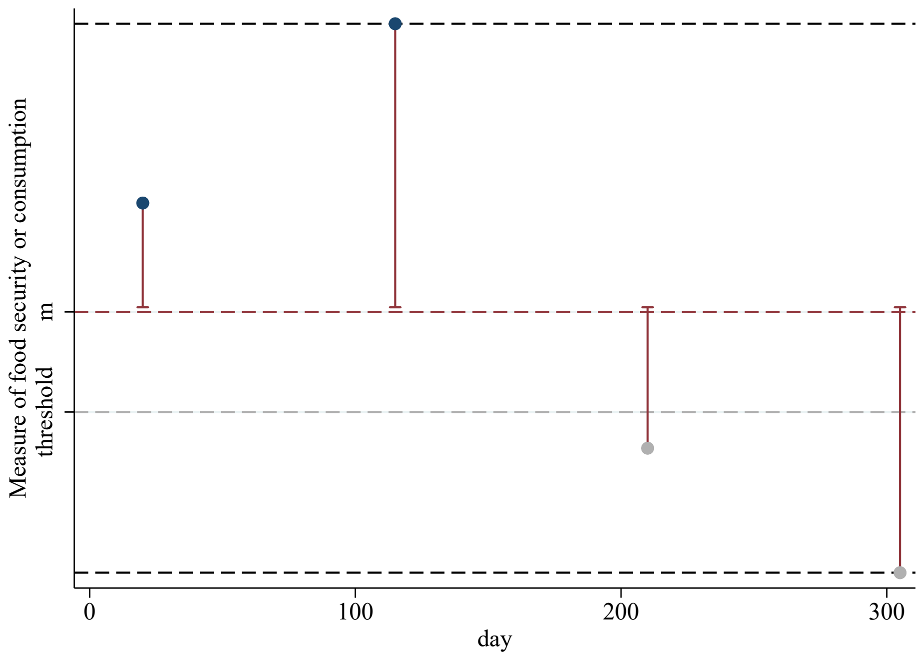


Figure 4: Example of intra-annual share below a threshold

Source: Authors' calculations a hypothetical sinosoid consumption path.

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