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Evaluating the impacts of cash and complementary agricultural support interventions in fragile settings

The case of Somalia

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Abstract

This study examines the FAO *cash plus agriculture* programme in Somalia. This multifaceted intervention provides agricultural inputs, training and cash transfers to vulnerable agropastoralist households living in districts and villages that experienced severe weather shocks. We exploit variations in the implementation of this programme to assess the effect of receiving inputs only and inputs plus cash on a range of protective and productive outcomes. Specifically, we make use of household survey data collected in 2019 and apply a quasi-experimental Inverse Probability Weighted Regression Analysis (IPWRA) matching approach to estimate the impact of the two different interventions on food security, assets, adoption of inputs and adoption of agricultural practices. We find positive and significant impacts on a number of productive outcomes and some difference between the two treatments: while inputs seem to increase asset wealth, cash plus reduces food insecurity and higher levels of income diversification, suggesting that the cash component facilitates investments in livelihoods diversification. Moreover, we find evidence of heterogeneous impacts under conditions of weather shocks, and between socioeconomic segments of the population.

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Abbreviations and acronyms

CYA	crop yields assessment
FSNAU	Food Security and Nutrition Analysis Unit
IPC	Integrated Food Security Phase Classification
SPI	standardized precipitation index
CHIRPS	Climate Hazards Group InfraRed Precipitation with Station data
TLU	tropical livestock units
FCS	food consumption score
IPWRA	doubly-robust inverse-probability-weighted regression-adjustment
CIA	conditional independent assumptions
ITT	intent-to-treat
GMM	generalized method of moments

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1. Introduction

The overlapping and reinforcing challenges of conflict, climate change, extreme and chronic poverty are affecting an increasing number of people worldwide and are hindering efforts to foster economic opportunities and the fulfilment of basic needs in many parts of the world (Jeong and Trako, 2022). As a consequence, the number of people in need of international humanitarian assistance is also increasing, with figures doubling from 132 million of people in need in 2019 to 274 in 2022 (UNOCHA, 2022). Conflict, fragility and violence alone drive 80 percent of all humanitarian needs, and it is estimated that by 2030 up to two-thirds of the world's extreme poor could live in fragile and conflict contexts (World Bank, 2022). UNHCR (2022) estimates that by the end of 2020, 84 million people were forcibly displaced as a result of prosecution, conflict, generalized violence, or other human rights violations.

Social protection is increasingly used as a tool to support basic needs for poor and vulnerable populations living in fragile and conflict-affected settings. In nonfragile contexts, extensive evidence demonstrates that social protection programmes, particularly social cash transfers, help reduce poverty and inequality, enhance livelihoods, and have long-term positive impacts on human capital development (Bastagli *et al.*, 2019). Evidence though suggests that cash alone is not a silver bullet for alleviating poverty, and that it is often insufficient to support a sustained improvement in economic wellbeing. While regular and predictable payments of cash or food support consumption and income growth, and enable recipients to take small entrepreneurial risks, complementary programmes are often necessary to achieve sustained economic opportunities (Handa *et al.,* 2014; Millan *et al.,* 2019).

In the last two decades multifaceted livelihoods programmes that bundle cash transfers with other complementary interventions have become increasingly common tools for supporting economic inclusion and poverty reduction, especially in rural areas (Andrews *et al.,* 2021). Among the range of different approaches promoted by governments, international agencies and non-governmental organizations so-called "graduation" and "cash plus" approaches are particularly common. The graduation into sustainable livelihoods approach (or simply "graduation") consists of a sequenced package of interventions aimed at tackling the multifaceted constraints faced by the poorest and most vulnerable households (Hashemi and De Montesquiou, 2011; Arevalo *et al.,* 2018). This generally includes a combination of cash or in-kind transfers, asset transfers, access to savings and credit, training and tailored coaching over 18–24 month periods. In contrast, cash plus programmes focus on wider socioeconomic outcomes, are not premised on a pre-determined trajectory out of poverty and are usually not strictly time bound (Carter *et al.,* 2019). Often cash plus programmes evolve from existing cash transfers, by layering additional provision of services and/or benefits, with the idea of strengthening positive impacts on specific domains, such as nutrition, health and income (Roelen *et al.,* 2017). In rural areas, "cash plus" interventions often seek to strengthen households' resilience to shocks and to increase their long-term economic prospect by combining cash with the provision of agricultural assets, training on agricultural or business skills, and/or farm inputs, like seeds or fertilizers (FAO, 2018).

Despite the proliferation of evidence on cash transfers and graduation/cash plus programmes, two important evidence gaps remain. First, there is little evidence on the impacts of these programmes in fragile state contexts (Puri *et al.,* 2017). Filling this gap is important because these types of interventions are increasingly seen as a mechanism to transition from recurrent humanitarian support to longer-term and sustained development interventions in fragile contexts (Bedoya *et al.,* 2019; Brune *et al.,* 2021). Most studies concentrate on basic needs outcomes, such as food security, coping strategies, food and non-food expenditure, assessing primarily the forms in which social assistance in humanitarian settings is delivered, namely cash transfers, in-kind or vouchers (Lind *et al.,* 2022). Further, the generation of rigorous evidence in fragile and humanitarian contexts is often constrained by challenges with creating a valid counterfactual group. Bakrania *et al.* (2021) identify several reasons why this is the case. First, large areas are typically affected during a humanitarian emergency, making it difficult to find unaffected locations or beneficiaries similar to the affected population for the purposes of comparison. This issue can be exacerbated by the presence of a multiplicity of actors, making it difficult to attribute impact to a single intervention in a context of multiple support. Moreover, sampling is challenging because populations in humanitarian emergencies are often transient or mobile. Finally, research cannot worsen humanitarian challenges and the principle of "*do no harm*" must be applied. If the individuals/households considered for the counterfactual suddenly become partly or fully eligible for a programme, they cannot be denied access. Fragile and humanitarian contexts are also inherently unpredictable, programmes often change rapidly in response to external events, and implementation cycles are short. This means that research questions and designs may change too. As a result, there is a disconnect between the academic fixation on internal validity and the use of experimental methods to understand the impacts of policy interventions and what is feasible in fragile contexts, leading to a gap in our understanding of what works and what does not. As discussed in a Special Issue in the Journal of Development Studies, quasi-experimental impact evaluation techniques are often more suitable for these contexts, and can be used to generate policy-relevant and rigorous evidence (Brück *et al.,* 2019).

The second critical evidence gap concerns productive and economic impacts and pathways of cash plus and graduation type programmes across socioeconomic groups and under conditions of weather shocks. Weather shocks are an important source of livelihood risk and vulnerability for rural households, particularly those in fragile rural contexts where livelihoods are highly dependent on rain-fed agriculture and pastoralism, and where risk management tools are extremely scarce (Kuriakose *et al.*, 2013; Hallegatte *et al.*, 2017; FAO and Red Cross Red Crescent Climate Centre, 2019). While there is emerging evidence on the impacts of receiving cash transfers when weather shocks occur, the bulk of this evidence focuses on the protective benefits of these interventions, including on household food security and consumption (Patnaik and Das, 2017; Lawlor *et al.*, 2019; Asfaw *et al.*, 2017; Dietrich and Schmerzeck, 2019; de Janvry *et al.*, 2006; Adhvaryu *et al.*, 2018; Fitz and League, 2021). Few studies explore the productive impact of these programmes in the context of weather shocks, or how impacts vary between different socioeconomic segments of rural populations. Filling this gap is important in order to improve the design and implementation of interventions to sustain and promote economic opportunities in the context of climate change and socioeconomic heterogeneity (Scognamillo and Sitko, 2021).

This article contributes to filling these knowledge gaps through an evaluation of the impacts of a cash plus intervention implemented in Somalia by the Food and Agriculture Organization of the United Nations (FAO). For this study, we use the Crop yields assessment (CYA) data collected in 2019 by the FAO Somalia in multiple regions of the country to monitor the effectiveness of the programmatic response to recurrent economic shocks suffered by the Somali rural population. This dataset includes vulnerable farmers that received support packages composed of cash, agricultural inputs and training, plus non beneficiaries. The study uses quasi-experimental techniques to understand if these interventions generate protective benefits on food security and productive impacts, in terms of promoting crop and income diversification, increased input use and adoption of improved agricultural practices. In this way the article contributes to the small literature evaluating cash and non-cash support in Somalia, while expanding this literature to explore potential complementarities between cash and other support interventions that make up the cash plus approach (Anguko 2014; Malik *et al.,* 2020; Hassan *et al.,* 2019; Dao *et al.*, 2021).

We pay particularly attention to the heterogeneous impacts of cash plus programmes along two dimensions. First, between households exposed to extreme weather events, measured using remote sensed and weather station date, and those who experienced average weather conditions in the survey years. From a policy perspective it is critical to ascertain if the impacts of these programmes are sustained in the context of weather shocks, given their increasing frequency and intensity (IPCC, 2014). If cash plus interventions were effective at building more resilient livelihoods, we would expect that the adverse impacts of weather shocks will be relatively lower for beneficiaries than non-beneficiary/ies. Second, we look at differential impacts between households with different levels of vulnerabilities in terms of access to services (i.e. distance to markets), demographics (i.e. gender of household head) and wealth endowments. This is an important gap to fill because many of the mediating factors that enable multifaceted programmes to have economic impacts are often absent or highly constrained in fragile settings (such as markets, roads, etc.)

2. The Somali context and cash plus intervention

In Somalia there are four broad categories of rural livelihoods: 1) pastoralism, where agroecological conditions can support only livestock herding; 2) agropastoralism in semi-arid areas, where livestock herding is often the dominant economic activity, though rainfall and ecological conditions allow the cultivation of cereals, mainly maize and sorghum; 3) riverine agriculture, along the Shabelle and Juba rivers, where cultivation of diverse crops beyond staple commodities is carried out and; 4) coastal, where fishing is combined with pastoralism (FSNAU, 2016). Approximately 49 percent of the non-urban population in 2014 was pastoral, 30 percent agropastoral and 16 percent working in irrigated/riverine agriculture (FSNAU, 2016). Thus, while pastoralism is dominant in rural areas, almost one third of the population also depends on crop agriculture.

Four main seasons characterize the seasonal weather patterns in Somalia: two rainy seasons and two dry seasons. The heaviest rains fall during the *gu* season (April to June) with lighter and more sporadic rains falling during the *deyr* season (October to December). Rainfall levels during these two seasons are important for both pastoral and agropastoral livelihoods, as they determine water and pasture availability for livestock and crop development and harvest levels (FSNAU, 2016). Like purely pastoralist households, agropastoral households also migrate out of their zones in search for pasture during the dry seasons, while returning for land preparation and sowing in the months prior to the rains.

Since 2016, Somalia has faced climate shocks for eight consecutive agricultural seasons (FAO, 2020a). From droughts to floods and cyclones, these have occurred with increasing frequency and have been exacerbated by plant pest outbreaks, including a serious upsurge in desert locusts beginning in 2019, the worst invasion in a quarter century, which further contributed to low agricultural production and undermined the food security, nutrition and coping capacities of millions of vulnerable people (FAO, 2020b). According to the Integrated Food Security Phase Classification (IPC),[1] 6.3 million Somalis were acutely food insecure (IPC Phase 2 and above) through December 2019, up from 4.6 million in late 2018. The situation deteriorated most significantly in rural areas, where the population in IPC 2 to 4 doubled and those in IPC 3 to 4 tripled (FAO, 2020a). Despite the relatively small population (16.7M), Somalia ranks 7th among the countries with the highest financial requirement to support the 5.5M people in need (UNOCHA, 2022).

In this context, the focus of the analysis in this article is a *cash plus agriculture* programme that started in 2016 in response to the recurrent crises faced by rural Somalis. This programme targeted agropastoral households with a short-term seasonal assistance package, which included unconditional cash transfers, alongside a multifaceted rural livelihood package and training. The programme was designed to combine emergency agricultural livelihood support with cash to help farming households restore and improve their own food production and provide them with cash to meet immediate food and basic needs in the period prior to crop harvest.

The selection of the areas and the households to be reached by the programme followed various stages. First, FAO relied on the figures provided by the Food Security and Nutrition Analysis Unit (FSNAU) to identify the areas for implementation (regions and districts) using the IPC system, including the areas categorized as in crisis (IPC Phase 3) or in emergency (IPC Phase 4).[2] After the geographical targeting, FAO selected

[1] The Integrated Food Security Phase Classification is a set of standardized tools that aims at providing a "common currency" for classifying the severity and magnitude of food insecurity. This approach uses international standards, which allow comparability of situations across countries and over time. More information on IPC is available at https://www.ipcinfo.org/

[2] A location is categorised as IPC Phase 3, or Acute Food and Livelihood Crisis, when at least 20 percent of households have significant food consumption gaps or are marginally able to meet minimum food needs only with irreversible

implementing partners among those registered and certified to implement agriculture activities by the Line Ministry (i.e. Ministry of Agriculture) and provided them with the numbers of households in need in the selected areas. The implementing partners then led the process of village and households' selection by conducting community consultation meetings and engaging representatives of the different segments of the community at districts and villages levels (i.e. Council Elders, Village Elders, Community representatives) to select the target villages and beneficiaries that met FAO's criteria.[3] FAO engages in coordination mechanisms such as the Food Security Cluster, and the Agriculture and Cash Working group and Government to ensure there is no overlapping in similar activities.

The agriculture livelihood package, disbursed as an e-voucher, was designed for different livelihood zones to adapt to farmers' preferences in each zone because of crops' growth habit, yield, palatability and economic value. The packages are distributed at the beginning of the farming season through local traders contracted by FAO and e-vouchers are valid for a period of three weeks to provide sufficient time for distribution and use to take place. As part of the package, each household receives a cereal, pulses and an assorted vegetable seed kits, as well as basic farm tools (i.e. a hoe and a fork hoe) and hermetic storage bags (between 15 and 30 bags). [4]

The main staple (cereal) differs such that the agropastoral receives 12 kgs of sorghum while riverine households receive 20 kgs of maize. To complement the main cereal, each beneficiary receives pulses: 10 kgs of cowpea and 12 kgs of mung bean which are not only a main source of plant protein but also drought tolerant, high yielding and surplus can be sold as a source of income. The provision of two pulses was meant to assist farmers to diversify their crops particularly in times of drought. The assorted vegetable kit, made up of leafy vegetables, roots and bulbs and fruits (specifically carrot, amaranth, okra, Ethiopian mustard, onion, tomato, watermelon and capsicum seeds), sought to provide essential vitamins and mineral elements to farming households. The input package also includes fertilizers, irrigation hours (South) and tractor hours (North). Due to resource constraints, however, households are entitled to receive the assistance package only for a single crop season or at least not for another two-three crop seasons, [5] even if they remain in or return to crises. This allows the implementers to enrol new eligible households in subsequent years.

Along with the material support, the agriculture livelihood package includes a training component. The training is delivered through a training of trainers model, with lead farmers teaching about good agricultural practices (GAP) and integrated pest management (IPM), covering practices ranging from input sourcing and selection, land preparation, crop enterprise establishment, soil fertility improvement, weed control, water use and management, pest and disease control, harvesting and post-harvest management. Participation to these training activities is voluntary.

Finally, the cash component is provided to beneficiaries in 3-6 monthly disbursements based on the duration of the cropping season, starting at the beginning of the farming season. During the registration of eligible

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coping strategies such as liquidating livelihood assets. Levels of acute malnutrition are high and above normal. A location is categorised as IPC Phase 4, or Humanitarian Emergency, when at least 20 percent of households face extreme food consumption gaps, resulting in very high levels of acute malnutrition and excess mortality; or households face an extreme loss of livelihood assets that will likely lead to food consumption gaps.

[3] FAO Household Targeting criteria include vulnerable female-headed households, households with chronically ill, disabled and/or elderly (65+ years) members unable to engage in productive activities, vulnerable child-headed households (over 16 years old), vulnerable households with more than two children under 5 years of age, registered/or hosted rural internally displaced persons who are unemployed and without any regular income or assets, households with children who are severely or moderately malnourished, and households with the least holding of land and/or livestock (classified as very poor in terms of asset holding in that village).

[4] Each household received between 15 and 30 bags depending on the area.

[5] The short-term horizon of this programme may limit the potential for households to consolidate gains in terms of resilience and self-reliance.

and selected households, the beneficiaries who do not have a sim card are provided with one during verification by the Mobile Money Operators, or, in some cases, with a mobile phone by FAO. The cash disbursements are planned to commence in April for the *gu* season and in October for the *deyr* season. However, in *deyr* 2019, while inputs distributions occurred in time - between October and December - cash disbursements faced significant delays and were distributed after the planned dates, throughout the entire year of 2020. According to field staff, disbursements dates varied depending on the beneficiary verification by FAO and the Mobile Money Operator due to challenges with access and availability of beneficiaries. As described in the data section, these administrative challenges, combined with the self-selection mechanism for the training, influenced the composition of the treatments received by households.

3. Conceptual Framework

The recent growth in cash plus and graduation interventions is based on both theory and empirical regularities in the literature. Evidence shows consistent findings of positive impacts of cash transfer programmes on a wide range of socioeconomic outcomes, such as food security and nutrition, household consumption and human capital formation (Bastagli *et al.*, 2019; Manley *et al.*, 2020) and, on the economic activities of beneficiaries, including farm and non-farm activities (Daidone *et al.*, 2019; Correa *et al.*, 2021). Further, there is promising evidence that these programmes can pave the way to sustained improves in wealth (Banerjee *et al.*, 2015; Bandiera *et al.*, 2016; Banerjee *et al.*, 2020).

From a theoretical point of view, social protection can play an important role in shaping economic decisions and behaviours by addressing key barriers that poor and vulnerable households typically face, namely: a) credit and liquidity constraints; b) access to technology, knowledge and financial services; c) risk aversion, and d) labour allocations. By providing a steady and predictable inflow of financial resources, cash transfers provide beneficiaries with liquidity to support investments in production and consumption, which is critical in many rural places where credit markets are absent or weak. The time horizons for productive investments is also found to be influenced by access to cash transfers. For example, evidence points to positive impacts of cash transfers on the adoption of sustainable agricultural practices, such as soil and water conservation structures, which tend to generate benefits after multiple years of adoption (Maggio, Mastrorillo and Sitko, 2021; Amadu *et al.*, 2020; Scognamillo and Sitko, 2021). Similarly, research shows that cash transfers can enable increased investments in off-farm economic activities (Asfaw *et al.*, 2014; Gilligan *et al.*, 2009). When bundled with other agricultural and financial interventions, as is typical in graduation or cash plus programmes, the impacts on household liquidity and credit constraints are enhanced (Veras Soares *et al.*, 2017).

Social protection programmes can also affect risk aversion, which is typically high among rural poor households. The high levels of uncertainty faced by rural households around weather conditions and prices can severely affect households' income, and willingness to make longer-term productive investments. This condition tends to undermine people's capacity and willingness to take economic risks with the consequence of trapping households in low equilibrium poverty traps (Carter and Barrett, 2006). By functioning as a safety net, social transfers can thus encourage households to engage in more risky, and profitable investments (Daidone *et al.*, 2019; Sitko, Scognamillo, and Malevolti, 2021; Schwab, 2020; Scognamillo and Sitko, 2021).

A third impact pathway is the access to technology, knowledge, inputs and factors of production, acquired directly from the complementary inventions provided by cash plus programmes, and indirectly through cash transfers provided (Tirivayi *et al.*, 2016). Lastly, social protection can bring more flexibility to household's labour allocation. Productivity can increase by shifting from low wage casual labour to own agricultural activities or by hiring labour. However, in cases where hired work were a substitute to own farm work, the additional time could be used in off-farm activities, which can put households on a growth trajectory (Prifti, Daidone and Davis, 2019; Correa *et al.*, 2021).

In humanitarian settings, evidence on productive and economic outcomes is extremely scarce for social protection programmes. In a recent literature review, Jeong and Trako (2022) show that most studies concentrate their analytical efforts mostly on "protective" outcomes, such as food security, food and non-food consumption, coping strategies and social cohesion. Some studies show at most limited impacts on assets (Lehmann & Masterson, 2014; Bonilla *et al.*, 2017; Lombardini & Mager, 2019; Schwab, 2019; Ivaschenko *et al.*, 2020; Quattrochi *et al.*, 2020). Schwab (2019) compares the productive effects of cash and food transfers in Yemen, finding modest productive impact of both modalities and suggest a role for liquidity and price risk channels. Quattrochi *et al.* (2020) evaluates the impacts of non-food vouchers to conflict-affected populations in eastern Democratic Republic of Congo and found no significant effect on income.

It is not surprising that impact evaluations in fragile contexts do not consider productive and economic outcomes, since the goal of cash and in-kind transfers and other social protection programmes in these settings is to provide immediate support to households in dire needs. The horizon of these interventions is short-term in nature, while requiring more time to generate impacts on the economic side. Further, even if some of the productive indicators can be relatively affected in the short term, for instance investment in agricultural inputs, the impacts are unlikely to be sustained for prolonged times in humanitarian settings, at least for a couple of reasons: 1) the population of eligible individuals/households is so large, and needs so compelling, that a mechanism of benefits' rationing will make the programmes unlikely to cover the same beneficiaries for an extended period of time; 2) conflicts and protracted crises (both natural and man-made) can provoke severe mass displacements, making impossible or at best unlikely for programme implementers to track people and provide them the support they need to transform their livelihoods.

4. Data

Household survey

The data used for this study comes from the Crop and Yield Assessment (CYA) survey, a household survey collected by FAO Somalia in collaboration with other development partners for the purpose of monitoring farmers' livelihood outcomes such as food security, farming practices and harvests, their exposure to shocks and participation in humanitarian and development programmes in Somalia. The data were collected twice during 2019, at the end of the *gu* and *deyr* farming seasons. Out of a total of eighteen regions (thirteen in Somalia and five in the claimed territory of Somaliland), the CYA survey collected data from eight regions, mostly from the south and central areas of the country, where agropastoral livelihoods are concentrated.

While data were collected for both agricultural seasons, this study uses the *deyr* season data only, because data from the *gu* season are incomplete. We identify households' treatment status from FAO administrative records reported in the survey. The components of the programme package should have been the same for all households. However, as described earlier, in practice operational issues were encountered in the implementation, with the result that the target population received various combinations of cash, inputs and training were delivered to the target population. Table 1 reports the frequency of the different treatment status. Some of the treatment categories are scarcely populated in this sample, which includes for instance only 10 and one households benefitting from the provision of inputs with training and provision of cash with training respectively. Because of this fuzzy implementation behaviour, we do not have sufficient statistical power to detect impacts on such small-sized groups. Further, pooling households in broader groups may alter the interpretation of results and jeopardize the analysis of potential synergies between programme components. For this reason, from the original sample of 1,524 households, we selected a sample of 1,287 households, confining the analysis to three decently sized evaluation groups: 1) non-beneficiary/ies (312 obs.); 2) inputs-only (398 obs.); 3) inputs + cash (577 obs.). This treatment definition allows us to investigate not only whether the programme had an impact on the outcomes of interest, but also to capture the differential effect that cash had compared to the provision of inputs only. This can be particularly informative for future programme design.

Primary outcomes of interest

We conduct the impact evaluation on seven main outcomes, and also extend the analysis to other variables that are a subset of the main indicators. The selection of indicators includes both protective and productive impacts. In particular, we measure the impacts of the programme on food security, assets, agricultural practices and livelihood strategies. We report the mean characteristics of the indicators studied in Table 2. Food security is proxied by the food consumption score (FCS), an index of diversity and frequency of foods consumed at the household level calculated based on the frequency that a household reported consuming during the past seven days (WFP, 2008). It is a standard indicator developed by the WFP, and used globally to measure food security and assess if households achieve acceptable or unacceptable food consumption. The score is a continuous variable with a possible range of 0–112, equal to the weighted sum of frequency of household consumption of each food group. The food consumption groups include starches, pulses, vegetables, fruit, meat, dairy, fats, and sugar. In the survey, households are asked how many days each of the food groups were consumed within the previous seven days.[6] The average FCS in the full sample equals 51.1, with a slightly higher value for the inputs only group compared to the cash plus inputs and the non-beneficiary/ies groups. Values above 35 are deemed consistent with an acceptable food consumption status. From the continuous FCS we also construct two binary variables of to capture the various levels of food

[6] The formula for FCS, with the standard weights is: FCS = (starches*2) + (pulses*3) + vegetables + fruit + (meat*4) + (dairy*4) + (fats*0.5) + (sugar*0.5).

insecurity. Poor food security is defined as a food consumption score under 21. Below such threshold, a household is expected not have eaten at least a staple and vegetables on a daily basis and therefore is considered to be severely food insecure (WFP, 2008). We then create another dummy variable to include, in addition to those below the score of 21, also those that have yet not an acceptable level of food insecurity but are considered as borderline. A borderline level of food security is defined as a food consumption score between 21.5 and 35. All those with a score below 35 are considered to have a not acceptable level of food security. Overall, we observe 12 percent of severely food insecure households, with a larger proportion for the inputs only group (17.8 percent), compared to the cash with inputs group (8 percent) and to non-beneficiary/ies (11.9 percent). And 29 percent of households who are categorized as poor or moderately poor food insecure, with similar differences across treatment categories, larger proportion among the inputs only group (36.2 percent), compared to the cash with inputs group (24.8 percent) and the comparison group (28.5 percent).

To proxy assets ownership, we use an agricultural assets index constructed through principal component analysis, which includes the number of the following agricultural items: ploughs, machetes, sickles, hoes, shovels, axes, hammers, and carts. In agropastoral areas of Somalia, as in many other rural areas in sub-Saharan Africa, livestock are an important store of wealth and often serve as a form of precautionary savings for households (Musa *et al.*, 2021). We summarize the ownership of livestock through the inverse hyperbolic sine transformation of tropical livestock units (TLU), thus allowing for the inclusion of zeros in our estimates.

Agricultural strategies are proxied through two indicators: number of inputs used and number of planted crops. The former is constructed as the sum of the number of inputs used among the following ones: adoption of improved seeds, pesticides, fertilizers, herbicides, use of improved farm tools, [7] and use of tractor. Overall, we observe large adoption rates of improved seeds (62 percent), while about one farmer out of five adopts other inputs such as fertilizers, pesticides and herbicides in their farming activities. Surprisingly we observe that up to 30 percent of farmers use tractors. Especially in relation to other countries in the region, this appears to be a relatively high share of households adopting tractors for their farming practices. This figure could be partially explained by the fact that one of the inputs of the programme is the provision of tractor hours. The number of planted crops comes from a list of 23 cultivated species. However, in practice only approximately a tenth of crops were planted by more than one percent of the sample of farmers. Sorghum, cowpeas and maize are the most cultivated crops in the target districts (70, 54 and 50 percent farmers have planted them in the 2019 *deyr* season respectively). Almost one third of farmers cultivate vegetables overall, even though this share seems to be driven by the very high share in the inputs plus cash group.

Lastly, we look at livelihood strategies through income diversification, proxied by the number of income sources, obtained by summing the following: farming, fishing, pastoral, agropastoral, family business (other than agriculture), employment (government wage or salary), private sector (wage or salary), and formal transfers. Overall, the average household in the sample relies on 1.6 income sources for their livelihoods. This means that half of the sample of farmers has only one source of income, which suggests a high level of livelihood risk exposure to idiosyncratic and covariate shocks.

Spatially-observed weather shocks

We use the information on the geographic locations of the households' villages to merge the household data with spatially explicit information on precipitation in order to identify households that experienced weather-related shocks during the reference period of the survey. In particular, we compute a standardized precipitation index (SPI) at the village level using precipitation data from Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS), with 0.05 degree of spatial resolution. The SPI is the most commonly

[7] We cannot list what is included in the definition of "improved farm tools" as this is how it was framed in the questionnaire.

used indicator worldwide for detecting and characterizing meteorological droughts and floods. The SPI indicator, which was developed by Mckee *at al.* (1993), measures precipitation anomalies at a given location. Mathematically, the SPI is based on the cumulative probability of a given rainfall event occurring. Historic rainfall data is smoothed using a moving width equal to the number of months desired (typically 1, 3, 6 or 12) and is fitted to a gamma distribution through a maximum likelihood estimator. Through a cumulative probability function of rainfall, SPI identifies spatial weather shocks of varying severity within a given reference period. Rainfall shocks are identified by using different standard deviation thresholds from historical means, where positive deviations indicate higher than normal rainfall and negative deviations lower. In Figure 1 we provide a visual representation of the average 3-months SPI in the 2019 *deyr* season calculated at the district centroids.[8] Severe and extreme wet conditions characterized the majority of districts in the country, especially Somaliland and Puntland. Further, no districts are found to have experienced moderate or severe/extreme drought. Villages included in the study sample are prevalently located in areas exposed to severe to extreme wet conditions (SPI3>1.5), while a few of them, especially those in Lower and Middle Shabelle, are located in areas that experienced near normal precipitations.

In the microeconometric analysis, we use a 3-months SPI measured at the village level.[9] We follow Cattaneo and Foreman (2021) and McGuirk, E. and M. Burke (2020) to define a rainfall shock in 2019 by creating a dummy variable that is equal to one when SPI3> 1.5 and zero otherwise. As shown in the lower panel of Table 3, around 57 percent of the farmers in this sample were exposed to these severe wet conditions. Mirroring the district-level graph, households exposed to negative deviations (dry conditions) were not found in 2019 for various cut-offs. In Figure 2 we provide the timeline of the project and of the survey implementation, linked to the cropping season and the SPI3 reference period.

Self-reported shocks

In addition to exogenous measures of weather shocks, the survey instrument used also collects data on self-reported shocks. Of these, locusts' attacks are the most widespread event with an average of 31 percent of farmers reporting having experienced a locust attack in the 12 months preceding the survey (upper panel of Table 3). This high incidence is not surprising as locusts are tied to above average rainfall conditions and heavier rains than usual were registered in the previous six months. The proportion though is quite different between the two treatments groups: approximately half of households receiving the inputs only package reported having experienced locusts' attacks, while among the inputs with cash group the proportion is around 20 percent.

In terms of weather-related shocks, around 18 percent of all households report having experienced a flood in 2019 and a very small proportion reporting a drought (5.8 percent). There is, therefore, a substantial difference between self-reported exposure to flooding and exposure identified through satellite data (56 percent). This difference may be due to the fact that high rainfall conditions measured through satellite data was not agronomically detrimental, and therefore were not perceived by respondents as an adverse weather shock. Indeed, in Somalia higher than normal rainfall can be beneficial in terms of crop productivity and forage availability. Conversely, the frequency of self-reported drought exposure is low (5.8 percent) and very consistent with the satellite data.

[8] Average calculated over the *deyr* season months of October, November and December.
[9] We obtained similar results while using SPI measured at different durations (6 and 12 months).

5. Empirical strategy

To examine the effects of the various treatments on the outcomes presented above the study relies on a matching approach to identify treatment and comparison groups. The matching method we implement for our analysis is the doubly-robust inverse-probability-weighted regression-adjustment (IPWRA), a model that in this context is preferred to other parametric and non-parametric matching methods. The estimator has several appealing features, in particular its doubly-robustness to misspecification of either the propensity score model or the conditional means (OLS) (Wooldridge, 2010). The use of IPWRA, and other parametric models, is superior to other non-parametric matching methods, such as Propensity Score Matching (PSM) when there are multiple treatments. A challenge that PSM faces in the context of multiple treatments is that common support can be extremely difficult to obtain, because it attempts binary treatment matching for all pairwise comparisons or it searches for triplets that match across the multiple treatment groups, with the result that many observations are often be dropped (Linden *et al.*, 2015). Conversely, IPWRA compares every treated observation to every comparison observation using weights, where higher weights are given to those observations with closer likelihood of being treated and lower to those more dissimilar. This implies that more observations are used and therefore precision is improved.

Thus, even when common support criteria can be satisfied through a PSM, IPWRA estimates would still be more efficient. Moreover, the IPWRA is also more flexible than PSM approaches, because in the second step the outcome model is fully specified, and it can be modelled with the functional form that is most suitable.

The selection of covariates to include in the treatment equation is not trivial as proving the conditional independence (conditional independent assumptions, CIA) (i.e. selection on observables) in observational studies can be a challenging process (Uysal, 2015). In this context, however, not only are we confident that this is not an issue for our estimates, because this assumption is relaxed with the doubly-robust IPWRA, but in practice the selection process of households also encompassed a forced source of variation. As mentioned above, the programme selects different households every crop season. Therefore, the approach of not targeting the same households every crop season with the intent to increase the number of beneficiary households introduces a sort of randomness in the selection of households, which helps when implementing matching approaches.

To satisfy the CIA, the set of variables included in the model should capture factors that affect both participation and outcome. To mimic the selection process, we should include the indicators of the official selection criteria of the programme,[10] which targets vulnerable households based on demographics, scarce labour endowments and limited assets. The decision on which variables should be included in the participation model should also take into account that the set of variables that satisfy matching conditions are not necessarily the most inclusive ones. Adding too many variables might lead to violations of those same conditions so we kept a limited set of variables (Smith and Todd, 2005). Interactions and squared terms are included to capture nonlinearities and improve balance. The final selection of the model should be based on the criteria used for the selection households in the programme, on the significance of variables, on the

[10] FAO Household Targeting criteria include vulnerable female-headed households, households with chronically ill, disabled and/or elderly (65+ years) members unable to engage in productive activities, vulnerable child-headed households (over 16 years old), vulnerable households with more than two children under 5 years of age, registered/or hosted rural internally displaced persons who are unemployed and without any regular income or assets, households with children who are severely or moderately malnourished, and households with the least holding of land and/ or livestock (classified as very poor in terms of asset holding in that village).

overlap and the balance of variables, and on the Akaike Information Criterion (the lower levels indicate a better is fit of the model) (Cattaneo *et al.*, 2013).

Based on these factors, we follow closely the official targeting criteria and include the demographic variables listed, with the exception of number of children under 5 years of age or whether any children were malnourished as the information is not available in the survey. In relation to the economic means, we included the land owned by the household, while we did not include livestock holdings as this variable may well be affected by the programme and the pre-programme information was not available. The participation model includes a set of demographic variables (female head, age of head and its squared, number of children 0–14, number of adults 15–64, and the interaction between the female head dummy and the age of the head), asset ownership (size of owned land and its squared). We also include access to service variables (i.e. access to improved toilet facility and distance to nearest market in minutes), and experiencing of shocks (i.e. the self-reported flood and locusts' attack shocks) as these are likely to influence not only participation but outcomes too.[11] In Table 4 we provide some descriptive statistics of the variables included in the participation equation. On average, farmers included in the inputs only group have a higher share of female heads, who are also older than the heads in the other two treatment groups. Inputs only households have also higher agricultural capital endowments, expressed by larger tropical livestock units and area of land owned. Non-beneficiaty/ies have better housing conditions, represented by access to improved sources sanitation and energy, while being located closer to markets. Finally, households benefitting from cash plus inputs have a larger number of children and adult members in working age, but also a larger proportion of disabled members.

In addition to the targeting criteria, we investigate whether differences in treatment status may be due to geographical selection. As mentioned in section 2, households that received inputs only are those that did not receive the cash disbursement by the time the survey was conducted. Two main reasons caused these differences. The first relates to the unavailability of households when mobile money operators were visiting the villages for the registration and verification of beneficiary households. The second reason relates to the inaccessibility to some areas due to excessive rains. It is unlikely that the differences in treatment status due to the first reason would be subject to selection as the unavailability of households may be casual. In Table 5 we report the distribution of treatment status by villages, which shows that one in four villages there were households that received either treatment. In addition, we cannot rule out that villages where a unique type of treatment status is registered did not have other types of treatment status. In other words, some villages may appear receiving only one type of treatment while in practice some households may receive different treatments, it is just that the random sample would not include all of them. In terms of geographical distribution, some of these delays, thus differences in treatment status, were due to weather conditions. This should be accounted for in our model as we include exposure to floods.

The overlap in the propensity scores distribution is verified through the graphs reported in Figure 4 where we report the kernel density of the probabilities of being in any group after reweighting. No spikes are detected in the extremes of the distribution, which means that all observations have a positive probability of being in each group. In addition, the overlapping distributions of each group shows that households have similar probabilities of being in each group, which means that the matching satisfies the unconfoundedness condition, i.e. having the same probability of being in each group.

The balance of covariates between the treatment groups – the other important condition for matching – is checked by comparing the raw and the weighted standardized differences and variance ratios between each of the treatment groups and the comparison group. As shown in Table 13 in the appendix, and graphically in Figure 5, the standardized differences of the weighted covariates get closer to zero and the variance ratios

[11] Table 12 in the Appendix reports the results from the multinomial logit for modelling the participation into the two treatments.

closer to one. After reweighting, there is no single covariate with a standardized difference above 0.25, none between 0.15 and 0.25, and only three between 0.10 and 0.15. As for the variance ratios, the weighting improves the closeness of the ratios to one, which is what it is aimed for. These results correspond to a situation in which the matching approach has generated equally balanced groups.

IPWRA estimation with multiple treatments follows a three-step process. The first step requires to estimate the parameters of the generalized propensity score model through a multinomial logit (or ordered logit if treatments follow an order) to obtain the inverse probability weights for each level of treatment. In the second step, the weights are used in the outcome model regression for each treatment level. In the final step, the IPWRA computes the average predicted outcomes for each treatment group using the GPS and the conditional means estimated in the first two steps. The difference of these weighted averages produces average treatment effects of the beneficiary group. The IPWRA is finally obtained via estimating the following regressions through weighted least squares:

$$Y_{hj} = \propto + \beta_1 Treat_1 + \beta_2 Treat_2 + \delta X_{hj} + \mu_j + \varepsilon_{hj} \qquad (1)$$

where Y_{hj} is the outcome of interest for household h from village *j*. *Treat₁* represents the inputs only treatment, and *Treat₂* represents the inputs with cash treatment. β_1 and β_2 are the intent-to-treat (ITT) estimators for the two treatment groups. δX_{hj} represents a set of demographics, assets, shocks, and access to basic service covariates that we include in our outcome model, including the following: gender, age, its square, marital status of the household head, and the interaction between gender and age of the head, the number of children, and adults in the household, whether any household member has some form of disability. We then control for size of owned land (in logarithms), and its square, and whether the household reported having experienced a flood and locusts' attacks. Access to sources of safe water, improved toilet facility, use of improved energy sources and distance to markets are also included. This last set of variables captures important characteristics of the villages. Because the model we use prevents us to include any geographical fixed-effect, the inclusion of these variables can help improve the estimates of the impacts as they tend to be quite homogenous within villages. Finally, μ_j and ε_{hj} are iid errors across villages and across households within villages.

The estimation of the standard errors requires bootstrapping the entire process. Alternatively, a one-step GMM procedure can be implemented to calculate more easily the standard error (Cattaneo *et al.*, 2013; Linden *et al.*, 2015). We opt for the latter approach because we use the STATA built-in command *teffects* that is based on GMM modelling. We also cluster the standard error at the village level.

Our analysis seeks also to understand if the addition of cash on top of inputs had differential impacts. We test the difference between the two treatment groups. Empirically, we do this by estimating the model by imposing as a base category in the multinomial logit the inputs only group. The model we estimate is the following:

$$Y_{hj} = \propto + \beta_3 Treat_3 + \beta_4 C_4 + \delta X_{hj} + \mu_j + \varepsilon_{hj} \qquad (2)$$

Where the β_1 in this case represents the differential effect of the cash compared to inputs only.

Finally, we explore whether there are any heterogeneous effects by estimating the two models for sub-groups of the population. In particular we conduct the analysis by: gender of household head, by exposure to flood (using the indicator constructed with satellite data), by distance to markets, and by asset ownership (proxied by land size).

6. Results

6.1 Main results

Table 6 summarizes the ITT estimates from the IPWRA model of the impact of the two treatments on outcomes of food security, assets, farming and income diversification. The table reports the three coefficients of interest, β_1, β_2 and β_3. The results show that, relative to the comparison group, receiving either inputs-only or inputs plus cash is associated with positive and significant impacts on a number of productive outcomes. These include the number of adopted improved inputs, the number of planted crops, and the number of income sources of the household. These positive productive relationships suggest that both of these programmes help to support economic opportunities and resilience for their beneficiaries.

However, two important differences are observed between the treatments. On the one hand, we find a positive and significant impact of the inputs-only treatment on asset wealth, and livestock owned, relative to the comparison group, but no impact for the cash plus treatment. On the other hand, we find a reduction in food insecurity, measured as a change in FCS<21 and in FCS<35 among the cash plus inputs group, and no significant protective impact from the input-only treatment. This suggests that cash recipients are directing some share of their transfers toward consumption, but not toward agricultural asset accumulation. This interpretation is further confirmed in the direct comparison of the two treatments. As shown in the bottom row of Table 6, we find that receiving cash plus inputs is associated with lower agricultural asset wealth, but higher levels of income diversification than the inputs-only group. Taken together, these outcomes are indicative of investments to diversify livelihoods away from agriculture facilitated by the cash component of the transfer, which in the context of Somalia is likely to be a rational response to the high levels of uncertainty in the agricultural sector and the financial barriers households face in diversify away from it. However, households receiving just the input transfers are investing in improved means of agricultural production through the acquisition of productive agricultural assets and livestock.

Table 7 and Table 8 report the results on the individual indicators of inputs use, adoption of agricultural practices and crops planted. Table 7 shows that both treatments have a positive effect on the probability of planting improved seeds and on adopting pesticides, despite the fact that pesticides are not part of the standard transfer provided by the programme.

The bottom row of the table shows the differential effects of receiving cash plus inputs relative to inputs alone. There are no statistically significant differences between the two treatments, with the exception of adoption of improved farm tools, with cash plus inputs being less likely to adopt them.

Finally, Table 8 shows that farmers receiving the cash plus inputs treatment are significantly more likely to plant more nutritious crops, such as cowpeas, vegetables and fruits, compared to those farmers that received the inputs only package. One potential explanation is that farmers receiving only inputs were more likely to sell the vegetable and pulse seeds in their input packets for cash. This is a finding that requires further investigation, as it has important and clear implications for the effectiveness of the project. The inputs only group is, instead, more likely to plant maize and beans than the cash plus inputs group, which could be explained by the geographical differences in maize and sorghum distribution.

Taken together, the results suggest that both treatments have positive and significant impacts on a range of productive outcomes, relative to the non-beneficiary/ies group. However, while the input only treatment is associated with household investments in asset accumulation for agricultural production, the additional of the cash transfer supports intensification of agriculture through the diversification of livelihood portfolios, and protective impacts in terms of improvements in food security.

6.2 Heterogeneous effects

We carry out the impact analysis by sub-groups of the population in order to understand the heterogeneous impacts of the two treatments. In particular, we explore the differences in impacts between households that experienced weather shocks during the reference period, households with different land size endowments, households with different market access conditions, and households headed by men compared to women.

Table 9 explores differences between households hit by extreme rainfall conditions in 2019 compared to those experiencing normal rainfall. As described in the data section, we identified severe and extreme wet conditions with a three months SPI>1.5. The results suggest the cash plus inputs treatment had a large protective effect on food security for those households living in areas that experienced a weather shock, with a large and negative effect on the probability of being poor or moderate food insecure (Column 3). The input only programme was, instead, successful at protecting agricultural assets relative to the comparison group. The coefficient in column 4 for those that experienced the shock is positive and statistically significant, while the coefficient for those that lived in areas with regular weather conditions instead is not significant. This indicates that the positive impact of the input transfer programme on agricultural assets found in the main model is driven mostly by households protecting their assets in the context of extreme rainfall events. On the other hand, the programme seemed to have no measurable impact on livestock holdings during extreme weather event, although the coefficient for both treatments is positive. Interestingly for the input only group we find a positive and significant effect under normal and extreme weather conditions. In relation to the differential effect of the cash, we observe a positive difference above the provision of inputs for income diversification and a negative impact for agricultural assets under extreme weather conditions. This negative impact seems to be driven by the large increase in agricultural assets experienced by the inputs only group in the context of the severe weather shock, rather than by a depletion of assets among the cash plus inputs group.

Next, we disaggregate the analysis between those that own more land (above the median) compared with those with less land (below the median). As reported in Table 10, cash plus inputs had positive and larger effects on those with more land, compared to those with smaller land endowments, particularly for food security. Among the inputs only beneficiaries, similar effects for both land size groups in relation to agricultural assets, livestock, and cropping practices. However, the positive effect of the inputs only on income diversification seems to be coming from those with more land. In addition, food insecurity improves for those with smaller land endowments.

Interestingly, when we split the sample by market access conditions, we find that the cash plus inputs transfer generates positive impacts on food security, relative to the comparison, for households residing close to markets (Table 11). For households distant to markets, there is no observed effect of the transfer. Households residing close to markets are likely to be more able to use their cash transfer to purchase food from retail markets than those in more isolated places. Farmers living in more remote areas benefit the most from the additional provision of cash in terms of their diversification of both crops and income sources. This suggests that cash is helping to overcome the barriers to diversification in these geographically disadvantaged locations, where opportunities to move away from subsistence agriculture are particularly constrained.

Finally, Table 12 reports the heterogeneous analysis by gender of household head. The results reveal similar patterns between female and male heads although positive impacts in the female group are found in more domains and from both treatments. Interestingly, while we observe improvements in food security in the full sample for the cash plus group, in the sub-sample with a female head similar effects are reported also for the group receiving only inputs.

7. Conclusions

Somalia has a long history of conflicts and fragilities connected to climate-related shocks and conflicts, which affect food and nutrition security and livelihoods, especially in the rural areas that are highly dependent on agricultural production. After the 2011 famine and the 2017 severe drought emergency, Somalia is yet facing another crisis, the worst crisis in more than forty years, with a devastating drought reaching unprecedented levels (UN News, 2022). The two-year historic dry spell is leaving nearly 50 percent of the population in need of emergency food assistance, with concrete risk of a famine occurring in some areas of the country by the end of the year (UNOCHA, 2022b). , In response to the 2017 crisis, FAO and other organizations have adopted an integrated approach, including programmatic cash plus that combine unconditional cash transfers with productive inputs, assets and technical training aimed at supporting beneficiaries to address their basic needs, while also engaging them in productive activities. In this article, we analysed the impacts of this short-term multifaceted programme implemented by FAO during the 2019 *deyr* wet season, using the Crop and Yield Assessment (CYA) survey, which was administered to monitor wellbeing of beneficiary and non-beneficiary/ies households living in agropastoral districts reached by FAO. Due to operational challenges, however, programme delivery was quite heterogeneous and not all beneficiary households received the complete package. We exploit this variation and focus on the two largest treatment groups: one composed of households that received only inputs and one of households that received cash disbursements in addition to inputs. In addition to having two different treatment groups, the composition of these two groups allows us to explore the differential effects of the cash in addition to the inputs package.

Overall, our results suggest that the programme successfully contributed to promoting income and crop diversity, and increased input use. The group of households benefitting exclusively from delivery of inputs increased ownership of agricultural assets and livestock, increased use of improved/hybrid seeds and farm tools, planted a greater variety of crops, including more maize, cowpeas and vegetables. We observe similar impacts for the group of farmers benefitting from both cash and inputs, on adoption of improved inputs, number of planted crops and income diversification. However, the cash plus group did not increase the assets, but faced a significant reduction of the share of food insecure households. We find a synergistic or differential effect of providing cash in some indicators related to income diversification, and planting of nutritious food crops, such as cowpeas, vegetables and fruits. The heterogeneity analysis shows some evidence concerning the protective role played by the cash plus approach during a severe weather shock that affected communities targeted by the programme. Further, it highlights the importance of proximity to markets in terms of food security for households benefitting from the cash.

Severe data limitations affect our impact evaluation study. While we are confident about the matching model used, our estimates suffer from multiple sources of bias that are typical of observational data. Beyond the usual caveats concerning endogeneity due to lack of randomisation, sample selection and unobserved heterogeneity, we have to stress that non-beneficiary/ies were also interviewed in treatment villages, which may have resulted in spillover effects to other households and to the broader local economy. This was however a somehow intentional consequence of the programme. Given the lack of resources to serve the full population in treated villages and the presence of strong network ties among rural Somalis, community-based targeting was considered unavoidable to make programme benefits cascading down indirectly to a broader set of recipients, avoiding negative community dynamics. Further, we cannot rule out entirely the possibility that the group of non-beneficiary/ies may have included households that were beneficiaries in the previous crop season. Despite being a short-term programme, with benefits delivered only for one planting season, there may be some long-lasting effects after the end of the crop season. If this were the case, eventually we would observe a downward bias and conservative estimates of the true impacts of the programme. Moreover, because of resource constraints and substantial need, beneficiary households typically received assistance only for a single cropping season even if they remained in or returned to crises, so that new, different eligible households could have been incorporated. For this reason, we can exclude in our sample the presence of beneficiaries that benefitted for multiple time periods.

Despite these caveats, our findings are in line with the emerging literature concerning the effectiveness of graduation/cash plus programmes. More robust evidence, however, is needed to identify which combination of social safety nets programme provides the greatest benefits for populations in need, especially for those living in the context of conflicts and fragilities, and in a cost-effective manner. On-going humanitarian crises related to climate change and other economic shocks highlight that the need for short-term relief will continue. Consequently, an emerging policy concern is how governments can effectively transition from short-term humanitarian to longer-term development assistance. Evidence on the interplay between the two types of interventions is necessary to ensure they work in concert. Evidence on effective programming is also necessary because there are limitations on state and donor capacity to continuously fund humanitarian assistance. Rigorous research in humanitarian settings is possible when researchers and programmers work together, particularly in the early stages when responses to humanitarian challenges are designed (Bruck *et al.*, 2019).

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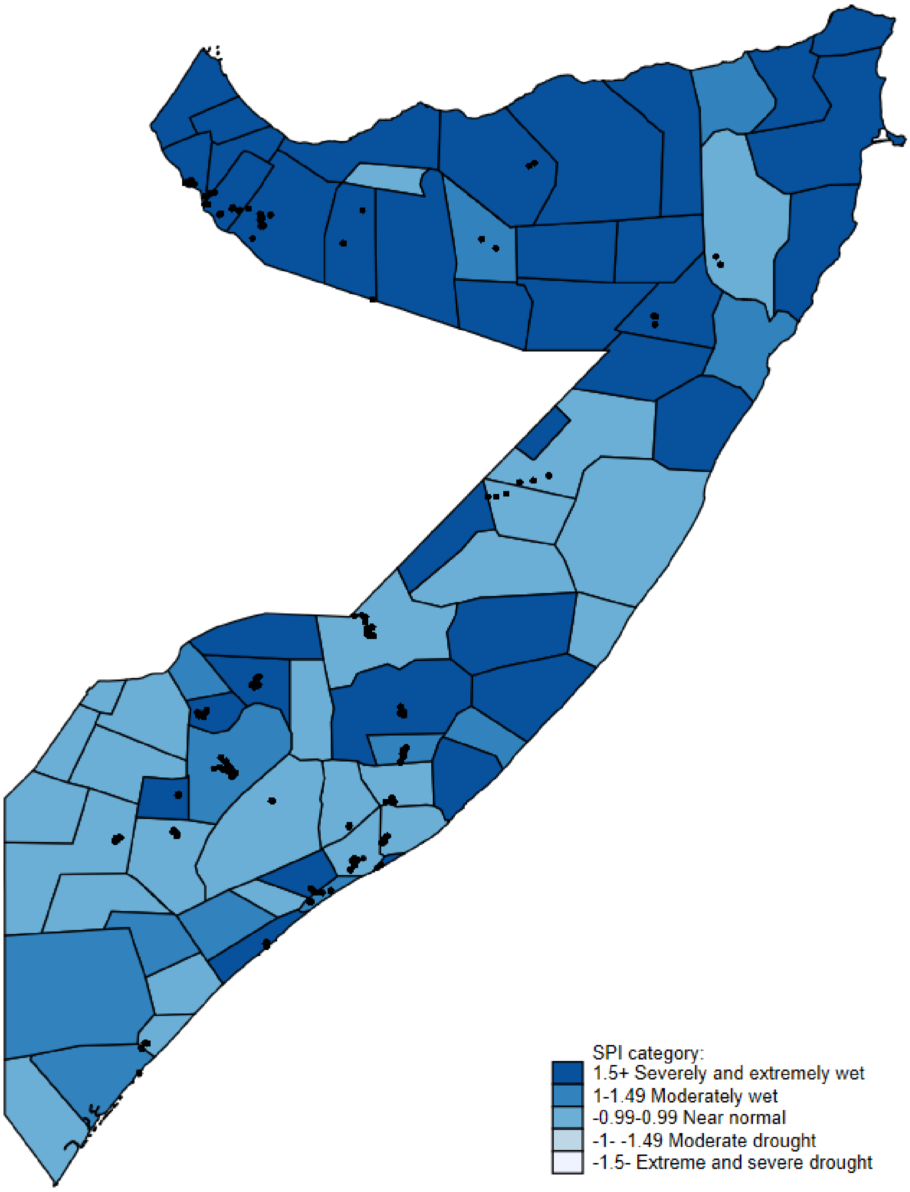
Annex

Figures

Figure A1. Average standard precipitation index at 3-months in 2019 *deyr* season



Note: Authors' elaboration from crop yields assessment (CYA) data and Climate Hazards Group InfraRed Precipitation with Station rainfall data. SPI stands for standardized precipitation index. Dots represent households included in the 2019 *deyr* CYA database.

Source: OCHA Services. 2022. *Somalia.* OCHA. Cited 28 November 2022. https://data.humdata.org/m/dataset/cod-ab-som

Figure A2. Timing of crop season and programme

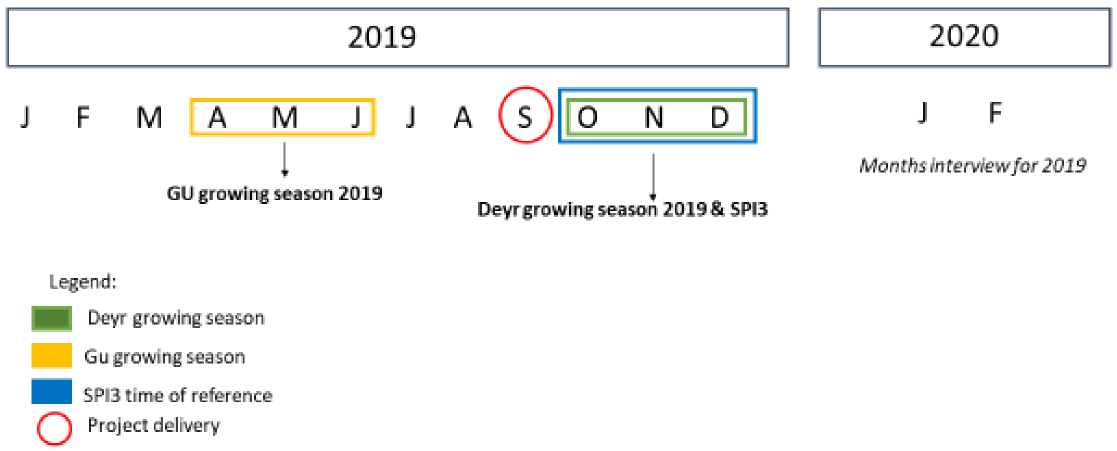
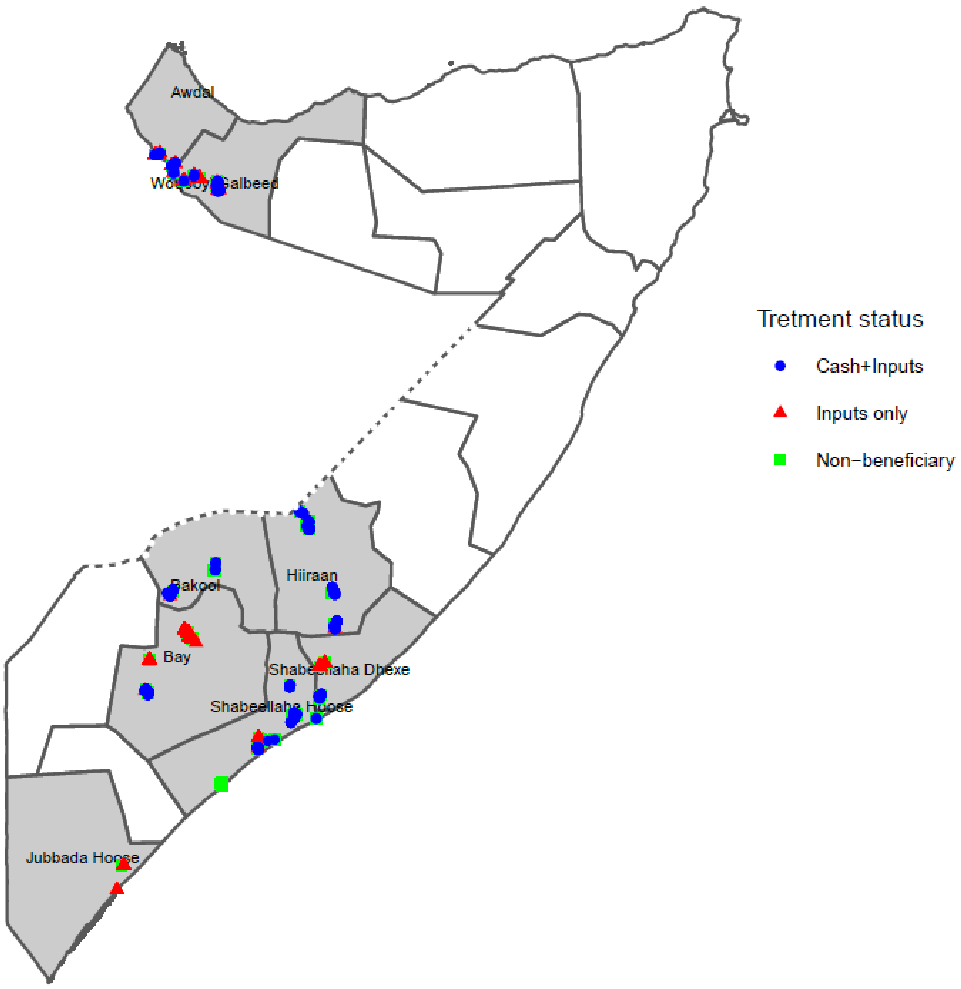


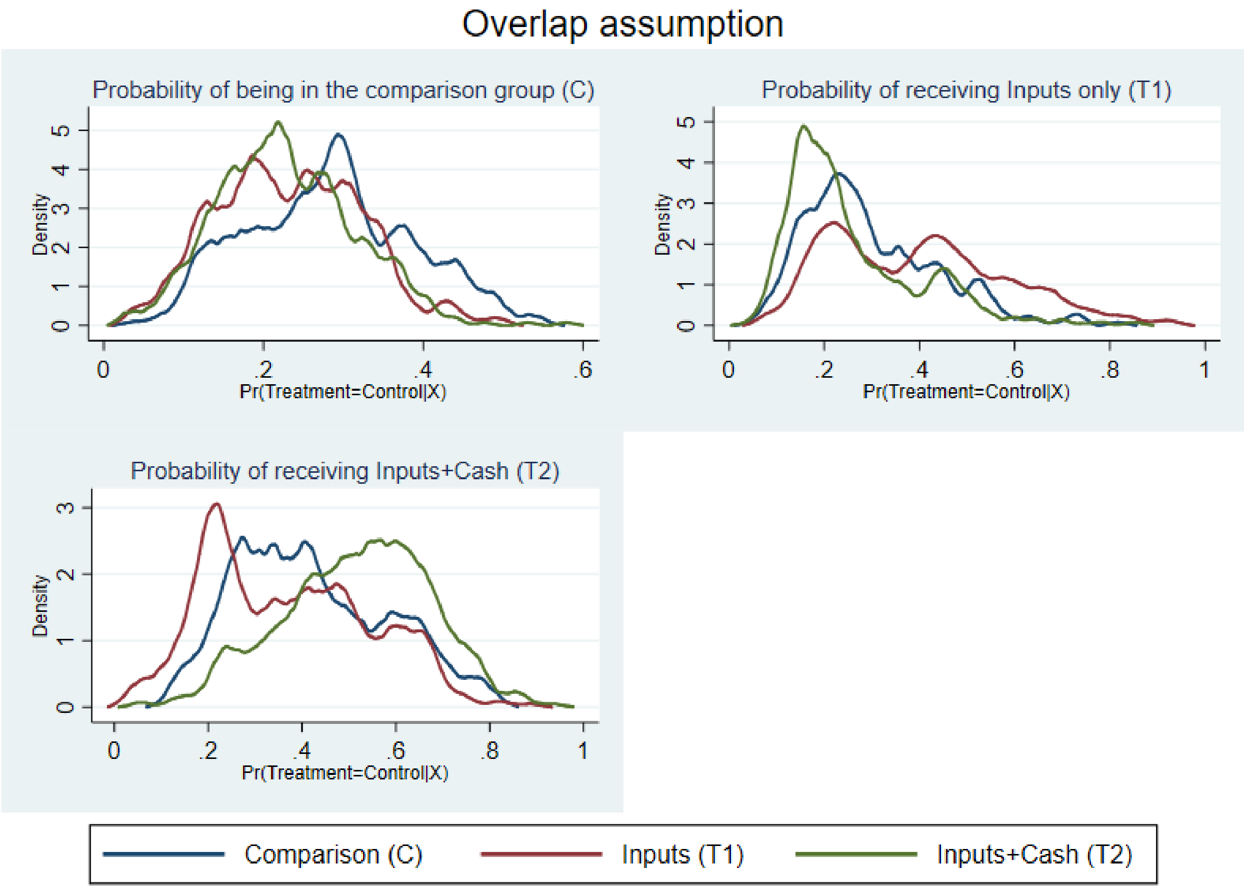
Figure A3. Geographical distribution of treatment status



Note: Authors' elaboration from crop yields assessment 2019 *deyr* season data.

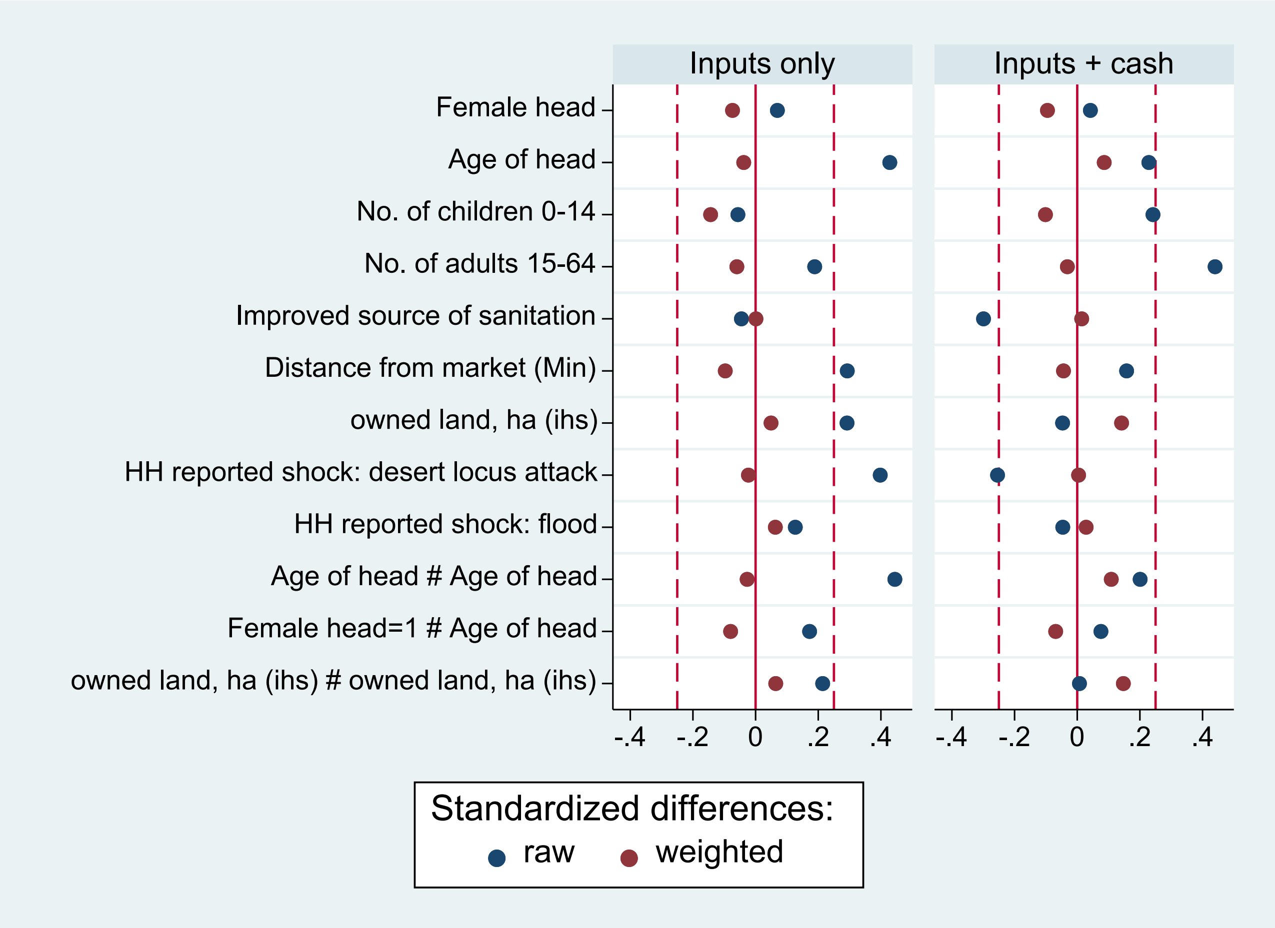
Source: OCHA Services. 2022. *Somalia.* OCHA. Cited 28 November 2022. https://data.humdata.org/m/dataset/cod-ab-som

Figure A4. Overlap assumption



Note: Authors' elaboration from crop yields assessment 2019 *deyr* season data.

Figure A5. Balance of covariates



Note: Authors' elaboration from crop yields assessment 2019 *deyr* season data.

Tables

Table 1. Treatment status

2019	Frequency	Percent
Non-beneficiary/ies	312	20.5
Inputs only	398	26.1
Cash + Inputs	577	37.9
Cash + Inputs + Training	122	8
Cash only	104	6.8
Inputs + Training Cash	10	0.7
+ Training	1	0.07
N	1 524	100

Note: Authors' elaboration from crop yields assessment 2019 *deyr* season data.

Table 2. Outcome means by treatment status

	All	Non-beneficiary/ies	Inputs	Inputs + Cash
Food consumption score	51.117	52.880	48.805	51.757
Poor FCS (<21)	0.120	0.119	0.178	0.080
Poor or moderate FCS (<35)	0.292	0.285	0.362	0.248
Agricultural assets	-0.003	0.011	0.080	-0.069
Tropical livestock units (IHS)	1.443	1.318	1.640	1.376
No. of adopted inputs	1.699	1.365	1.905	1.737
Adoption improved seeds	0.626	0.513	0.734	0.614
Adoption pesticides	0.190	0.141	0.236	0.185
Adoption fertilizers	0.185	0.131	0.188	0.211
Adoption herbicides	0.108	0.058	0.090	0.147
Adopted improved farm tools	0.285	0.260	0.394	0.224
Used tractor	0.304	0.263	0.261	0.355
No. of crops planted	2.451	1.740	2.485	2.811
Planted maize	0.507	0.471	0.593	0.466
Planted sorghum	0.705	0.670	0.796	0.660
Planted cowpeas	0.549	0.311	0.518	0.700
Planted other legumes	0.068	0.067	0.123	0.029
Planted oil crops	0.044	0.032	0.050	0.047
Planted vegetables	0.286	0.099	0.219	0.433
Planted fruit	0.094	0.038	0.048	0.156
# income sources	1.585	1.298	1.595	1.733
Observations	1,287	312	398	577

Note: Authors' elaboration from crop yields assessment 2019 *deyr* season data. IHS stands for inverse hyperbolic sine transformation.

Table 3. Incidence of shocks by treatment status

	All	Non-beneficiary/ies	Inputs only	Inputs + Cash
Self-reported shocks				
HH reported shock: any weather related	0.207	0.196	0.261	0.177
HH reported shock: flood	0.181	0.173	0.224	0.156
HH reported shock: drought	0.058	0.054	0.111	0.024
HH reported shock: desert locus attack	0.312	0.301	0.492	0.192
Spatially-observed weather shocks				
Flood *Deyr* SPI3>1.5	0.566	0.523	0.638	0.536
Observations	1,287	312	398	577

Note: Authors' elaboration from crop yields assessment 2019 *deyr* season data. SPI stands for standardized precipitation index.

Table 4. Means of covariates by treatment status before adjustment by matching

	All	Non-beneficiary/ies	Inputs	Inputs + Cash
Female head	0.375	0.356	0.389	0.376
Age of head	42.523	39.795	45.025	42.272
Head married	0.891	0.885	0.859	0.917
Head yrs of education	2.650	2.609	2.673	2.657
No. of children 0-14	3.231	3.080	2.987	3.480
No. of adults 15-64	3.260	2.872	3.141	3.553
Household member with disability	0.083	0.074	0.078	0.092
Improved source of water	0.544	0.612	0.480	0.551
Improved source of sanitation	0.427	0.500	0.477	0.354
Improved source of energy	0.511	0.554	0.377	0.581
Distance from market (Min)	86.846	76.740	96.138	85.901
Tropical livestock units (ihs)	1.443	1.318	1.640	1.376
Owned land, ha (ihs)	1.332	1.275	1.521	1.233
Observations	1,287	312	398	577

Note: Authors' elaboration from crop yields assessment 2019 *deyr* season data. IHS stands for inverse hyperbolic sine transformation. The variables reported include those used for modeling participation into treatments and those used as controls in the outcome regressions.

Table 5. Distribution of treatment status by village

Beneficiary group	**Frequency**	**Percentage**
Non beneficiaries, Inputs only & cash plus Inputs	11	14%
Non beneficiaries & Inputs only	12	16%
Non beneficiaries & cash plus Inputs	15	20%
Inputs only & cash plus Inputs	5	7%
Cash plus Inputs	14	18%
Inputs only	8	11%
Non beneficiaries	11	14%
Total	76	100%

Note: Authors' elaboration from crop yields assessment 2019 *deyr* season data.

Table 6. Impact of cash plus on main outcomes

	Food consumption score	Poor food security (FCS<21)	Moderate and poor food security (FCS<35)	Agricultural assets	Livestock (TLU)	No. of adopted improved inputs	No. of planted crops	No. of income sources
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Input only vs C	2.361	0.002	-0.051	0.346	0.308	0.609	0.597	0.267
	(2.803)	(0.036)	(0.062)	(0.179)*	(0.156)**	(0.126)***	(0.164)***	(0.097)***
Cash + Input vs C	6.822	-0.094	-0.192	0.276	-0.042	0.450	0.814	0.415
	(6.401)	(0.051)*	(0.085)**	(0.264)	(0.205)	(0.208)**	(0.174)***	(0.088)***
Inputs + Cash vs Inputs	-3.299	-0.012	-0.005	-0.521	-0.176	-0.061	0.311	0.184
	(4.640)	(0.038)	(0.066)	(0.282)*	(0.190)	(0.171)	(0.198)	(0.105)*
N	1,287	1,287	1,287	1,287	1,287	1,287	1,287	1,287
Comparison mean	52.880	0.119	0.285	0.011	1.318	1.365	1.740	1.298

Notes: * *p*<0.1; ** *p*<0.05; *** *p*<0.01. Standard errors clustered at village level in parentheses. C represents the comparison group, TLU stands for tropical livestock units.

Table 7. Impact of cash plus on inputs use

	Planted improved seeds (1)	Adopted pesticides (2)	Adopted synthetic fertilizers (3)	Adopted herbicides (4)	Adopted improved farm tools (5)	Used tractor (6)
Input only vs C	0.292	0.126	0.066	0.023	0.126	-0.020
	(0.045)***	(0.074)*	(0.029)**	(0.044)	(0.062)**	(0.054)
Cash + Input vs C	0.193	0.135	0.096	0.066	-0.052	0.009
	(0.094)**	(0.066)**	(0.059)	(0.043)	(0.072)	(0.057)
Inputs + Cash vs Inputs	-0.059	0.010	0.066	0.064	-0.130	-0.018
	(0.082)	(0.063)	(0.058)	(0.047)	(0.076)*	(0.068)
N	1,287	1,287	1,287	1,287	1,287	1,287
Comparison mean	0.513	0.141	0.131	0.058	0.260	0.263

Notes: * *p*<0.1; ** *p*<0.05; *** *p*<0.01. Standard errors clustered at village level in parentheses. C represents the comparison group.

Table 8. Impact of cash plus on planted crops

	Planted maize (1)	Planted sorghum (2)	Planted cowpeas (3)	Planted other legumes (4)	Planted oil crops (5)	Planted vegetables (6)	Planted fruit (7)
Input only vs C	0.189	-0.011	0.157	0.059	0.007	0.122	0.008
	(0.075)**	(0.060)	(0.074)**	(0.056)	(0.023)	(0.044)***	(0.026)
Cash + Input vs C	-0.011	-0.072	0.394	-0.047	-0.008	0.305	0.054
	(0.075)	(0.063)	(0.070)***	(0.031)	(0.026)	(0.063)***	(0.029)*
Inputs + Cash vs Inputs	-0.197	-0.034	0.179	-0.095	-0.008	0.172	0.116
	(0.086)**	(0.098)	(0.084)**	(0.034)***	(0.024)	(0.078)**	(0.030)***
N	1,287	1,287	1,287	1,287	1,287	1,287	1,287
Comparison mean	0.471	0.670	0.311	0.067	0.032	0.099	0.038

Notes: * *p*<0.1; ** *p*<0.05; *** *p*<0.01. Standard errors clustered at village level in parentheses.

Table 9. Impact of cash plus on main outcomes, by exposure to flood shock

Flood shock: (SPI3≥1.5)	Food consumption score (1)	Poor food security (FCS<21) (2)	Moderate and poor food security (FCS<35) (3)	Agricultural assets (4)	Livestock (TLU) (5)	No. of adopted improved inputs (6)	No. of planted crops (7)	No. of income sources (8)
Input only vs C	0.868	-0.004	-0.054	0.610	0.119	0.519	0.295	0.073
	(3.728)	(0.046)	(0.063)	(0.203)***	(0.170)	(0.131)***	(0.162)*	(0.087)
Cash + Input vs C	6.336	-0.033	-0.209	-0.244	0.159	0.213	0.618	0.394
	(7.884)	(0.077)	(0.098)**	(0.243)	(0.265)	(0.191)	(0.280)**	(0.101)***
Cash + Input vs Inputs	-1.612	0.015	0.005	-0.965	0.064	-0.039	0.258	0.324
	(6.756)	(0.049)	(0.088)	(0.247)***	(0.233)	(0.232)	(0.268)	(0.106)***
N	729	729	729	729	729	729	729	729
No flood shock: (SPI3<1.5)								
Input only vs C	0.602	-0.032	-0.044	0.117	0.408	0.660	1.032	0.528
	(6.293)	(0.057)	(0.096)	(0.191)	(0.207)**	(0.197)***	(0.191)***	(0.150)***
Cash + Input vs C	-6.002	-0.029	-0.032	0.261	-0.564	0.304	0.916	0.355
	(10.511)	(0.062)	(0.072)	(0.342)	(0.537)	(0.341)	(0.249)***	(0.140)**
Cash + Input vs Inputs	-9.751	0.011	0.002	-0.089	-0.505	-0.362	0.058	-0.175
	(4.350)**	(0.050)	(0.078)	(0.376)	(0.341)	(0.234)	(0.212)	(0.144)
N	558	558	558	558	558	558	558	558

Notes: * *p*<0.1; ** *p*<0.05; *** *p*<0.01. Standard errors clustered at village level in parentheses. C represents the comparison group. FCS stands for food consumption score, TLU for tropical livestock units, and SPI for standardized precipitation index.

Table 10. Impact of cash plus on main outcomes, by land ownership

More land (above the median)	Food consumption score (1)	Poor food security (FCS<21) (2)	Moderate and poor food security (FCS<35) (3)	Agricultural assets (4)	Livestock (TLU) (5)	No. of adopted improved inputs (6)	No. of planted crops (7)	No. of income sources (8)
Input only vs C	-0.037	-0.001	0.038	0.173	0.254	0.391	0.672	0.281
	(2.758)	(0.034)	(0.066)	(0.207)	(0.143)*	(0.095)***	(0.166)***	(0.116)**
Cash + Input vs C	7.779	-0.167	-0.186	0.509	-0.095	0.452	0.768	0.410
	(7.893)	(0.055)***	(0.087)**	(0.294)*	(0.270)	(0.208)**	(0.232)***	(0.081)***
Cash + Input vs Inputs	-0.288	-0.104	-0.152	-0.271	-0.387	-0.124	-0.109	0.136
	(5.671)	(0.051)**	(0.084)*	(0.429)	(0.262)	(0.191)	(0.195)	(0.155)
N	691	691	691	691	691	691	691	691
Less land (below the median)								
Input only vs C	10.723	-0.050	-0.148	0.488	0.388	0.984	0.681	0.130
	(4.320)**	(0.059)	(0.088)*	(0.348)	(0.212)*	(0.323)***	(0.246)***	(0.146)
Cash + Input vs C	2.510	0.061	-0.052	-0.091	0.268	0.430	1.212	0.378
	(6.717)	(0.099)	(0.109)	(0.342)	(0.252)	(0.301)	(0.310)***	(0.218)*
Cash + Input vs Inputs	-13.244	0.094	0.136	-0.843	0.066	-0.005	0.513	0.088
	(6.007)**	(0.039)**	(0.086)	(0.315)***	(0.249)	(0.227)	(0.272)*	(0.141)
N	596	596	596	596	596	596	596	596

Notes: * *p*<0.1; ** *p*<0.05; *** *p*<0.01. Standard errors clustered at village level in parentheses. C represents the comparison group. FCS stands for food consumption score and TLU for tropical livestock units.

Table 11. Impact of cash plus on main outcomes, by distance to markets

More distant from market (above the median)	Food consumption score (1)	Poor food security (FCS<21) (2)	Moderate and poor food security (FCS<35) (3)	Agricultural assets (4)	Livestock (TLU) (5)	No. of adopted improved inputs (6)	No. of planted crops (7)	No. of income sources (8)
Input only vs C	-4.084	-0.088	-0.032	0.549	0.163	0.511	0.438	0.423
	(6.540)	(0.048)*	(0.089)	(0.180)***	(0.213)	(0.188)***	(0.145)***	(0.119)***
Cash + Input vs C	-14.568	0.004	-0.019	0.163	-0.383	-0.204	0.928	0.613
	(14.144)	(0.104)	(0.152)	(0.206)	(0.380)	(0.335)	(0.293)***	(0.192)***
Cash + Input vs Inputs	-11.535	0.054	0.054	-0.229	-0.264	0.195	0.541	0.243
	(5.878)**	(0.053)	(0.097)	(0.284)	(0.305)	(0.257)	(0.270)**	(0.163)
N	621	621	621	621	621	621	621	621
Closer to market (below the median)								
Input only vs C	-3.938	0.099	0.071	0.211	0.056	0.393	0.518	0.037
	(3.480)	(0.059)*	(0.060)	(0.256)	(0.166)	(0.159)**	(0.216)**	(0.085)
Cash + Input vs C	8.975	-0.077	-0.164	-0.163	0.233	0.397	0.369	0.333
	(5.615)	(0.048)	(0.086)*	(0.272)	(0.183)	(0.172)**	(0.212)*	(0.078)***
Cash + Input vs Inputs	5.418	-0.093	-0.116	-0.280	0.100	0.132	-0.065	0.235
	(5.130)	(0.062)	(0.074)	(0.336)	(0.221)	(0.208)	(0.270)	(0.097)**
N	666	666	666	666	666	666	666	666

Notes: * *p*<0.1; ** *p*<0.05; *** *p*<0.01. Standard errors clustered at village level in parentheses. C represents the comparison group. FCS stands for food consumption score and TLU for tropical livestock units.

Table 12. Impact of cash plus on main outcomes, by gender of the head

Head: female	Food consumption score (1)	Poor food security (FCS<21) (2)	Moderate and poor food security (FCS<35) (3)	Agricultural assets (4)	Livestock (TLU) (5)	No. of adopted improved inputs (6)	No. of planted crops (7)	No. of income sources (8)
Input only vs C	-1.794	-0.090	-0.020	0.759	0.212	0.557	0.479	0.312
	(5.995)	(0.043)**	(0.087)	(0.204)***	(0.214)	(0.213)***	(0.159)***	(0.103)***
Cash + Input vs C	-0.735	-0.131	-0.179	0.249	0.009	0.569	0.669	0.496
	(11.113)	(0.085)	(0.126)	(0.336)	(0.272)	(0.279)**	(0.217)***	(0.130)***
Cash + Input vs Inputs	-2.833	0.012	-0.060	-0.732	-0.138	-0.090	0.430	0.086
	(5.475)	(0.056)	(0.088)	(0.371)**	(0.246)	(0.259)	(0.241)*	(0.149)
N	483	483	483	483	483	483	483	483
Head: male								
Input only vs C	2.097	0.034	-0.024	0.042	0.359	0.578	0.697	0.196
	(3.344)	(0.054)	(0.068)	(0.196)	(0.151)**	(0.143)***	(0.189)***	(0.126)
Cash + Input vs C	8.180	-0.086	-0.163	0.247	-0.110	0.259	0.928	0.317
	(5.825)	(0.051)*	(0.068)**	(0.270)	(0.253)	(0.184)	(0.173)***	(0.086)***
Cash + Input vs Inputs	-3.083	-0.019	0.027	-0.283	-0.226	-0.069	0.302	0.213
	(5.050)	(0.039)	(0.065)	(0.275)	(0.190)	(0.181)	(0.225)	(0.105)**
N	804	804	804	804	804	804	804	804

Notes: * *p*<0.1; ** *p*<0.05; *** *p*<0.01. Standard errors clustered at village level in parentheses. C represents the comparison group. FCS stands for food consumption score and TLU for tropical livestock units.

Table 13. Standardized differences

	Standardized difference		Ratio		Standardized difference		Ratio		Standardized difference		Ratio	
	Raw	Weighted	Raw	Weighted	Raw	Weighted	Raw	Weighted	Raw	Weighted	Raw	Weighted
	Inputs only v. C				**Cash + Inputs v. C**				**Cash + Inputs v Inputs**			
Female head	0.070	-0.074	1.037	0.973	0.042	-0.095	1.022	0.963	-0.027	0.015	0.986	1.010
Age of head	0.428	-0.038	1.415	1.069	0.229	0.086	0.900	1.226	-0.230	-0.029	0.636	1.079
No. of children 0-14	-0.056	-0.143	1.007	0.939	0.242	-0.101	1.027	0.999	0.297	-0.066	1.020	0.876
No. of adults 15-64	0.189	-0.060	1.160	0.992	0.440	-0.031	1.548	1.199	0.258	0.081	1.334	1.081
Distance from market (Min)	-0.045	0.001	0.997	1.000	-0.299	0.014	0.913	1.001	-0.253	-0.062	0.915	1.001
Improved source of water	0.293	-0.097	2.030	0.745	0.158	-0.044	1.328	0.888	-0.147	-0.019	0.655	0.765
Owned land, ha (ihs)	0.292	0.049	0.906	1.093	-0.047	0.142	1.171	1.129	-0.327	-0.021	1.293	1.044
HH reported shock: desert locus attack	0.398	-0.023	1.186	1.000	-0.254	0.004	0.737	1.000	-0.666	-0.059	0.621	0.952
HH reported shock: flood	0.127	0.063	1.212	1.094	-0.046	0.028	0.918	1.043	-0.173	-0.008	0.758	0.986
Age of head sq	0.445	-0.027	1.706	1.081	0.201	0.109	0.979	1.427	-0.274	-0.017	0.574	1.160
Female head * Age of head	0.172	-0.080	1.438	0.969	0.076	-0.069	1.100	1.030	-0.100	0.011	0.765	0.995
Owned land, ha (ihs) sq	0.214	0.064	0.815	0.993	0.007	0.147	1.234	1.294	-0.194	-0.005	1.514	1.262

Table 14. Multinomial logit

	Inputs	Inputs + Cash
Female head	-0.050	0.576
	(0.720)	(0.610)
Age of head	-0.051	0.078
	(0.052)	(0.063)
No. of children 0-14	-0.012	0.145*
	(0.075)	(0.080)
No. of adults 15-64	0.092	0.252***
	(0.078)	(0.074)
Improved source of sanitation	0.091	-0.496
	(0.427)	(0.413)
Distance from market (Min)	0.005**	0.002
	(0.002)	(0.002)
Land ha (ihs)	0.447	-0.466
	(0.506)	(0.384)
HH reported shock: desert locus attack	0.572	-0.434
	(0.501)	(0.450)
HH reported shock: flood	0.381	-0.200
	(0.457)	(0.380)
Age of head # Age of head	0.001*	-0.001
	(0.001)	(0.001)
Female head # Age of head	0.005	-0.009
	(0.017)	(0.014)
Land sq	-0.085	0.139
	(0.121)	(0.108)
Pseudo-R2	0.092	
Observations	1,287	
AIC	2544.23	

Notes: * *p*<0.1 ** *p*<0.05; *** *p*<0.01. Standard errors clustered at village level in parentheses.

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