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Can Digital Cash Transfers Serve Those in Active Conflict?

Evidence from a Randomized Intervention in Sudan

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Abstract

This paper evaluates the impact of digital transfers on the well-being of households grappling with active conflict in Sudan. Considering the case of Sudan, where active conflict and funding gaps continue to hamper the delivery of humanitarian services, we aim to address the following questions: (i) Can digital cash transfers improve food and nutrition security outcomes of beneficiaries in conflict-affected settings?; (ii) Can digital transfers to an other-wise inaccessible population improve subjective well-being, mental health, and stress in the face of recurrent conflicts?; and (iii) Who benefits more from digital transfers, and do the impacts of digital transfers vary depending on the size of transfers or socioeconomic characteristics of households? To address these questions, we design a randomized controlled trial (RCT) involving digital transfers of different sizes to randomly selected urban households in Sudan. Digital transfers reached nearly all targeted beneficiaries, with about a quarter of households receiving them through their friends and relatives and hence incurring some transaction fees. Overall, digital transfers mitigated deterioration in food insecurity (by 7-8 percentage points) and improved subjective well-being and mental health. Interestingly, we find that the digital transfers are more beneficial (impactful) for those grappling with active conflict. Digital transfers also appear to be less effective for poorer households and households of a larger size. These findings highlight the potential of digital transfers to support those grappling with armed conflict.

Keywords: Digital transfer; cash transfer; armed conflict; Sudan

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1. Introduction

The proliferation of armed conflicts in Africa continues to increase demand for humanitarian and social assistance. Globally, these man-made and natural disasters are increasing the funding gap in humanitarian assistance (UN OCHA, 2023). Moreover, armed conflicts in Africa are complicating the targeting and delivery of humanitarian services. Widespread and active conflicts limit the reach, breadth, and delivery of humanitarian and social assistance programs, which can ultimately impact the efficacy of these programs (e.g., Ghorpade, 2017; Lind et al., 2022). Delivering aid and social assistance in fragile and conflict-affected settings is also prone to aid diversion and misappropriation, with several cases being documented over the last few years (e.g., see Devex, 2023; Lischer, 2003; Shimada, 2025).[1] Because of these constraints, humanitarian organizations are grappling with the double burden of widening funding gaps and increasing challenges to delivering humanitarian aid to vulnerable households under the control of hostile state and non-state actors. In Sudan, warring military and paramilitary actors control large areas, and their military confrontations continue to impede access to humanitarian services. The outbreak of the war between the Sudanese Armed Forces (SAF) and the Rapid Support Forces (RSF) has ravished the livelihood of millions and displaced several million people. With competing global and regional crises, the demand for humanitarian assistance triggered by the conflict between the SAF and RSF has proven difficult to satisfy.

The increasing funding gap and intricacies associated with cost-effectively delivering humanitarian assistance to hard-to-reach populations demand innovative technological solutions that can address compounding constraints (including those arising from road blockage or inaccessibility due to active conflict and violence). The advent of digital technologies and digital transfers and their potential to address the above challenges remains an active area of inquiry (e.g., Callen et al., 2025).[2] While emerging studies show the potential of digital transfers to address complex delivery challenges and associated social pressures (Dodgson et al., 2015; Wormald et al., 2021; Field et al., 2021; Suri et al., 2023; Riley, 2024) in stable settings, the question as to whether digital transfers can serve those in active conflicts, an otherwise inaccessible population, remains broadly unknown. Using the case of Afghanistan, Callen et al. (2025) is probably the first (systematic) attempt to evaluate the cost-efficacy and potential of digital transfers to serve

[1] In particular, aid diversion by military actors, and hence the siphoning of humanitarian aid to support warring parties to a conflict, have been documented in protracted settings, including in Africa and beyond (Devex, 2023; Lischer, 2003; Shimada, 2025).

[2] Digital transfers involve the transfer of money or associated values from one account to another using a digital device or channel. This includes payments through bank transfers, mobile money, or prepaid cards.

those in active conflict. Callen et al. (2025) show that beyond relaxing access to an otherwise inaccessible population, digital transfers can significantly reduce the delivery cost of humanitarian services.[3] However, given that digital transfers require some basic infrastructure and level of tech-literacy among the population, identifying when and where digital transfers can deliver humanitarian services can inform the scale-up of such technologies in delivering humanitarian services. Beyond delivering humanitarian services through digital transfers, whether such payments are utilized for intended purposes and their ultimate impact on households grappling with the adverse consequences of armed conflict remains an important empirical question. The effectiveness of digital transfers in fragile and conflict-affected settings may depend on a range of factors, including existing digital infrastructure, tech-literacy levels of potential beneficiaries, access to markets, and transaction costs associated with converting digital transfers to cash and related services. Although recent attempts show heterogeneous impacts of cash transfers based on their conditionalities, design, and transfer size (De Janvry et al., 2006; Filmer and Schady, 2011; Kondylis and Loeser, 2021), the optimal size of digital cash transfers for different types of households is underexplored, though there is an increasing recognition that it is one of the reasons for the varying level of efficacy of conventional cash transfer programs (Aizer et al., 2016). While a handful of studies show diminishing returns (e.g., Filmer and Schady, 2011; Haushofer and Shapiro, 2016) to transfer size, others find no differential impact of the size of transfer (Jaroszewicz et al., 2022; Kondylis and Loeser, 2021). Despite these findings, little is known about the optimal level of transfer needed for effective humanitarian response and how variations in transfer amounts moderate the effectiveness of humanitarian response in fragile and conflict-affected settings as well as how the modality of transfer (cash versus digital) affects marginal returns to each additional transfer. Although the World Food Programme (WFP) and other humanitarian organizations estimate the cost of a basic food basket to support an average-sized family, such estimates are less likely to capture the rapidly changing evolution of prices, markets, and related infrastructure during an active conflict.

This paper introduces a randomized digital transfer to support urban households in Sudan, some of which are grappling with and living in active conflict areas. With the objective of evaluating the implication of differences in transfer sizes, we introduce two variants of transfer: one which delivers an amount equivalent to the WFP's (maximum) monthly ration for a family of five and another with a slightly larger transfer amount. Empirical evidence about whether

[3] The World Food Programme reports that the delivery cost for cash-based transfers amounts to about 17 percent (17 cents per dollar of aid delivered) while Callen et al. (2025) shows that this falls to 7 percent (7 cents per dollar of aid).

such transfers can be utilized and are effective in fragile settings remains scarce (Callen et al., 2025). This project aims to fill these important knowledge gaps considering the understudied context of the armed conflict in Sudan. We raise three important questions: (i) Can digital cash transfers improve food/nutrition security in conflict-affected settings?; (ii) Can digital transfers improve subjective well-being and mental health in the face of conflicts?; and (iii) Who benefits more from digital transfers, and do welfare impacts of digital transfers vary by the size of transfers? Understanding whether digital transfers can serve an otherwise inaccessible population and identifying who benefits more from these transfers can address some of the thorny questions humanitarian organizations are facing.

There are several plausible mechanisms through which digital transfers can serve those grappling with armed conflict. Most importantly, armed conflict are likely to disrupt livelihoods and trigger income losses, which increases poverty and hence the need for humanitarian and social assistance. Thus, the digital transfers offered can help households smooth consumption (Haushofer and Shapiro, 2016; Christian et al., 2019; Alloush and Wu, 2023; Alloush, 2024). Furthermore, active conflicts usually lead to suspension of traditional and physical distribution of humanitarian assistance, implying that digital transfers can substitute missing humanitarian services. Finally, digital transfers can address social pressures (Riley, 2024) and even be more useful than conventional humanitarian services.

Our findings can be summarized as follows. First, digital transfers reached nearly all targeted beneficiaries. About a quarter of respondents incurred some transaction fees as they received the transfers through friends' and relatives' mobile bank accounts. This implies that even in urban areas, financial inclusion remains a challenge. This is further exacerbated by conflict adversities such as poor network coverage or loss of mobile phones as a result of fragile security conditions. Second, the digital transfers mitigated deterioration in food security (by 7-8 percentage points) and improved subjective well-being and mental health. While control group households reported deterioration in food security after the baseline survey, those who received the digital transfer were significantly protected. Third, we find that the digital transfers are more beneficial (impactful) for those grappling with active conflict—that is, those residing in active conflict areas, compared to those in relatively safer regions. The impacts of digital transfers appear to be greater among those living in areas predominantly under the control of the Rapid Support Forces (RSF), suggesting a greater need for humanitarian assistance among these populations. Fourth, the digital transfers appear to be less effective for poorer households and for households of a larger size, suggestive evidence about the insufficiency of the transfers for households of larger size. Poorer households with limited income sources and those households with larger family size did not witness significant improvements in welfare and mental health outcomes because of the digital transfers. These findings highlight the potential of digital transfers to support those grappling with armed conflict who are otherwise inaccessible by conventional humanitarian services, while highlighting the insufficiency of current humanitarian services, especially for larger households.

This study contributes to three strands of literature on humanitarian and social protection programming. First, it contributes to the broader literature on the potential of cash transfers to serve as important humanitarian instruments to cushion the adverse impacts of armed conflict (Jeong and Trako, 2022). While a plethora of studies show the positive impact of conditional and unconditional cash transfers in stable settings (De Janvry et al., 2006; Adato and Hoddinott, 2010; Baird et al., 2013; Galiani and McEwan, 2013; Haushofer and Shapiro, 2016; Aizer et al., 2016; Abay et al., 2023), the impact of cash transfers in conflict-settings as well as their potential to mitigate adverse impacts of armed conflict remains limited or at best mixed (Ecker et al., 2024; Premand and Rohner, 2024; Kosec and Mo, 2025).[4] Second, our study contributes to the emerging literature on the potential of digital transfers to reach and support an otherwise inaccessible and vulnerable population (Callen et al., 2025). While the use of digital transfers in active conflict remains new, several studies show that digital transfers can improve financial inclusion and empower women (Kipchumba and Sulaiman, 2021; Riley, 2024; Greco et al., 2025); ensure transparency and security (Suri, 2017; Suri et al., 2023; Idris, 2024); reduce social pressure (Riley, 2024); and reduce transaction costs (Suri, 2017; Callen et al., 2025). Our findings indicate that some of these gains and benefits can be accrued by potential beneficiaries in conflict-affected settings. The finding that digital transfers can be more useful for those households under active conflict reinforces the potential of these transfers to address service delivery and inaccessibility challenges while also reducing the cost of delivering humanitarian aid (Callen et al., 2025). Indeed, this implies that welfare returns to cash transfers may be relatively larger in active conflict settings where the need for such assistance can be higher. Finally, our findings contribute to the evolving debate about the optimal size of transfers as well as associated targeting of these transfers to different types and groups of households. The heterogeneous

[4] A recent review by Kosec and Mo (2025) highlights some of these mixed findings associated with the unintended consequences of cash transfers on conflict, governance, and social cohesion as well potential factors that may explain these mixed findings, including targeting of these interventions (Della Guardia et al., 2022; Cameron and Shah, 2014; Idris, 2017), as well as whether these transfers are government-led or managed by other entities (Rohner and Thoenig, 2021; Premand and Rohner, 2024).

effects of digital transfers across small and larger households suggest that relatively modest transfers may not sufficiently address the relatively higher needs (or multifaceted constraints) among larger and poorer households. In stable settings, there are three factors and theoretical hypotheses that may explain and justify the effectiveness of varying level of transfer sizes: a "scarcity poverty trap", a situation where households need a "big push" to escape out of poverty (Banerjee et al., 2015; Kondylis and Loeser, 2021; Balboni et al., 2022); a "frictional poverty trap", which represents market failures and associated constraints (Ghatak, 2015; Kondylis and Loeser, 2021); and decreasing or increasing returns to investments (Kondylis and Loeser, 2021). In conflict-affected settings, a "scarcity poverty trap" along with conflict-induced market failures and service disruptions are likely to increase the need for humanitarian assistance to satisfy basic needs.

2. Literature and context

2.1. The role of cash transfers in conflict-affected settings

Over the last few decades, humanitarian needs have increased significantly due to the surge in armed conflict and man-made disasters (UN OCHA, 2023). In response to this surge, cash-based assistance services are being deployed as important instruments to address hunger and poverty in conflict-affected settings (Jeong and Trako, 2022). Despite the growing use of cash and cash-plus interventions in humanitarian settings, there exists limited rigorous evidence on when and for whom different variants of cash transfers programs serve in these settings (Tappis and Doocy, 2018; Jeong and Trako, 2022).[5] The limited number of carefully executed studies show positive impacts on food security outcomes, but mixed results on broader welfare and development outcomes (Jeong and Trako, 2022; Tappis and Doocy, 2018; Jeong and Trako, 2022; Premand and Rohner, 2024; Kosec and Mo, 2025; Sabates-Wheeler et al., 2025).[6]

Beyond increasing demand for humanitarian assistance, armed conflicts present substantial obstacles to the delivery of aid due to insecurity, infrastructural damage, and restricted access (Callen et al., 2025; Abay et al., 2025; World Food Programme, 2021). These conditions,

[5] Tappis and Doocy (2018) and Jeong and Trako (2022) offer comprehensive review of the impact of alternative cash-based and in-kind humanitarian responses on a number of welfare outcomes while Aurino and Giunti (2022) offers a review of the limited number of studies on the impact of humanitarian aid programs (in-kind or cash transfers) to mitigate child malnutrition. Sabates-Wheeler et al. (2025) offer review of cash-plus and related livelihood interventions in fragile and conflict-affected settings. Accordingly, "most cash-plus interventions are not designed or delivered in ways suitable for crises".

[6] While there exists a large literature on the impact and potential of cash transfers in stable settings (De Janvry et al., 2006; Adato and Hoddinott, 2010; Baird et al., 2013; Galiani and McEwan, 2013; Haushofer and Shapiro, 2016; Aizer et al., 2016; Abay et al., 2023), whether these lessons apply to conflict-affected and protracted settings remains ambiguous.

characterized by disrupted markets, weakened institutions, and logistical constraints, complicate the implementation, targeting, and reach of social protection and humanitarian programs (Ghorpade, 2017, 2020; Lind et al., 2022). In fragile and conflict-affected settings, households face a distinctive set of challenges and constraints that shape both the demand and effectiveness of different modalities of humanitarian assistance. Traditional delivery methods in such settings often incur high logistical and financial costs (Callen et al., 2025) and can be prone to aid diversion and misappropriation (Devex, 2023; Shimada, 2025). Against this backdrop, there is growing optimism for and debate about whether digital cash transfers offer innovative and potentially transformative approaches to delivering assistance in these challenging contexts. Emerging evidence suggests that digital transfers can lower overall delivery and transaction costs (Callen et al., 2025; Suri, 2017), advance financial inclusion, and promote women's empowerment (Aron, 2018; Riley, 2024; Kipchumba and Sulaiman, 2021; Better Than Cash Alliance, 2025; Greco et al., 2025). Digital delivery of humanitarian assistance can streamline coordination, reduce delays, and enhance transparency for donors (Idris, 2024). It may also safeguard beneficiary privacy and enable the use of local supply chains while limiting dependence on local authorities, thus mitigating risks of aid diversion (Callen et al., 2025; Maghsoudi et al., 2023; Keen, 1991; Shimada, 2025). Furthermore, digital modalities may help address social dynamics such as intra-household or community-level pressure to share resources (Riley, 2024). Riley (2024) finds that recipients subject to strong familial expectations to redistribute aid tend to prefer mobile money transfers, which offer greater discretion.

For donors and implementing agencies, digital transfers offer a more decentralized and transparent alternative to the traditional in-kind or physical cash modalities. They also reduce the logistical burden on recipients, who would otherwise incur travel costs and time losses to access distribution points (Callen et al., 2025). Callen et al. (2025) estimates that the cost of delivering digital transfers is approximately 40 percent lower than the WFP's global average for cash-based assistance. Additionally, digital cash transfers can promote accessibility to assistance even during active conflicts (World Bank, 2024). However, digitalizing humanitarian aid is not always free of risks and the "digital divide" may exacerbate inequities if they are not regulated effectively (Mehrabi et al., 2021; Abd Elkreem, 2025).

2.2. The case of Sudan

Sudan offers a nexus consisting of a widened funding gap, active-conflict, and limited digital infrastructure. Even before the eruption of the armed conflict in 2023, digital infrastructure, literacy, and financial services have been at their nascent stages, whereby access to financial services stood at only 15 percent as of 2014 (Bank, 2022; Demirgüç-Kunt et al., 2015). In 2017/18, the Sudanese Telecommunications and Postal Regulatory Authority (TPRA) indicated that almost 28 million people have mobile phones, 12 million of whom have access to the internet. In 2017, the number of bank accounts increased to 5.5 million, up from 2.9 million in 2013 (Bank, 2022). Despite some previous attempts by the WFP to use digital transfers, limited digital infrastructure and literacy has hampered these efforts and most humanitarian and social assistance continues to be delivered through cash-at-hand and in-kind transfers (Abd Elkreem, 2025). Prior to the April 2023 conflict, multiple assessments were conducted to assess reachability of digital cash assistance (Jaspars et al., 2022). For example, Jaspars et al. (2022) document the growing use of digital technologies and digital transfers over time, even in regions such as Darfur.[7]

More recently, and after the launch of platforms like Bank of Khartoum's *Bankak* mobile application, Faisal Islamic Bank's *Fawry*, and *Cashi* mobile money, the use of digital cash is becoming more apparent. The transfer of airtime followed by cashing out has also grown to be a popular means of money transfer in Sudan given the gaps in internet coverage (Telecommunications and Authority, 2018). Despite increasing uptake through the years, digital payment systems in Sudan continued to face multi-faceted divides, characterized by low financial awareness and literacy (Bank, 2022). An assessment undertaken by FSD Africa (2022) highlights that many populations in peripheral regions lack the know-how about utilizing smartphones, the internet, and digital technologies. Digital uptake rates in peripheral regions including Darfur, South Kordofan, Blue Nile, and White Nile continue to lag in comparison to urban centers like Khartoum (WFP, 2020; FEWSNET, 2021; Abd Elkreem, 2025). Additionally, the existing literature showcases a strong gender divide in both the ownership and use of internet and phones, whereby, across all segments, women have limited access to the internet and mobile phones (FSD Africa, 2022).

[7] Following the revolution in 2019, digital assistance resurfaced as a key means of delivering cash-based transfer programs such as *Thamarat*[8], whereby social welfare programs started to adopt digital platforms, financial institutions, and telecommunication entities to facilitate efficient digital cash delivery (Abd Elkreem, 2025; Smith, 2025).

However, the ongoing conflict has significantly disrupted the limited pre-existing digital infrastructure and the banking sector, and weakened the regulatory capacity of the government, thus constraining the use of cash within the humanitarian system (Idris, 2024; Mercy Corps, 2023; Smith, 2025). Amid the multi-faceted disruptions to in-person assistance-provision (cash-at-hand and in-kind assistance), digitalization of food assistance provides life-saving measures for otherwise inaccessible households (Abd Elkreem, 2025; Abay et al., 2025). Evidence from digital cash transfers implemented by various organizations in Sudan (Abay et al., 2025; MercyCorps, 2023; Cash Consortium of Sudan, 2024) show increased demand for such interventions amid challenges faced by beneficiaries.

Despite these challenges, many potential beneficiaries continue to express preference for digital transfers, whereby two-thirds of urban households prefer digital cash transfers over cash or in-kind assistance (Abay et al., 2025). This seemingly paradoxical trend highlights that demand for digital transfers is shaped not only by delivery feasibility but also by perceived safety and risk (Abay et al., 2025; Sarwar et al., 2023). In the context of active conflict in Sudan, digital cash transfers can promote greater scalability of assistance, faster transfers, and improved transparency and safety (MercyCorps, 2023).

2.3. The armed conflict in Sudan

Sudan's political situation has been highly volatile for decades, leaving thousands of people across the country in need of humanitarian assistance. Prior to the most recent episode of armed conflict which erupted in April 2023, Sudan has been grappling with a protracted nationwide food security crisis. The crisis has been exacerbated over the years due to hyperinflation, climate shocks, and political instability, which has led to deterioration in overall livelihoods (Thomas and De Waal, 2022; Diouf and Sheeran, 2010). Necessitated by considerable humanitarian needs, humanitarian assistance has been the "lifeline" for a substantial share of the population. The eruption of the most recent violent conflict between the SAF and the RSF in April 2023 has made Sudan one of the world's largest humanitarian crises today (Ahmed et al., 2025). According to UNHCR (2025), over 7.8 million individuals have been internally displaced as of August 31, 2025, and a further 4.1 million have been displaced into neighboring countries since April 15, 2023. The impact of demographic displacement amid scarce resources and limited access to humanitarian assistance has been particularly severe. Despite continued efforts to reach the most affected populations, the humanitarian response has fallen considerably short of addressing the magnitude of the crisis, with nearly 30.4 million people still in dire need of humanitarian assistance (Humanitarian Action, 2025b). In 2025, and due to the funding gap, humanitarian efforts have only reached about 13 million people with at least one form of assistance (Humanitarian Action, 2025b).

The conflict continues to inflict significant loss of life in Sudan. For instance, as of November 2024, the conflict has resulted in an estimated 28,700 fatalities, including more than 7,500 civilians killed in direct attacks (ACLED, 2024). The armed conflict has evolved dynamically in ways that complicate and inhibit planning and delivery of humanitarian assistance. For example, Figure 1 below shows the evolution in the number of fatalities in Quarter 3 (the time in which we collected our baseline data) and Quarter 4 of 2024 (immediately before our intervention). These patterns showcase a stark increase in the number of fatalities in regions of conflict as well as the shift in the concentration of fatalities across the conflict states, including Darfur, Kordofan, Khartoum, and Gezira regions. These are consistent with the evolution of the armed conflict on the ground as well as the shifting of positions and control of states across the SAF and RSF.

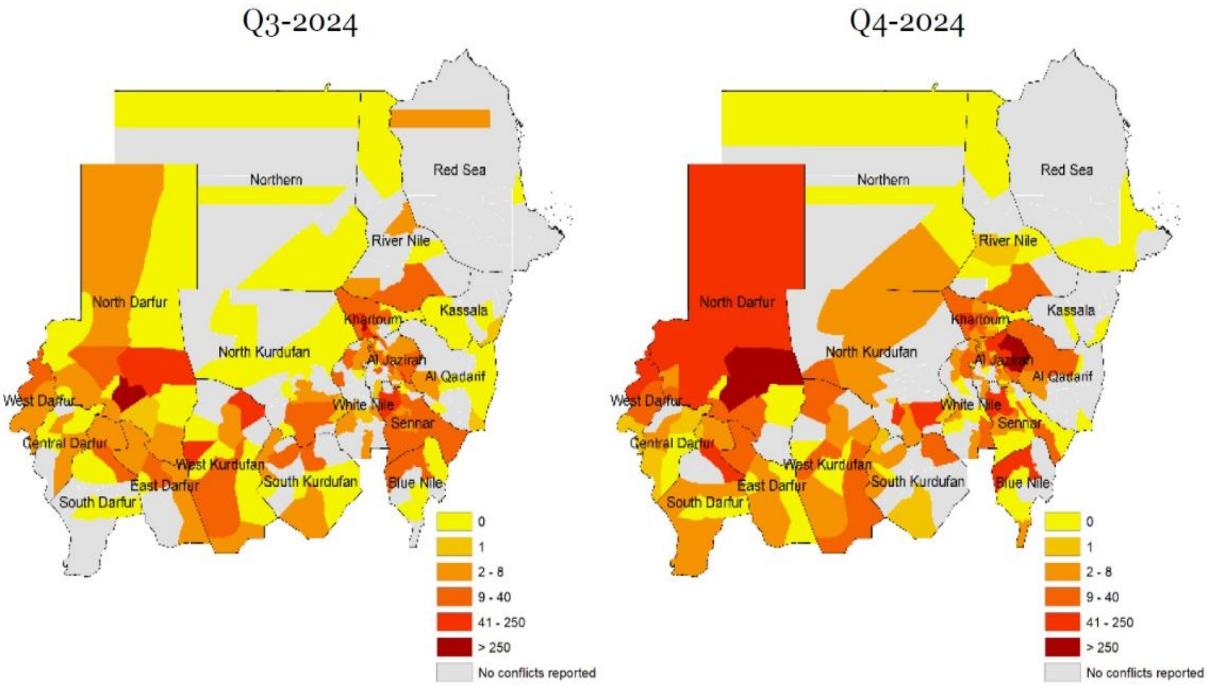

Figure 1: Fatalities between July-December 2024. Source: Authors' compilation based on ACLED data.

In addition to the widening funding gap for humanitarian services, the delivery of humanitarian assistance is further challenged by weak governance structures and active hostilities in some states. The continuation of active hostilities in many regions, blockages of trade routes, the lack of security on alternative remote desert roads, and fluctuating exchange rate are forcing humanitarian organizations to rely on costly, inefficient, and ineffective alternative means to deliver humanitarian assistance (Siddig et al., 2025; Abushama et al., 2023; Kirui et al., 2023; SPARC, 2024).

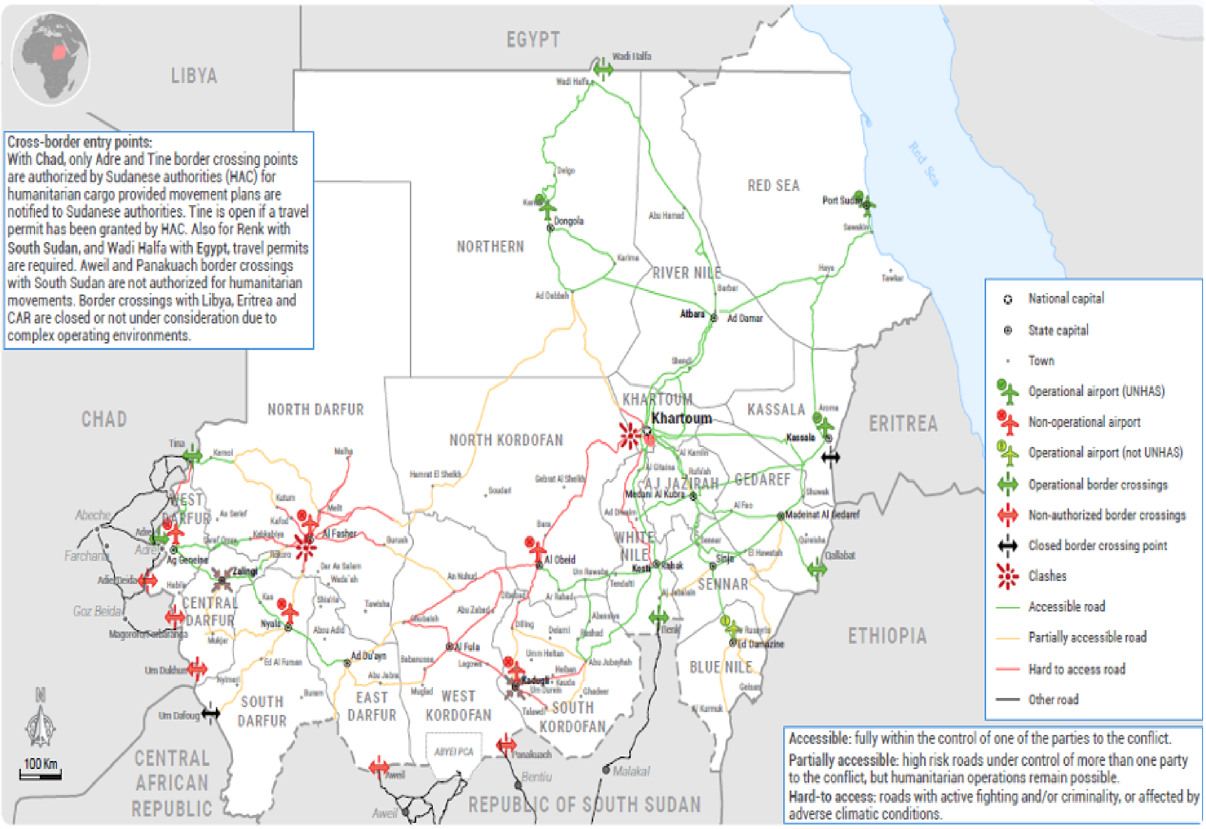

Figure 2: Humanitarian Access Constraint Map (May 2025). Source: UNOCHA, 2025

Regional control of land area by the SAF, RSF, or both in contested states and cities further complicates the movement of humanitarian assistance given the multi-layered and varying security clearance and approvals processes, leaving millions of people with limited and/or delayed access to assistance (Humanitarian Action, 2025a; Abushama et al., 2023). Figure 2 shows access and logistical constraints of humanitarian assistance imposed by the evolving landscape of conflict, whereby movement between the eastern and western regions of Sudan remains challenging in comparison to movements within SAF-controlled and RSF-controlled regions. With these constraints, humanitarian response is expected to shift from traditional in-kind assistance to variants of cash assistance (Cash Consortium for Sudan, 2024; Mercy Corps and CALP Network, 2023). Disruptions to the banking and telecommunications infrastructure in Sudan have forced humanitarian organizations to adopt and deploy alternative modalities for delivering cash to those in need (Cash Consortium for Sudan, 2024; Mercy Corps and CALP Network, 2023).[9]

3. Data, experimental design, and descriptive statistics

3.1. Data and Experimental Design

This study utilizes panel data collected at four distinct survey phases from urban households across Sudan between 2024 and 2025: (1) baseline, (2) pre-transfer, (3) post-transfer, and (4) endline. Given the challenges in physically reaching urban households at the time of data collection, all four rounds were conducted via computer-assisted telephone interviewing (CATI) to ensure accessibility to households grappling with conflict.

The baseline data for this study is derived from the Sudan Urban Household Survey 2024 (SUHS) conducted by the International Food Policy Research Institute (IFPRI) and United Nations Development Programme (UNDP) (IFPRI and UNDP, 2024). The baseline survey was conducted between May and July 2024 via CATI. It covers 3,000 households across 145 localities in all 18 states, sampled randomly from a database of 50,000 households compiled by WFP, IFPRI, and other partners (IFPRI and UNDP, 2024). A stratified sampling design by state was employed to ensure coverage of all states in Sudan. While we acknowledge that CATI surveys can be limited in reach given that access to telephones is not universal in Sudan, particularly among the poorest internally displaced persons (IDPs) and because of network disruptions due to the conflict, they nonetheless provide essential data otherwise under-discovered.

After the baseline data but prior to the digital transfer intervention, we conducted a pre-transfer survey in order to determine households' preferred mode of digital transfer and their associated account details.[10] During the pre-transfer survey, we reached out to about 90 percent of the original 3,000 households surveyed at baseline. About 3 percent of the total households sampled reported no interest in receiving the digital transfer, resulting in a sample of 2,586 households who were interested. Based on the pre-transfer survey, four different modalities were preferred by households' receiving digital cash transfers: Bankak (51 percent); Fawry (2 percent); Cashi (3 percent), and airtime credit (45 percent). These modalities vary slightly in nature. Bankak

[9] In doing so, they have strategically engaged multiple financial service providers (FSPs)—including banks, microfinance institutions, and money transfer agents—to enhance delivery mechanisms. These FSPs allow aid delivery even during network disruptions and in active conflicts. By working closely with implementing agencies, they help overcome liquidity shortages and access barriers, thereby ensuring more reliable and flexible assistance to affected populations (Cash Consortium for Sudan, 2024; Cash Consortium of Sudan, 2024; UNHCR, 2024; World Food Programme, 2024).

[10] The baseline survey was conducted several months prior to the pre-transfer survey; thus, the pre-transfer survey served as a validation tool of accessibility and bank account details.

and Fawry are mobile banking applications linked to two major commercial banks in Sudan–the Bank of Khartoum (Bankak) and Faisal Islamic Bank (Fawry), respectively. Cashi is an electronic payment platform through which cash transfers, bill payments, and other transactions are delivered. Airtime credit transfers are simple airtime transfers from other mobile phones or banking applications, which are cashed out in kiosks and local shops for use.

Immediately after the pre-transfer survey and after excluding those not interested in the digital transfers, we randomly assigned the 2,586 urban households into one of three groups: a control group and two treatment groups.[11] Approximately 38 percent of the sample (990 households) was assigned to a pure **control group (C)** that received no digital cash transfer. The remaining 62 percent of the sample was split between two treatment groups. The first **treatment group (T1)**, consisting of 795 households, received US$50–an amount equivalent to the monthly ration value provided by WFP for a household of five, the maximum number of household members they can accommodate. The second **treatment group (T2)**, comprised of 801 households, received $75. This higher amount was selected to test whether a larger transfer yields stronger outcomes. Figure 3 illustrates the random assignment and allocation across control and treatment arms. Randomization was stratified by state to account for geographic heterogeneity and by transfer delivery modality to reflect user preferences. We then executed the digital transfer between January and February 2025. The digital cash transfer was a one-time transfer.[12]

Following the intervention, we conducted a post-transfer survey with the two treatment groups with the aim of validating the receipt of the transfer by the beneficiary households amid ongoing network challenges as well as gauging households' perceptions about the amount and use of transfer. The post-transfer survey reached 1,579 households–about 99 percent of the treatment sample groups. The post-transfer survey was conducted in February 2025, 2-3 weeks after receipt of the transfer. This survey verified whether respondents received the transfer and the amount received; whether they cashed the transfer out; whether they incurred transaction fees; how the funds were spent; and who made spending decisions. These latter two questions provided insights into household perceptions and behavior about the transfer. Almost all treatment group households confirmed receiving the transfer.

[11] To ensure statistical power, we calculated the minimum required sample size for each arm, based on our primary outcomes. Although our total baseline sample was fixed, the power calculations allowed us to assess how our sample size compared to ideal scenarios. Our power analysis–detailed in the pre-analysis plan (AEARCTR-0015321)–shows that the actual sample size exceeds the minimum required for detecting meaningful impacts on most outcomes.

[12] A local survey firm called *Consulsat* disbursed the transfers using the preferred mode of delivery for each household.

Finally, we conducted the endline survey from mid-February to mid-March 2025, partly coinciding with the holy month of Ramadan, a period of fasting in majority-Muslim Sudan. This timing was intentional, as we also sought to observe whether Ramadan influenced the impact of cash transfers on household food consumption, well-being, or spending behavior.[13] Because of this survey timing, we randomly assigned about 60 percent of the sample to be interviewed pre-Ramadan, with the remaining 40 percent to be interviewed during Ramadan (see Figure 3). We do so for two reasons. First, we wanted to isolate potential confounding issues that might arise due to fasting and change in lifestyles and consumption patterns as a result of Ramadan. Because we are sufficiently powered using only the 60 percent of our sample surveyed pre-Ramadan, we therefore use this 60 percent of sample households for our main analysis in this paper (see Figure 3).[14] Second, using the remaining 40 percent of the sample, we aimed to address additional research questions and heterogeneities. However, we do report some results using the full sample in our robustness exercise to show that the main results hold even in the full sample.

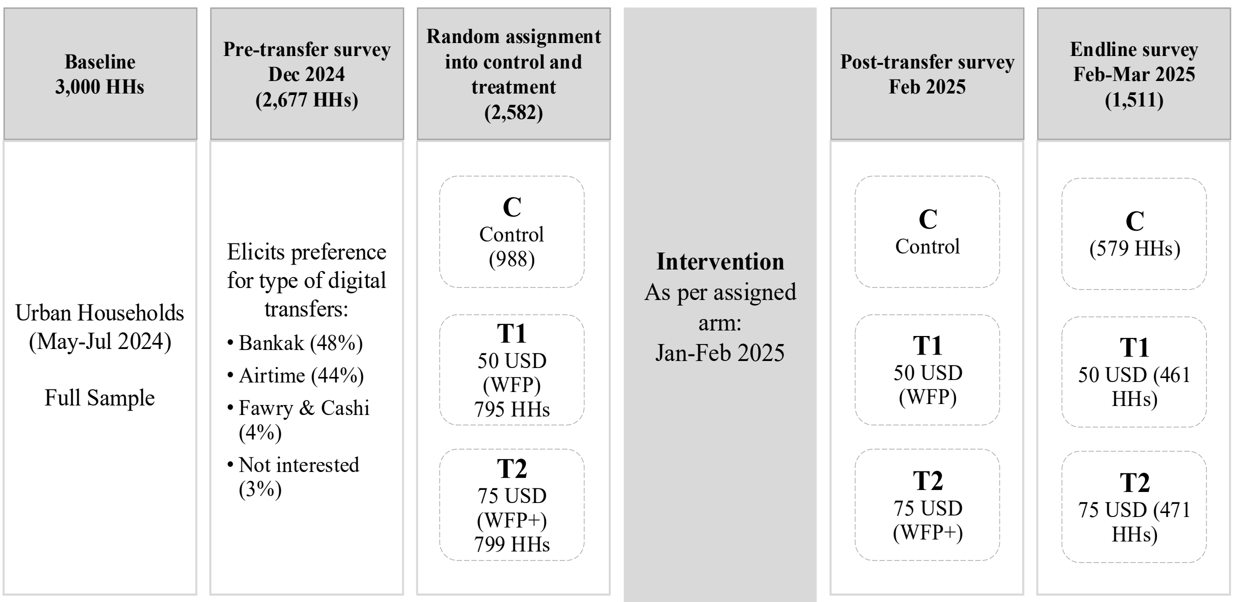

Figure 3: Experimental design

[13]We aim to address these issues in a separate paper.
[14]Attrition in the endline survey was only 3 percent.

3.2. Outcome variables and descriptive statistics

As described in our pre-analysis plan (AEARCTR-0015321), the main outcome variables include Food Consumption Score (FCS), Household Dietary Diversity Score (HDDS), Food Insecurity Experience Scale (FIES), subjective well-being, perceived stress, and anxiety. The last three indicators capture aspects of emotional and mental well-being of urban households. The FCS, developed by WFP (2008), captures dietary quantity and diversity, is based on a 7-day recall, and, based on the frequency and consumption of various food groups, weighs them according to nutritional value and dietary adequacy. The HDDS is also based on a 7-day recall following FAO guidelines and measures household-level food security through dietary diversity (FAO, 2016). Respondents report on consumption frequencies across food groups over the past week. These food groups are then re-categorized into eight groups and scored between 0 and 8 (Hoddinott and Yohannes, 2002; Hatløy et al., 2000). The FIES, developed by FAO (2014), uses an 8-item questionnaire to assess access to sufficient and nutritious food in the last 30 days. Summed responses then receive a score ranging from 0 to 8.

Subjective well-being is measured at endline using three questions on happiness, satisfaction, and economic outlook. Stress is measured using Cohen's Perceived Stress Scale (PSS) (Cohen et al., 1994), a 10-item module eliciting various types of symptoms of stress. The responses from these items are summed to create a stress score which ranges from 0 (low stress) to 40 (high stress).[15] Anxiety is measured using a modified Generalized Anxiety Disorder (GAD-7) tool, a 7-item module measuring symptoms of anxiety in the past 2 weeks. We aggregate these responses to generate a continuous GAD score.

Furthermore, through the pre-transfer survey, we collect data on transfer modality preferences, examining whether respondents favor delivery via mobile apps (Bankak, Fawry, or Cashi) or mobile airtime credit. Bankak (48 percent) and airtime credit (44 percent) are the most popular modalities for digital cash transfers, with female respondents slightly more likely to prefer airtime credit. Later, at endline, respondents explained the reason behind their choices, citing ease of access as the main reason for choosing either modality. When asked about the planned purpose of the transfer, we found that, irrespective of choice of modality of transfer, about 65 percent of households aimed to use the transfer for food, signaling increased food insecurity and access to resources for food. Additionally, about 24 percent of households reported paying

[15] We construct two binary indicators for moderate-to-severe stress (if PSS is more than or equal to 14) and severe stress (if PSS is more than or to equal 27), captured at baseline, pre-transfer, and endline.

some transaction fee to access or cash out the digital transfer, with the rate being higher among those who received transfers through airtime credit.

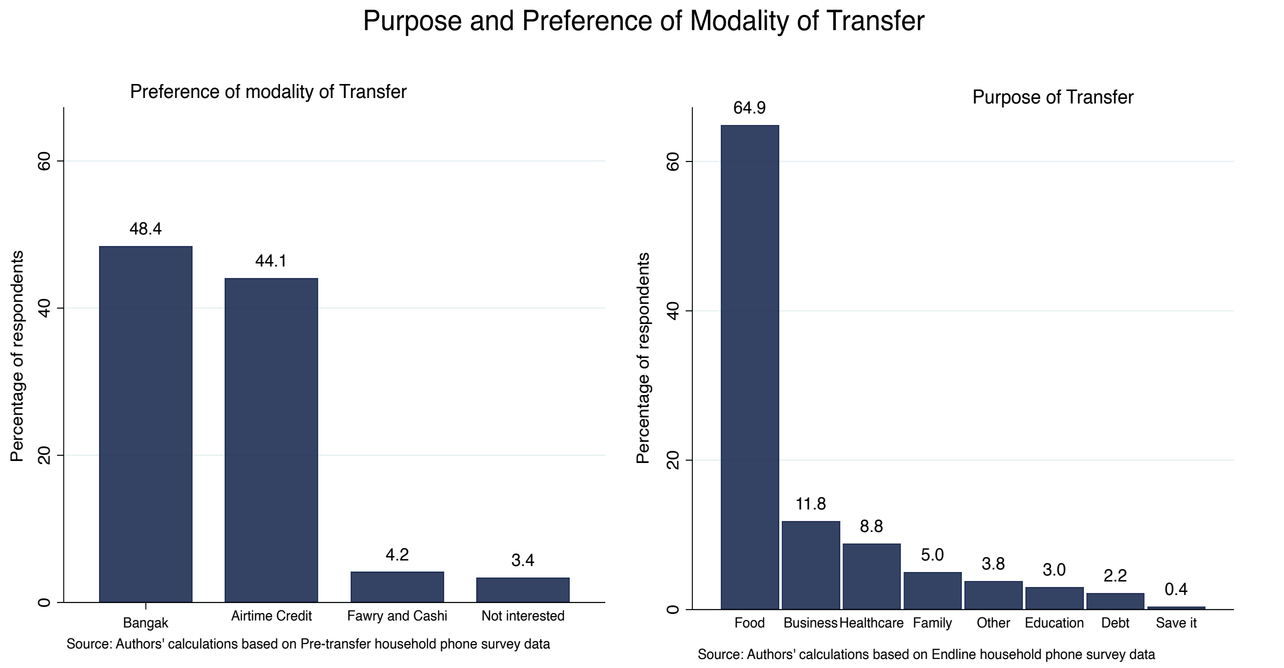

Figure 4: Preference of modality of transfer and purpose of transfer

Between the baseline and pre-transfer surveys, conflict and violence incidents escalated in many parts of Sudan, further exacerbating economic deterioration and worsening livelihoods. Figure 5 shows that, at baseline, only 16 percent of households reported being much poorer than before the conflict started, compared to 42 percent of households just a few months later during the pre-transfer survey. This implies that transfers may be more effective in mitigating the deterioration in food security and economic well-being during conflicts rather than before.

Using the pre-transfer sample of 2,586 households, we conducted a balance test. As discussed above, we randomly assign the 2,586 pre-transfer sample households into pre-Ramadan and Ramadan samples, and this paper mainly uses the pre-Ramadan sample. Table 1 presents the balance test for the full sample while Appendix Table A1 shows that the pre-Ramadan and Ramadan samples are well balanced. The randomization yielded balanced samples across the control and two treatment groups as well as across pre-Ramadan and Ramadan samples. Moreover, the p-values from pairwise t-tests show no statistically significant differences in the key outcome variables.[16]

[16]We only observe mild differences in certain demographic characteristics, such as household head's marital status and households' access to electricity.

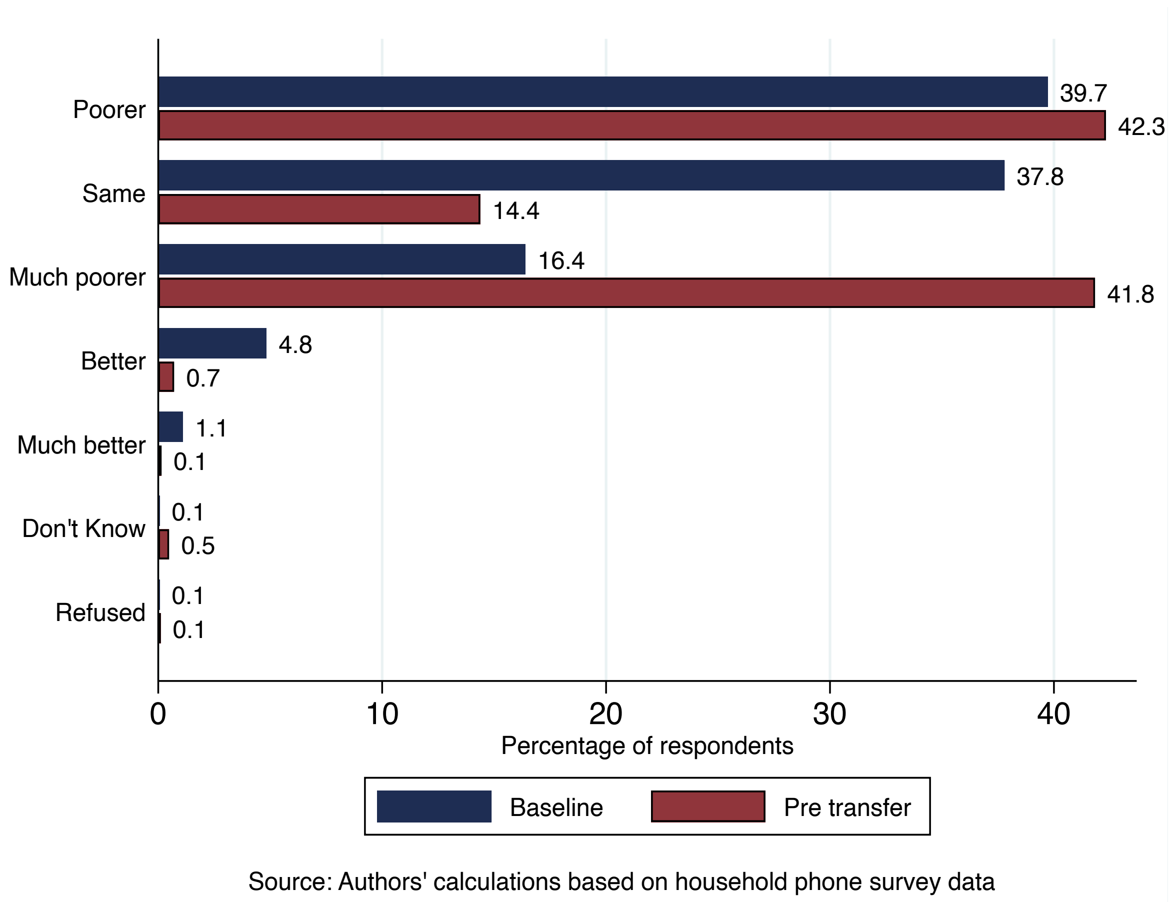

Figure 5: Economic situation before the digital transfer

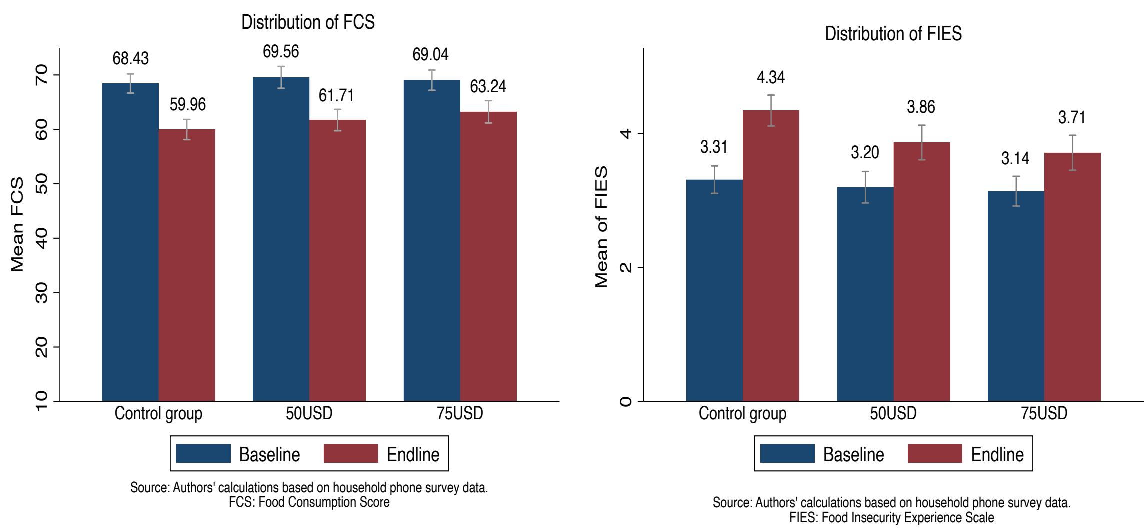

Figure 6: Food security outcomes at baseline and endline

Table 1: Balance test between treatment and control groups

	Mean			Pairwise t-test(P-value)		
	Control	\$50	\$75	Control vs \$50	Control vs \$75	\$50 vs \$75
Main outcomes						
FCS (0 - 112)	68.31	69.81	69.08	0.17	0.44	0.51
	(1.15)	(1.30)	(1.20)			
DDS (0 - 8)	6.96	7.07	7.03	0.04**	0.20	0.49
	(0.07)	(0.07)	(0.08)			
FIES (0 - 8)	3.29	3.13	3.25	0.11	0.68	0.29
	(0.12)	(0.13)	(0.10)			
No food stock (No stock=1)	0.34	0.35	0.33	0.74	0.52	0.33
	(0.02)	(0.02)	(0.02)			
Stress (0 - 40)	22.24	21.82	21.95	0.17	0.39	0.69
	(0.23)	(0.22)	(0.32)			
Moderate stress (moderate=1)	0.92	0.91	0.92	0.70	1.00	0.71
	(0.01)	(0.01)	(0.01)			
severe stress (severe=1)	0.26	0.23	0.24	0.23	0.54	0.63
	(0.02)	(0.01)	(0.02)			
Household characteristics						
Respondent gender (male=1)	0.38	0.36	0.39	0.22	0.83	0.21
	(0.01)	(0.02)	(0.02)			
Head gender (male=1)	0.89	0.87	0.89	0.18	1.00	0.25
	(0.01)	(0.01)	(0.01)			
Head age	43.97	44.63	44.18	0.27	0.70	0.45
	(0.42)	(0.48)	(0.41)			
Head education: low	0.22	0.20	0.20	0.40	0.46	0.94
	(0.02)	(0.02)	(0.02)			
Head education: medium	0.50	0.49	0.52	0.75	0.49	0.33
	(0.02)	(0.02)	(0.02)			
Head education: high	0.28	0.31	0.28	0.21	0.84	0.20
	(0.02)	(0.03)	(0.02)			
Household size	8.80	8.76	8.83	0.80	0.89	0.71
	(0.21)	(0.16)	(0.19)			
Married	0.82	0.83	0.86	0.77	0.04**	0.11
	(0.01)	(0.01)	(0.01)			
Poor or poorer than many	0.56	0.55	0.54	0.70	0.47	0.70
	(0.02)	(0.02)	(0.02)			
Exposure to street violence	0.29	0.30	0.29	0.83	0.92	0.78
	(0.02)	(0.02)	(0.02)			
Exposure to intrahousehold violence	0.01	0.01	0.02	0.91	0.23	0.31
	(0.00)	(0.00)	(0.00)			
Exposure to sexual violence	0.01	0.00	0.01	0.36	0.31	0.12
	(0.00)	(0.00)	(0.00)			
Exposure to SAF RSF	0.13	0.13	0.15	1.00	0.27	0.29
	(0.02)	(0.02)	(0.02)			
Feeling insecure	0.20	0.19	0.19	0.71	0.54	0.85
	(0.03)	(0.02)	(0.02)			
Have electricity	0.88	0.87	0.90	0.85	0.05*	0.09*
	(0.02)	(0.02)	(0.02)			
Able to visit market	0.86	0.87	0.86	0.61	0.81	0.71
	(0.02)	(0.01)	(0.01)			
Received assistance	0.46	0.46	0.46	0.99	0.98	0.96
	(0.02)	(0.02)	(0.02)			
House material: brick	0.50	0.51	0.51	0.73	0.62	0.89
	(0.03)	(0.03)	(0.03)			
House material: mud	0.23	0.23	0.24	0.96	0.78	0.72
	(0.03)	(0.02)	(0.02)			
Have bank account	0.58	0.57	0.59	0.77	0.51	0.32
	(0.02)	(0.03)	(0.03)			
Modality of transfer (Bankak=1)	0.50	0.51	0.50	0.67	0.89	0.84
	(0.01)	(0.02)	(0.02)			
Modality of transfer (Fawry/cashi=1)	0.05	0.04	0.04	0.10*	0.62	0.48
	(0.01)	(0.01)	(0.01)			
Modality of transfer (Airtime=1)	0.45	0.46	0.46	0.86	0.91	0.97
	(0.01)	(0.02)	(0.02)			
RSF controlled areas	0.05	0.04	0.05	0.53	0.94	0.57
	(0.01)	(0.01)	(0.01)			
Number battle events	-0.01	0.00	0.06	0.71	0.13	0.06*
	(0.11)	(0.12)	(0.14)			
Observations	988	795	799			

Notes. This table compares household baseline characteristics as well as baseline outcomes across the control and two treatment arms. Columns (1) - (3) report mean values and standard errors. The last three columns report p-values from pairwise comparisons and t-tests. Standard errors are clustered at locality level, *** p<0.01, ** p<0.05, * p<0.1.

Figure 6 highlights the dynamics in key outcomes across baseline and endline. At baseline, control group households recorded an average FCS of nearly 68 (out of 112), consumed an average of 7 food groups (as measured by the HDDS), and had an average FIES score of 3.3. At baseline, households in both treatment groups and the control group have comparable food security levels as confirmed by the balance tests discussed earlier.

As conditions worsened after the baseline survey, our endline results reflect declines in FCS and HDDS, and deterioration in food security across all groups. However,recipients of digital transfers, particularly the $75 recipients, were significantly protected and hence witnessed smaller reductions in FCS and HDDS, and less severe experiences of food insecurity. These results suggest that digital cash transfers can shield households from steep deterioration in food insecurity outcomes.

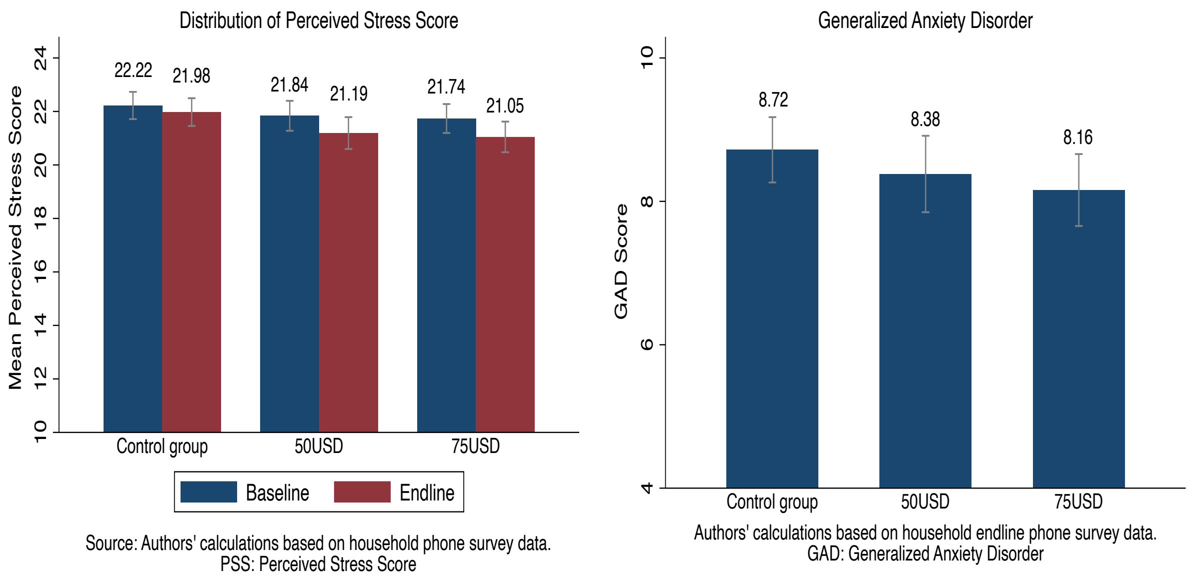

Figure 7: Mental health outcomes at baseline and endline

The mental health outcomes shown in Figure 7 reveal similar patterns. Respondents who received the digital transfer reported an improvement in stress levels, with lower PSS scores and an overall reduction in the proportion of respondents reporting severe stress—particularly among those who received the higher transfer amount.[17] They also exhibited lower anxiety levels (as measured by the GAD-7 score). A more formal test of these differences and associated estimation results is provided in Section 5.

[17]Respondents in both treatment arms reported higher levels of happiness, life satisfaction, and perceived economic well-being at endline.

4. Empirical strategy

The intervention introduced in this study facilitates the transfer of a significant amount of money to households through digital means, which can generate meaningful impacts on household welfare, especially for those in need of humanitarian assistance. These transfers are likely to represent a large share of household expenditure in our sample. The smallest transfer we delivered is equivalent to the maximum monthly ration WFP delivers to households in Sudan. Thus, we anticipate that these transfers can improve short-term welfare outcomes, especially for those grappling with the adverse effects of armed conflict.

The random assignment of the digital transfer allows us to observe exogenous variation in access to transfer across control and treatment group households as well as across those receiving the small or relatively large transfers. This facilitates simple mean comparisons to evaluate the impact of the digital transfer and the size of transfers. However, we also have baseline and endline measures for most of the outcomes, which allow even more saturated and powered estimations. In a stochastic environments like Sudan, where active conflict has displaced millions, temporal correlations in our outcomes of interest may not be strong, implying that an analysis of covariance (ANCOVA) can offer more efficiency and power than a standard difference-in-differences approach (McKenzie, 2012). Thus, we start by estimating the following ANCOVA specification and gradually disaggregate these treatment arms into different transfer sizes:

$$W_{ht=1} = \gamma_0 W_{hst=0} + \gamma_1 T_h + \gamma_2 HH_h + S_s + \mu_h \tag{1}$$

$$W_{ht=1} = \theta_0 W_{ht=0} + \theta_1 T1_h + \theta_2 T2_h + \theta_2 HH_h + S_s + \varepsilon_h \tag{2}$$

Where $W_{ht=1}$ stands for welfare indicators such as dietary diversity score, subjective well-being, perceived stress, and anxiety while $W_{hst=0}$ captures baseline values of corresponding outcomes, in our case values measured some 6-7 months before the endline survey. T_h stands for a binary indicator assuming a value of 1 for those households assigned to receive digital transfer and 0 for those households assigned to the control group. HH_h captures a vector of baseline household characteristics. S_s stands for state fixed effects while μ_h is an idiosyncratic error term. The expression in equation 1 aggregates both types (sizes) of the digital transfer, and hence γ_1 captures the average effect across the two levels of transfer.

The expression in equation 2 disaggregates the digital transfers into the two types of treatment: \$50 and \$75. Hence, $T1_h$ and $T2_h$ stand for indicator variables for those households assigned to receive the small and relatively larger digital transfers, respectively. Note that households which did not receive digital transfer serve as the control group. As we randomly assign households into the treatment arms, γ_1 captures the impact of assignment to the digital transfer while θ_1 and θ_2 identify the impact of assignment to the two different transfer sizes (treatment arms). Comparing the size of the parameters θ_1 and θ_2 helps to test important hypotheses related to the size of transfers in moderating the impact of cash transfers.

However, not every household assigned to the treatment arms involving actual cash transfers will utilize the transfer before the endline survey. For example, although we conduct the transfer and notify households via SMS, households may not notice and utilize the transfer. In that sense, the empirical specification in equation 1-2 and associated estimates (γ_1, θ_1, and θ_2) should be interpreted as intention to treat (ITT) estimates rather than impacts on those actually utilizing the digital transfers. However, in contexts involving interventions of the type of digital transfers where implementing organizations have limited capacity and role to ensure actual utilization of transfers, the ITT estimates are equally informative and useful.

The impacts of the digital transfers are likely to differ across households given with varying socioeconomic characteristics and underlying conditions. For example, we hypothesize that digital transfers may be more effective and useful for those households grappling with the adverse effects of armed conflict. To explore this hypothesis, we expand the expressions in equations 1-2 by interacting the treatment assignment with community-level exposure to conflict. For this purpose, we compile data on exposure to armed conflict from the Armed Conflict Location Event Data (ACLED) (Raleigh et al., 2010). The ACLED database is widely used to study the consequences of conflicts in different settings and records event-based information for different types of conflict events, including battles, attacks against civilians, remote violence, and protests and riots. Some of these conflict events have intensified recently in Sudan, affording us important spatial variation in exposure to armed conflict. Most importantly, since the outbreak of the armed conflict between the SAF and RSF in April 2023, battles are the most dominant type of conflict events recorded by the ACLED database.[18] Thus, we focus on battles, to capture both the most dominant and consequential form of conflict.

We focus on battles realized since the start of the armed conflict in Sudan (April 2023) and aggregate the number of battles realized up to the time of the digital transfer. As we lack GPS coordinates of households' residence, we aggregate and count realized battle events at the

[18]For example, out of the total conflict events recorded in ACLED in 2023, 39 percent of them represent battles.

locality level (equivalent to district in the United States). More specifically, we estimate the following interacted specification:

$$W_{ht=1} = \beta_0 W_{ht=0} + \beta_1 T1_h + \beta_2 T2_h + \beta_3 \text{Battles}_{hl} + \beta_4 (T1_h \times \text{Battles}_{hl}) + \beta_5 (T2_h \times \text{Battles}_{hl}) + S_s + \varepsilon_h \tag{3}$$

Where all terms except $Battles_{hl}$ are as defined above. $Battles_{hl}$ stands for a measure of community-level exposure to armed conflict, namely battles, which we compile from the ACLED database. For facilitating interpretation, we standardize the number of battle events realized in each locality by demeaning them. Thus, while β_1 and β_2 capture the impact of the digital transfers at the average level of exposure to armed conflict, β_4 and β_5 detects potential differential impacts of the digital transfers across households with varying level of exposure to armed conflict. We hypothesize that those households grappling with armed conflict may have acute needs for humanitarian assistance and hence the digital transfers may be more effective for these households. Armed conflicts may also limit households' access to conventional humanitarian and social assistance services (Ghorpade, 2020) and remittance services (Ghorpade, 2017), making the digital transfers the only assistance these households receive.

We also hypothesize that the effect of digital cash transfers may vary across poor and non-poor households, as well as across households of large and small sizes. The impact of digital transfers may vary across households depending on: (i) their relative need for humanitarian assistance; (ii) the size of the transfer vis-à-vis household needs; (iii) whether the transfers are infra-marginal or extra-marginal[19]; and (iv) whether the digital transfers serve as substitutes or complements to households' consumption. If the digital transfers are infra-marginal–less than the amount needed to cover basic food needs of beneficiaries–and are not complemented by other sources of assistance, they may not necessarily improve the welfare of poor and large households. But such transfers can be more effective for non-poor and small households, and those households with some additional complementary source of income. We probe these heterogeneities by extending the empirical specification in equation 2 using interaction terms and sample splits. For this purpose, we use pre-transfer measures and indicators of relative economic status (poverty) and

[19]The transfers are defined as infra(extra)-marginal if the amount of the digital transfer is less (greater) than what specific target beneficiaries would spend (Cunha, 2014; Cunha et al., 2019).

test this hypothesis by interacting the treatment indicators specified above as follows:

$$
\begin{aligned}
W_{ht=1} = \delta_0 W_{ht=0} + \delta_1 T1_h + \delta_2 T2_h + \delta_3 \text{Poor}_{ht=0} + \delta_4 (T1_h \times \text{Poor}_{ht=0}) + \\
\delta_5 (T2_h \times \text{Poor}_{ht=0}) + S_s + \epsilon_h
\end{aligned} \tag{4}
$$

where all terms except $Poor_{ht=0}$ are as defined before. $Poor_{ht=0}$ is an indicator variable assuming a value of 1 for those households classified as poor using various indicators in the baseline survey. The coefficient associated with the interaction terms between access to digital cash transfers and an indicator for poor households (δ_4 and δ_5) allows us to test whether the digital transfers are particularly impactful for poor households. Beyond poverty, we also explore heterogeneities across small and large households, as well as across those households with and without additional income-generating activities. We do so by changing the interacted variables in equation 4.

Households living in the same community are likely to face similar shocks and markets and food environments, which can generate spatial correlation of unobserved effects (error terms) across households from the same community. Thus, standard errors are clustered at the locality level.

5. Empirical results and discussion

In this section, we first report and discuss the impact of access to digital transfers on food security indicators. Next, we examine the impact of digital transfers on subjective well-being and mental health. Finally, we explore and report potential heterogeneous impacts of the intervention.

5.1. Effect of digital transfer on food security

Tables 2 and 3 present the impact of digital transfers on different measures of food security estimated using equations 1 and 2. All specifications in Tables 2 and 3 control for state fixed effects. While the odd columns control only for assignment to the digital transfer, the even columns control for outcomes and household characteristics measured at baseline. Specifically, Columns (1) and (2) of Table 2 present the impact of digital transfers on households' food consumption score with and without controlling for household and demographic characteristics. The food consumption score (FCS) is constructed based on a 7-day recall period, which reflects the availability and quantity of food consumed over the previous week by most household members. The score gives weight to each of the 8 food groups included in our dietary diversity module. Column (1) shows that households in the digital transfer treatment group have an FCS of 2.3-2.5 points higher than the control group. The results remain robust even after controlling a range of household characteristics. Columns (3) and (4) present estimated results from equation 2 when the treatment group is disaggregated into the two different treatment arms (transfer sizes of $50 and $75). The effects reported in columns (3) and (4) show that the $75 transfer led to a 5-6 percent increase in FCS. The estimated coefficients associated with the different transfer sizes are not statistically different from each other, as shown at the bottom of Table 2 through the pairwise t-test statistics. Columns (5) through (8) present the impact of digital transfer on households' dietary diversity score (DDS). Column (5) of Table 2 shows that access to digital transfers increases DDS by approximately 4 percent relative to the control group. Columns (7) and (8) present the impact of different transfer sizes. However, the results remain similar across both transfer sizes as demonstrated by pairwise t-test statistics shown at the bottom of Table 2.

Table 2: Impact of digital cash transfer on food security: food consumption and dietary diversity score

	Food Consumption Score				Dietary Diversity Score			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	2.496**	2.254**			0.231***	0.218***		
	(1.106)	(1.088)			(0.068)	(0.067)		
Treatment:50 USD			1.710	1.484			0.245***	0.234***
			(1.145)	(1.129)			(0.073)	(0.072)
Treatment:75 USD			3.266**	3.006**			0.218**	0.202**
			(1.515)	(1.492)			(0.089)	(0.088)
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Mean of control	59.99	59.99	59.99	59.99	6.65	6.65	6.65	6.65
P-value (50 vs 75 USD)			0.31	0.32			0.77	0.73
Observations	1,509	1,509	1,509	1,509	1,509	1,509	1,509	1,509

Notes. This table reports results from ANCOVA regressions of food consumption score (FCS) (columns 1-4) and dietary diversity score (DDS) (columns 5-8). Treatment is a binary variable taking a value of 1 for those households assigned to the digital cash transfer intervention and 0 otherwise. Controls include: respondent gender, respondent age, education level of the household head, household size, access to electricity, marital status, housing condition, and having a bank account. Standard errors, clustered at locality level, are given in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3 presents the impact of digital transfers on another commonly used indicator of food insecurity: the food insecurity experience scale (FIES). We use both continuous FIES values (ranging between 0 and 8) as well as a binary indicator taking a value of 1 if the FIES is greater than 0 and 0 otherwise. Columns (1) and (2) show that access to the digital transfer program decreases food insecurity by approximately 12 percent relative to the control group. Columns (3) and (4) present the impact of the two treatment arms of different transfer sizes. The estimated results show that both transfer sizes lead to significantly reduced food insecurity. As expected, the effect is stronger for the relatively larger transfer size, although this difference is not statistically significant, as shown by the pairwise t-test reported at the bottom of Table 3. While the results in columns (1)-(4) are based on continuous FIES, the estimates in columns (5) through (8) use a binary measure of exposure to food insecurity. More specifically, the digital transfer program decreases the probability of being food insecure by about 6 percentage points (Column (5)). These estimated coefficients remain robust even after controlling for a battery of baseline household characteristics (Column (6)). The results reported in columns (7) and (8) indicate that the relatively small transfer size has no statistically significant effect on food insecurity, while the relatively modest transfer decreases food insecurity by 7-8 percentage points. However, as shown at the bottom of Table 3, through the pairwise t-test statistics, the estimated coefficients associated with the different transfer sizes are not statistically different from each other.

Table 3: Impact of digital cash transfer on food security: food insecurity experience scale

	Food Insecurity Experience Scale (FIES)				Food Insecurity (FIES>= 1)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	-0.566***	-0.549***			-0.055***	-0.052***		
	(0.130)	(0.129)			(0.017)	(0.017)		
Treatment:50 USD			-0.483***	-0.467***			-0.034	-0.031
			(0.147)	(0.149)			(0.022)	(0.022)
Treatment:75 USD			-0.648***	-0.629***			-0.076***	-0.073***
			(0.174)	(0.171)			(0.025)	(0.025)
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes
R-squared	0.027	0.034	0.028	0.035	0.017	0.026	0.018	0.028
Mean of control	4.36	4.36	4.36	4.36	0.83	0.83	0.83	0.83
50 USD vs 75 USD			0.39	0.39			0.18	0.18
Observations	1,489	1,489	1,489	1,489	1,509	1,509	1,509	1,509

Notes. This table reports results from ANCOVA regressions of Food Insecurity Experience Scale (FIES) (columns 1-4) and food insecurity (FIES>1) (columns 5-8). Treatment is a binary variable taking a value of 1 for those households assigned to the digital cash transfer intervention and 0 otherwise. Controls include: respondent gender, respondent age, education level of the household head, household size, access to electricity, marital status, housing condition, and having a bank account. Standard errors, clustered at locality level, are given in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Although direct evidence of the impact of digital transfers in conflict-affected settings remains scant, our finings corroborate emerging studies showing the positive impact of cash transfers on food and nutrition security (Callen et al., 2025; Manley et al., 2020; Ecker et al., 2024). Our paper is closest to the study by Callen et al. (2025), which evaluates the impact of digital transfers on the food security and mental well-being of extremely poor, women-headed households in Afghanistan. Their findings show that digital transfers led to significant improvements in food security and subjective well-being. Similarly, Hidrobo et al. (2014) shows that cash transfers in Ecuador improved both caloric intake and dietary diversity, while Hoddinott et al. (2018) reports an increase in nutrient-rich food consumption as a result of cash and in-kind transfers in Niger. The digital nature of our intervention, which ensures timely, efficient delivery and reduces transaction costs in fragile and conflict-affected settings, contributes to these observed gains by suggesting that, in diverse settings, the flexibility of cash may empower households to make context-specific food purchasing decisions and enhance dietary adequacy.

Importantly, we observe that even a relatively modest transfer of \$50 yields significant improvements across multiple outcome indicators. This is in line with findings from Kondylis and Loeser (2021), who show that even small interventions can produce meaningful and persistent effects when they relax key constraints. In our context, several reinforcing factors explain these impacts. First, in low-income and conflict-affected settings, \$50 represents a substantial portion of monthly consumption. When households are liquidity-constrained, even small transfers enable them to meet urgent needs such as food, health care, or debt repayment, resulting in immediate welfare gains and reduced stress. Second, the use of digital platforms enhances delivery efficiency and timeliness, increasing the perceived reliability and usefulness of the transfers (Aker et al., 2016). Digital transfers also reduce transaction costs, leakage, and allow greater autonomy in spending decisions, all of which have been associated with improved psychological well-being (Gentilini, 2016). Lastly, behavioral and psychosocial mechanisms further amplify these effects. Cash transfers, particularly when delivered digitally, can improve recipients' sense of agency and control–core aspects of subjective well-being. This resonates with findings from Banerjee et al. (2015), who document that multi-faceted support to the poor, including cash transfers, can lead to sustained gains in consumption, mental health, and perceived economic status across diverse contexts.

5.2. Effect of digital transfer on subjective well-being

In this section, we discuss the impact of digital transfers on subjective well-being, measured through commonly used questions to elicit general happiness, overall life satisfaction, and perceived economic condition. To measure general happiness, we elicit overall happiness in a five-scale response, ranging from “not at all happy” to “very happy”. For overall satisfaction, we use a Cantrip Ladder (0–10 scale). We used a five-step economic ladder (ranging from “very bad to “very good”) to measure perceived economic conditions. Together, they provide a multidimensional view of well-being beyond income, reflecting both emotional states and personal economic perceptions. Based on these values, we generate two types of measures and indicators for our regression. First, we generate binary indicators of happiness (assuming a value of 1 for those reporting “happy” or “very happy”); perceived economic condition (assuming a value of 1 for those reporting an economic condition of “good” or “very good”); and binary indicator of life satisfaction (assuming a value of 1 for those reporting 6 or above in the 10-scale ladder). Second, using the raw values of responses associated with the three domains of subjective well-being, we construct a unidimensional subjective well-being index using factor analysis of these three domains. To ease interpretation, we standardize this index to assume a mean of 0 and a standard deviation of 1. Subjective well-being questions were administered only during the endline survey, forcing us to estimate equation 1 and 2 without controlling for baseline subjective well-being.

As with food security, digital cash transfers positively affect subjective well-being. Beneficiaries of the digital cash transfer reported improvements in happiness, life satisfaction, and perceived economic condition. Table 4 provides estimation results from our model in equation 1, which compares subjective well-being between treatment and control groups. Columns (1) and (2) show the impact of access to digital transfers on emotional well-being, as well as the probability of reporting being “happy” or “very happy”. Columns (3) and (4) present estimation results on the impact of the intervention on life satisfaction. Columns (5) and (6) provide the corresponding estimates for perceived measures of economic conditions. Finally, in columns(7) and (8), we report impacts on a composite measure of subjective well-being. The estimation results in Table 4 show that the digital transfers improved subjective well-being. Column (1) shows that the digital transfer increased emotional well-being (happiness) by 10 percentage points (15 percent relative to the control group). Column (2) indicates both transfer sizes have a similar impact on happiness, as evident by the t-test at the bottom of Table 4. Columns (3) and (4) show that assignment to digital transfer increased life satisfaction. Columns (5) and (6) also indicate that the digital transfer significantly improved perceived economic condition. Column (5) shows that assignment to the digital transfer increased the probability of perceiving a ”good” or “very good” economic condition by 7 percentage points (37 percent). Finally, Column (7) shows that access to digital transfer increased overall subjective well-being by 0.19 standard deviations. The pairwise t-tests reported at the bottom of Table 4 show that the impact of the digital transfer remains similar under different transfer sizes. These results are consistent with evidence from Kenya, where Haushofer and Shapiro (2016) finds that cash transfers led to sustained gains in life satisfaction and perceived economic security. Alloush and Wu (2023) similarly document positive effects on happiness among Syrian refugees. These improvements can be partially explained by the autonomy and dignity conferred through cash transfers, especially when delivered via digital means that enhance privacy and convenience (Gentilini, 2016).

Table 4: Impact of digital cash transfer on subjective well-being

	Happy or very happy		Satisfied		Good economic condition		SWB index (std)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	0.101***		0.041*		0.073***		0.186***	
	(0.023)		(0.024)		(0.024)		(0.053)	
Treatment:50USD		0.104***		0.046*		0.065**		0.185***
		(0.028)		(0.027)		(0.028)		(0.063)
Treatment:75USD		0.098***		0.036		0.082***		0.187***
		(0.026)		(0.031)		(0.026)		(0.063)
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.033	0.033	0.029	0.029	0.033	0.033	0.027	0.027
Mean of control	0.65	0.65	0.58	0.58	0.19	0.19		
50 USD vs 75 USD		0.83		0.78		0.51		0.97
Observations	1,509	1,509	1,509	1,509	1,509	1,509	1,499	1,499

Notes. This table reports results from ANCOVA regressions and associated treatment effects of digital transfers on happiness (columns 1–2), life satisfaction (columns 3–4), and perceived economic condition (columns 5–6), and standardized subjective well-being index (columns 7-8). Happiness is measured as a binary indicator equal to 1 if the respondent reports being "happy" or "very happy". Life satisfaction is a binary indicator equal to 1 if the respondent rates their overall life satisfaction above 5 on a 0–10 scale. Perceived economic condition is a binary indicator equal to 1 if the respondent reports their economic situation as "good" or "very good". Treatment is a binary variable taking a value of 1 for those households assigned to the digital cash transfer intervention and 0 otherwise. Controls include: respondent gender, respondent age, education level of the household head, household size, access to electricity, marital status, housing condition, and having a bank account. Standard errors, clustered at locality level, are given in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

5.3. Effect of digital transfer on mental health

This section examines the impacts of digital cash transfers on mental health. As discussed, we elicited households' mental health using Cohen's Perceived Stress Scale (PSS) and Generalized Anxiety Disorder (GAD) Score. We also generated binary indicators for perceived severe stress and severe anxiety taking the value of 1 if for PSS ≥ 27 and GAD ≥ 15, respectively, and 0 otherwise. The first four columns of Table 5 present the impact on perceived stress, and the next four show the impact on symptoms of anxiety. While the odd-numbered columns present estimation results for the binary treatment, the even-numbered columns show the estimated coefficients for the disaggregated treatment groups (transfer sizes of \$50 and \$75). All regression specifications in Table 5 control for state fixed effects and household characteristics.

Table 5: Impact of digital cash transfer on mental health

	Stress		Severe stress		GAD score		Severe anxiety	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	-0.832**		-0.039*		-0.419		-0.003	
	(0.374)		(0.020)		(0.308)		(0.009)	
Treatment: 50 USD		-0.810**		-0.025		-0.315		0.002
		(0.373)		(0.022)		(0.308)		(0.011)
Treatment:75 USD		-0.853*		-0.052**		-0.521		-0.008
		(0.513)		(0.025)		(0.462)		(0.013)
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.030	0.030	0.023	0.023	0.030	0.031	0.011	0.011
Mean of control	21.98	21.98	0.24	0.24	8.71	8.71	0.09	0.09
50 USD vs 75 USD		0.93		0.29		0.67		0.53
Observations	1,475	1,475	1,475	1,475	1,486	1,486	3,018	3,018

Notes. This table reports results from ANCOVA regressions of stress (columns 1-2) and severe stress (columns 3-4) and regression with high-dimensional fixed effects of Generalized Anxiety Disorder (GAD) score (columns 5-6) and severe anxiety (columns 7-8). Stress is measured using the 10-item Perceived Stress Scale, with responses ranging from 0 (low stress) to 40 (high stress). Severe stress is defined as PSS ≥ 27 (binary indicator). Anxiety is measured using the Generalized Anxiety Disorder (GAD-7) scale, ranging from 0 to 21, with severe anxiety defined as GAD ≥ 15 (binary indicator). Treatment is a binary variable taking a value of 1 for those households assigned to the digital cash transfer intervention and 0 otherwise. Controls include: respondent gender, respondent age, education level of the household head, household size, access to electricity, marital status, housing condition, and having a bank account. Standard errors, clustered at locality level, are given in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

The estimated coefficients on the treatment variable are negative for all stress and anxiety-related outcomes, but the coefficients are statistically significant for the stress indicators only. Columns (1) and (3) show that assignment to the treatment decreases symptoms of stress by 0.83 points, which is 4 percent less relative to the control group and severe stress by approximately 16 percent (4 percentage points). Columns (2) and (4) reveal that transfer size does not have a significantly significant effect on reported stress symptoms. Columns (5) through (8) show that the impact of the digital transfer on symptoms of anxiety is as expected, that is, the estimated coefficients are not statistically significant. Overall, we observe notable reductions in psychological distress among beneficiaries, as measured by lower PSS and GAD scores. These findings echo results from Malawi, where Baird et al. (2018) show that cash transfers reduced psychological distress among young women, and from Kenya, where mental health improvements persisted years after the initial transfer (Haushofer and Shapiro, 2018). By easing liquidity constraints, digital cash transfers allow households to meet urgent needs such as food, health care, and debt repayment, thereby reducing stress and anxiety. Furthermore, the predictability and perceived reliability of digital payments may enhance psychological security.

5.4. Heterogeneity analyses

In sections 5.1 through 5.3, we show that the digital cash transfer program positively and significantly improved food security, subjective well-being, and mental health of beneficiary households. This section discusses whether these effects vary based on households' exposure to shocks (conflict) and observable characteristics such as poverty status, household size and income sources.

Table 6 shows that the impacts of the digital cash transfer program are larger in conflict-affected localities. Households' exposure to conflict (number of battles) is associated with lower food security (Columns (1)-(3)) and subjective well-being (Column (4)), and higher symptoms of stress and anxiety (Columns (5)-(6)). Interestingly, the coefficients associated with the interaction terms between exposure to battles and the treatment indicators capture the role of access to digital cash transfer in cushioning the adverse effects of conflict events (Table 6). More specifically, the estimated coefficients in the first two columns show that the impact of the digital transfers increase alongside increased number of battles, with the latter signaling an increase in humanitarian needs. Similarly, Column (4) shows that relative to households in the control group and not in active conflict, the digital cash transfer increases subjective well-being for households that grapple with a higher number of battle events. The last two columns also show that digital cash transfer reduces symptoms of stress and anxiety for households in conflict-affected contexts compared to those households in stable environments and those in control group.

Table 6: Heterogeneous impact of digital cash transfer by exposure to battle events

	Food security			Subjective well-being	Mental health	
	(1)	(2)	(3)	(4)	(5)	(6)
	FCS	DDS	FIES	Subjective well-being index	Stress	Anxiety Score
Treatment: 50 USD	1.755	0.248***	-0.483***	0.197***	-0.804**	-0.338
	(1.205)	(0.072)	(0.148)	(0.067)	(0.373)	(0.306)
Treatment:75 USD	3.279**	0.217**	-0.645***	0.197***	-0.872*	-0.569
	(1.520)	(0.091)	(0.175)	(0.065)	(0.520)	(0.474)
Number of battles (standardized)	-0.646*	-0.060	-0.028	-0.103***	0.177	0.503**
	(0.344)	(0.040)	(0.051)	(0.028)	(0.125)	(0.240)
Treatment: 50 USD # Battles	3.062***	0.202***	-0.031	0.147*	-0.507*	-0.717*
	(1.154)	(0.070)	(0.118)	(0.077)	(0.270)	(0.406)
Treatment: 75 USD# Battles	0.301	0.106*	-0.072	0.124***	-0.178	-0.315
	(0.953)	(0.059)	(0.087)	(0.034)	(0.267)	(0.377)
State FE	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.019	0.025	0.028	0.025	0.023	0.027
Mean of control	59.99	6.65	4.36	-0.12	21.98	8.71
Observations	1,509	1,509	1,489	1,499	1,475	1,486

Notes. The dependent variables in Columns 1, 2 and 3 are FCS, DDS, and FIES, respectively. In column 4, the dependent variable is subjective well-being index. In columns 5 and 6, the dependent variables are stress and GAD score. Treatment 50 USD and 75 USD are binary indicators taking a value of 1 for those households assigned to the digital cash transfer intervention and 0 otherwise. Standard errors, clustered at locality level, are given in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Additionally, Figure 8 and Table A2 present the impact of digital transfers among states controlled by the SAF and RSF. The impact of the digital cash transfer is higher among beneficiaries living in states controlled by RSF. The greater impact observed in RSF-controlled areas could stem from a combination of structural and contextual factors such as liquidity constraints related to the currency changes in SAF-controlled areas, increased violence incidents, and clashes. In general, RSF-controlled states had a lower baseline of food security and mental health outcomes. Thus, the same intervention might yield larger marginal improvements compared to SAF-controlled areas. The estimated coefficients in Table A2 in the appendix also show similar results.

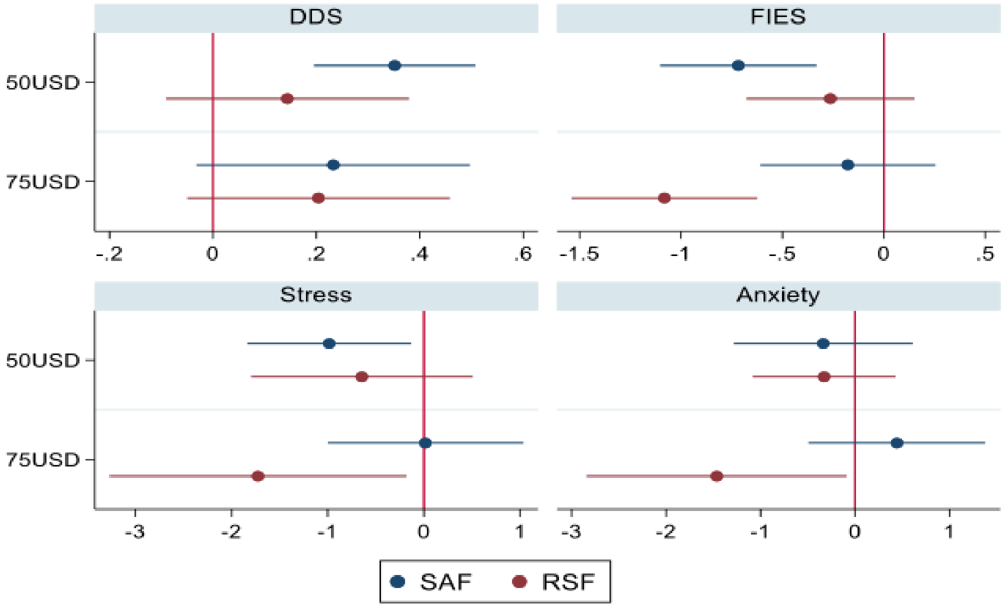

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Figure 8: The impact of digital transfer is higher among states controlled by RSF

Similarly, we investigate whether the impact of the digital transfer is larger or smaller for relatively poor households. Figure 9 shows that the impact of the digital transfer program is lower for those relatively poorer or poorest households. More specifically, the impact of digital cash transfer on DDS and FIES is more pronounced among the non-poor households. Similarly, the digital cash transfer leads to a large reduction in symptoms of stress and anxiety among the non-poor. This may be due to the fact that poorest households often face multiple and overlapping deprivations such as chronic food insecurity, health issues, debt, or lack of basic services, which may dilute the impact of a modest transfer. A $50 digital transfer, for example, may be used to pay off debts or cover urgent needs, rather than allowing for investment in nutrition, well-being, and health. Table A3 in the appendix also shows similar results. This is consistent with findings in the literature. For instance, Baird et al. (2018) and Banerjee et al. (2015) show that poorest households may need more sustained or multifaceted support to improve food and nutrition security and other outcomes.

Figures 10 and 11 present the heterogeneous impact of the digital cash transfer by household size and income source, respectively. Figure 10 shows that the impact of the digital cash transfer is larger for beneficiaries with relatively smaller household size. The estimated coefficients in Table A4 in the appendix also show similar results, estimated using equation 4. The relatively lower impact of digital cash transfers on larger households can be attributed to several factors. First, when a fixed transfer amount ($50 and $75) is distributed across a larger household members, the per capita value of the transfer diminishes. This may weaken the effectiveness of the transfer. Additionally, intra-household allocation of resources can be more complex in larger households, potentially leading to less efficient use of the funds. This pattern aligns with findings from prior studies, which show that the effectiveness of cash transfers tends to be lower for larger households unless the transfer size is adjusted proportionally (Aizawa, 2020; Ongudi et al., 2024).

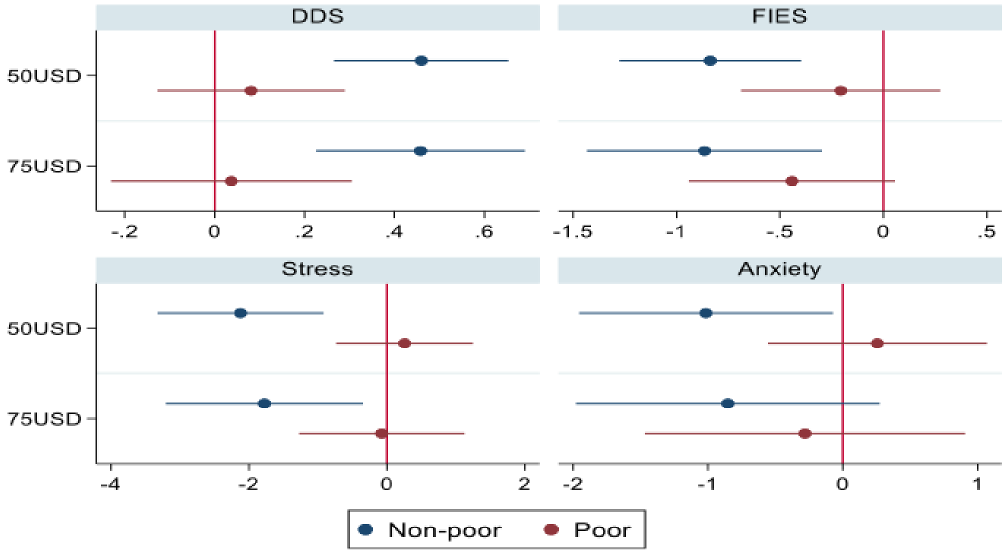

Figure 9: The impact of digital transfer is lower for those who are relatively poor or the poorest

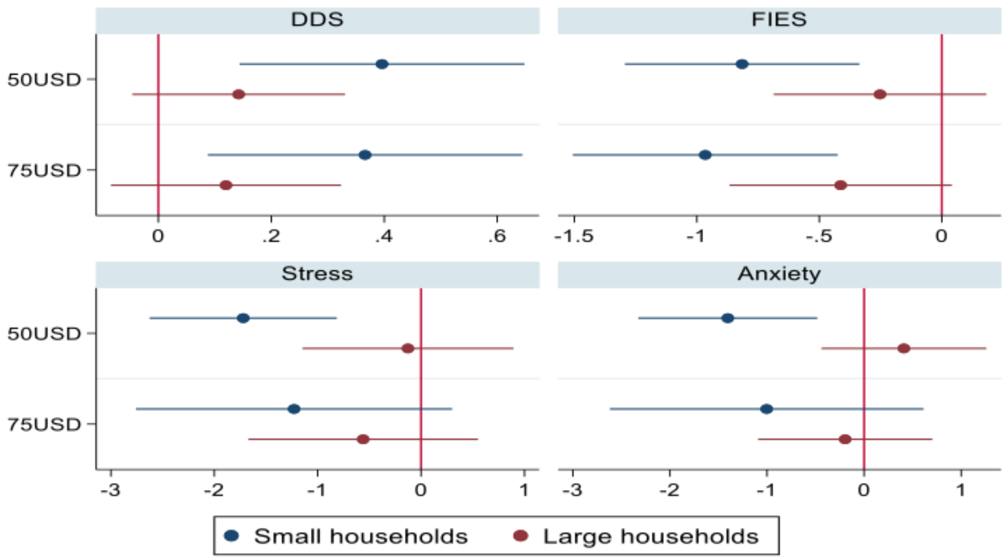

Figure 10: The impact of digital transfer is lower for relatively large households

Finally, Figure 11, as well as the estimated coefficients in Table A5 in the appendix, show that the impact of the digital cash transfer is lower for those without additional sources of income. The lower impact of digital transfers for households without additional income sources is intuitive. Households often suffer from financial constraints, meaning that a modest transfer may be quickly absorbed by urgent needs, leaving little room for improvements in well-being, nutrition, or stress. This suggests that those households with complementary source of income and capacity are more likely to benefit from the digital transfers than those without complementary sources of income (Haushofer et al., 2025). In addition, households without alternative income sources may be less resilient to shocks, making the transfer's effects negligible and short-lived. Furthermore, the psychological strain of severe financial insecurity can reduce beneficiaries' ability to make decisions or use the transfer strategically. Overall, the heterogeneous results shown in this section suggest potential gains to targeting to improve the effectiveness of the transfers. For example, some of these heterogeneities suggest that targeting based on deprivation versus expected impact may generate varying level of effectiveness (Haushofer et al., 2025).

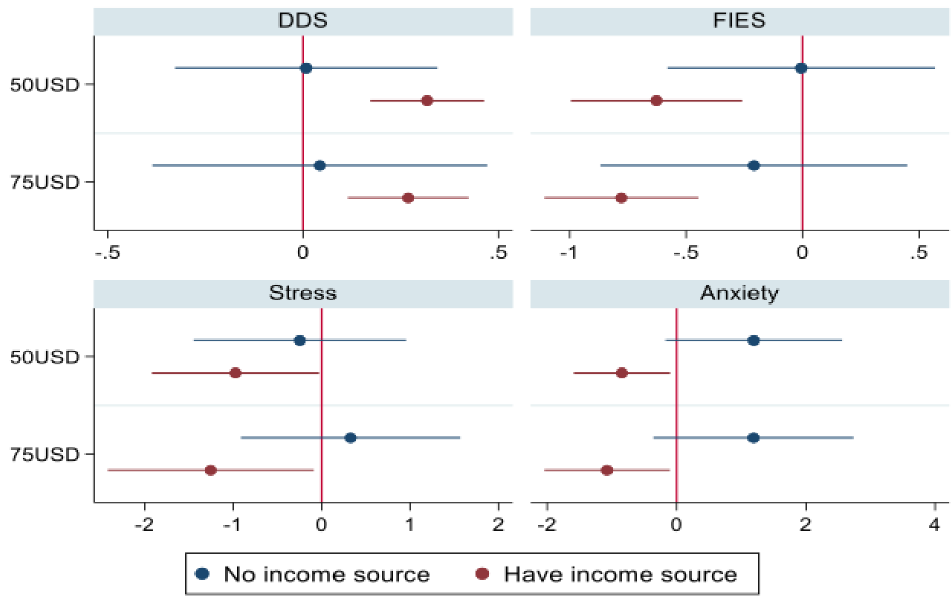

Figure 11: The impact of digital transfer is lower for those without additional income

5.5. Robustness checks

While the main results reported in this paper are based on the pre-Ramadan sample, we revisit and establish the robustness of our findings using the full sample. Tables A6 through A9 in the appendix show that our main findings in Tables 2 through 4 remain robust. Table A6 presents the impact of access to digital transfers on both FCS and DDS. The estimated coefficients show that households with access to the digital cash transfer report 2.2 and 0.2 higher FCS and DDS, respectively, relative to the control group. Table A6 also presents the estimated results from the two treatment arms involving different transfer sizes ($50 and $75). The results show that the $50 and $75 transfer sizes led to 3 and 4 percent increases in FCS, respectively. As shown at the bottom of Table A6 the estimated coefficients associated with the different transfer sizes are not statistically different from each other.

Table A7 presents the impact of access to digital transfer on FIES. Specifically, households assigned to the treatment group report about 8 percent lower FIES relative to the control group. As expected, the effect is stronger and statistically significant for the relatively larger transfer size ($75). However, the estimated coefficients across the transfer sizes are not statistically different from each other. Table A8 presents the impact of access to the digital transfer on subjective well-being, showing that access to digital transfer increases happiness by 6 percentage points (8 percent relative to the control group). Both transfer sizes have a similar impact on happiness, as shown at the bottom of Table A8. The last two columns of Table A8, show the estimated coefficients on the subjective well-being index. The results show that access to digital transfer increases subjective well-being by 0.84 standard deviation. Table A9 shows impacts on mental health indicators, which generally show weaker effects.

6. Conclusion

Delivering humanitarian assistance amid active conflict and reaching vulnerable populations under the control of hostile military and paramilitary actors remains a daunting task with multifaceted risks. Digital services and transfers are attracting substantial attention for their potential to cost-effectively deliver aid to otherwise inaccessible populations (Callen et al., 2025). Their effectiveness, and the conditions under which they can serve those grappling with active conflict, remain an active area of inquiry. In this paper, we evaluate the potential and impact of digital cash transfers to support urban households grappling with active conflict in Sudan, where conflict and funding gaps continue to hamper the delivery of humanitarian services. We ask whether digital cash transfers can reach those affected by armed conflict and improve food and nutrition security outcomes of beneficiaries in conflict-affected settings. Similarly, we examine whether such transfers can improve subjective well-being and mental health, as well as whether these impacts vary by the size of transfers or socioeconomic characteristics of households. We address these research objectives and questions using a randomized controlled trial (RCT) involving digital cash transfers of different sizes to randomly selected urban residents in Sudan.

The digital transfers reached nearly all targeted beneficiaries, with about a quarter of respondents having received them through their friends and relatives, and hence incurring some transaction fees. Nonetheless, we find that digital transfers have significant potential to support those grappling with armed conflict, and who are otherwise not easily accessible. We find that digital transfers mitigated deterioration in food insecurity and improved subjective well-being and mental health, while the control group suffered from deterioration in food security outcomes following the baseline survey. These findings suggest that those who received digital cash transfers were considerably protected. Interestingly, we find that the digital transfers are more beneficial (impactful) for those grappling with active conflict, relative to those living in stable environments. The impacts of digital transfers appear to be higher among those facing active conflict or those living in areas under the control of the Rapid Support Forces (RSF), suggesting a higher need for humanitarian assistance among those populations. Notably, a majority of these areas have suffered recurring conflicts and worsening livelihood conditions compared to other regions in Sudan. Similarly, the transfers appear to be less effective for those households with larger household sizes as well as poorer households, while the effects appear to be stronger for small households and those with additional sources of income. Poorer households with limited income sources and households of a larger size did not witness significant improvements in the welfare and mental health outcomes because of the digital cash transfer.

Our findings offer important insights: digital transfers can serve as important humanitarian instruments to cushion the adverse impacts of armed conflict. This corroborates emerging literature about the potential of digital transfers to reach and support an otherwise inaccessible and vulnerable population (Callen et al., 2025). The heterogeneous results on the impact of the digital transfers highlight potential varying returns to digital transfers across various groups. Some of these findings highlight that current practices and humanitarian services may not be sufficient for all types of households, implying the potential of targeting to improve the effectiveness of these humanitarian services. These results suggest that the optimal digital transfer may vary across households and contexts (Kondylis and Loeser, 2021), depending on their underlying socioeconomic conditions and constraints. Furthermore, these findings suggest potential gains to targeting, including those targeting approaches considering multidimensional criteria beyond deprivation (Haushofer et al., 2025; Abay et al., 2024; Lee et al., 2025).

Despite the unique contributions highlighted above, our study suffers from some limitations.

First, armed conflict disrupts in-person data collection efforts, forcing us to rely on Computer-Assisted Telephone Interviews (CATI), which limit the amount of information we can capture. Besides limiting the breadth of data we collect, CATI can introduce some misreporting and associated biases, although the outcomes we study in this paper are shown to be robust to such biases (Abate et al., 2023). Second, because of the limitation in the breadth of data we can collect, we fail to capture potential additional important effects of digital transfers, including on intra-household outcomes. Third, the time between our intervention (digital cash transfer) and follow-up data collection is relatively short, implying that the impacts we capture are immediate effects and may represent the full effect of the transfers, especially if households save the money for later use.

References

Abate, G. T., De Brauw, A., Hirvonen, K., and Wolle, A. (2023). Measuring consumption over the phone: Evidence from a survey experiment in urban Ethiopia. *Journal of Development Economics*, 161:103026.

Abay, K. A., Abushama, H., Mohamed, S., and Siddig, K. (2025). Rethinking delivery modalities in conflict-affected settings: Why beneficiaries in Sudan prefer digital transfers.

Abay, K. A., Berhane, G., Gilligan, D. O., Tafere, K., and Taffesse, A. S. (2024). *Targeting social assistance in fragile settings: An experiment on community-based targeting.* International Food Policy Research Institute.

Abay, K. A., Berhane, G., Hoddinott, J., and Tafere, K. (2023). COVID-19 and food security in Ethiopia: Do social protection programs protect? *Economic Development and Cultural Change*, 71(2):373–402.

Abd Elkreem, T. (2025). Digital food assistance in Sudan.

Abushama, H., Resnick, D., Siddig, K., and Kirui, O. K. (2023). *Political and economic drivers of Sudan's armed conflict: Implications for the agri-food system.* International Food Policy Research Institute.

ACLED (2024). Foreign Meddling and Fragmentation Fuel the War in Sudan. Conflict Watchlist 2025: Sudan. https://acleddata.com/conflict-watchlist-2025/sudan/. Accessed August 2025.

Adato, M. and Hoddinott, J. (2010). *Conditional cash transfers in Latin America.* International Food Policy Research Institute.

Ahmed, M., Raouf, M., and Siddig, K. (2025). What Are the Economic and Poverty Implications for Sudan If the Conflict Continues Through 2025? *The Journal of Development Studies*, pages 1–22.

Aizawa, T. (2020). Do cash transfers increase nutritional intakes? Experimental evidence from an unconditional cash transfer in Kenya. *Health Policy and Planning*, 35(7):784–798.

Aizer, A., Eli, S., Ferrie, J., and Lleras-Muney, A. (2016). The long-run impact of cash transfers to poor families. *American Economic Review*, 106(4):935–971.

Aker, J. C., Boumnijel, R., McClelland, A., and Tierney, N. (2016). Payment mechanisms and antipoverty programs: Evidence from a mobile money cash transfer experiment in Niger. *Economic Development and Cultural Change*, 65(1):1–37.

Alloush, M. (2024). Income, psychological well-being, and the dynamics of poverty. *Economic Development and Cultural Change*, 72(4):000–000.

Alloush, M. and Wu, S. (2023). Income Improves Subjective Well-Being: Evidence from South Africa. *Economic Development and Cultural Change*, 71(2):485–517.

Aron, J. (2018). Mobile money and the economy: A review of the evidence. *The World Bank Research Observer*, 33(2):135–188.

Aurino, E. and Giunti, S. (2022). Social protection for child development in crisis: A review of evidence and knowledge gaps. *The World Bank Research Observer*, 37(2):229–263.

Baird, S., De Hoop, J., and Özler, B. (2013). Income shocks and adolescent mental health. *Journal of Human Resources*, 48(2):370–403.

Baird, S., McKenzie, D., and Özler, B. (2018). The effects of cash transfers on adult labor market outcomes. *IZA Journal of Development and Migration*, 8:1–20.

Balboni, C., Bandiera, O., Burgess, R., Ghatak, M., and Heil, A. (2022). Why do people stay poor? *The Quarterly Journal of Economics*, 137(2):785–844.

Banerjee, A., Duflo, E., Goldberg, N., Karlan, D., Osei, R., Parienté, W., Shapiro, J., Thuysbaert, B., and Udry, C. (2015). A multifaceted program causes lasting progress for the very poor: Evidence from six countries. *Science*, 348(6236):1260799.

Bank, W. (2022). Digital Economy for Africa (DE4A): Diagnostic Assessment for the Republic of Sudan. Technical report, World Bank. Accessed: 2025-09-10.

Better Than Cash Alliance (2025). *Responsible digital payments: Powering financial inclusion, economic growth, and digital transformation*. Better Than Cash Alliance.

Callen, M., Fajardo-Steinhäuser, M., Findley, M. G., and Ghani, T. (2025). Can digital aid deliver during humanitarian crises? *Management Science*.

Cameron, L. and Shah, M. (2014). Can mistargeting destroy social capital and stimulate crime? Evidence from a cash transfer program in Indonesia. *Economic Development and Cultural Change*, 62(2):381–415.

Cash Consortium for Sudan (2024). The Cash Consortium for Sudan (CCS): A Feasible, Life-Saving, Urgent Case for Cash at Scale in Sudan. https://reliefweb.int/report/sudan/cash-consortium-sudan-ccs-feasible-life-saving-urgent-case-cash-scale-sudan-april-2024. Accessed August 2, 2025.

Cash Consortium of Sudan (2024). Cash Works: Time to Act and Save Lives amid Starvation in Sudan. https://voiceeu.org/publications/cash-works-time-to-act-and-save-lives-amid-starvation-in-sudan-cash-consortium-of-sudan.pdf. Accessed August 2, 2025.

Christian, C., Hensel, L., and Roth, C. (2019). Income shocks and suicides: Causal evidence from Indonesia. *Review of Economics and Statistics*, 101(5):905–920.

Cohen, S., Kamarck, T., and Mermelstein, R. (1994). Perceived stress scale (pss). *Mind Garden. https://doi. org/10.1007/978-3-030-77644-2_91-1.*

Cunha, J. M. (2014). Testing paternalism: Cash versus in-kind transfers. *American Economic Journal: Applied Economics*, 6(2):195–230.

Cunha, J. M., De Giorgi, G., and Jayachandran, S. (2019). The price effects of cash versus in-kind transfers. *The Review of Economic Studies*, 86(1):240–281.

De Janvry, A., Finan, F., Sadoulet, E., and Vakis, R. (2006). Can conditional cash transfer programs serve as safety nets in keeping children at school and from working when exposed to shocks? *Journal of Development Economics*, 79(2):349–373.

Della Guardia, A., Lake, M., and Schnitzer, P. (2022). Selective inclusion in cash transfer programs: Unintended consequences for social cohesion. *World Development*, 157:105922.

Demirgüç-Kunt, A., Klapper, L. F., Singer, D., and Van Oudheusden, P. (2015). The global findex database 2014: Measuring financial inclusion around the world. *World Bank Policy Research Working Paper*, (7255).

Devex (2023). USAID pauses food aid to Ethiopia's Tigray region due to theft. https://www.devex.com/news/usaid-pauses-food-aid-to-ethiopia-s-tigray-region-due-to-theft-105457.

Diouf, J. and Sheeran, J. (2010). The state of food insecurity in the world: Addressing food insecurity in protracted crises. *World Food Program and Food and Agriculture Organization of the United Nations (FAO) Joint Report.*

Dodgson, M., Gann, D., Wladawsky-Berger, I., Sultan, N., and George, G. (2015). Managing digital money.

Ecker, O., Al-Malk, A., and Maystadt, J.-F. (2024). Civil conflict, cash transfers, and child nutrition in Yemen. *Economic Development and Cultural Change*, 72(4):000–000.

FAO (2014). FIES Basics – The Food Insecurity Experience Scale: Measuring food insecurity through people's experiences. Technical report, Food and Agriculture Organization of the United Nations (FAO).

FAO (2016). Voices of the Hungry: Methods for Estimating Comparable Prevalence Rates of Food Insecurity Experienced by Adults throughout the World. Technical report, FAO. Accessed: 2025-08-27.

FEWSNET (2021). Conflict and amacroeconomic crisis drive above-average needs through September 2021. FEWSNET. Accessed on 31 August 2025.

Field, E., Pande, R., Rigol, N., Schaner, S., and Troyer Moore, C. (2021). On her own account: How strengthening women's financial control impacts labor supply and gender norms. *American Economic Review*, 111(7):2342–2375.

Filmer, D. and Schady, N. (2011). Does more cash in conditional cash transfer programs always lead to larger impacts on school attendance? *Journal of Development Economics*, 96(1):150–157.

FSD Africa (2022). Supporting Digital Payments in Cash Programming Sudan. FSD Africa. Accessed on 31 August 2025.

Galiani, S. and McEwan, P. J. (2013). The heterogeneous impact of conditional cash transfers. *Journal of Public Economics*, 103:85–96.

Gentilini, U. (2016). Revisiting the "cash versus food" debate: New evidence for an old puzzle? *The World Bank Research Observer*, 31(1):135–167.

Ghatak, M. (2015). Theories of poverty traps and anti-poverty policies. *The World Bank Economic Review*, 29(suppl_1):S77–S105.

Ghorpade, Y. (2017). Extending a lifeline or cutting losses? The effects of conflict on household receipts of remittances in Pakistan. *World Development*, 99:230–252.

Ghorpade, Y. (2020). Calamity, conflict, and cash transfers: How violence affects access to aid in Pakistan. *Economic Development and Cultural Change*, 68(4):1131–1184.

Greco, G., Gulesci, S., Prabhakar, P., and Sulaiman, M. (2025). (Digital) cash transfers, privacy and women's empowerment: Evidence from Uganda. Technical report, Trinity College Dublin, Economics Department.

Hatløy, A., Hallund, J., Diarra, M. M., and Oshaug, A. (2000). Food variety, socioeconomic status and nutritional status in urban and rural areas in Koutiala (Mali). *Public Health Nutrition*, 3(1):57–65.

Haushofer, J., Niehaus, P., Paramo, C., Miguel, E., and Walker, M. (2025). Targeting impact versus deprivation. *American Economic Review*, 115(6):1936–1974.

Haushofer, J. and Shapiro, J. (2016). The short-term impact of unconditional cash transfers to the poor: Experimental evidence from Kenya. *The Quarterly Journal of Economics*, 131(4):1973–2042.

Haushofer, J. and Shapiro, J. (2018). The long-term impact of unconditional cash transfers: Experimental evidence from Kenya. *Busara Center for Behavioral Economics, Nairobi, Kenya*, 10.

Hidrobo, M., Hoddinott, J., Peterman, A., Margolies, A., and Moreira, V. (2014). Cash, food, or vouchers? Evidence from a randomized experiment in northern Ecuador. *Journal of Development Economics*, 107:144–156.

Hoddinott, J., Sandström, S., and Upton, J. (2018). The impact of cash and food transfers: Evidence from a randomized intervention in Niger. *American Journal of Agricultural Economics*, 100(4):1032–1049.

Hoddinott, J. F. and Yohannes, Y. (2002). Dietary diversity as a food security indicator.

Humanitarian Action (2025a). Sudan: Humanitarian needs and response plan 2025 – overview. https://www.unocha.org/publications/report/sudan/sudan-humanitarian-needs-and-response-plan-2025-overview. Accessed August 2, 2025.

Humanitarian Action (2025b). Sudan humanitarian response plan 2025. Technical report, Humanitarian Action. Accessed: 2025-09-08.

Idris, I. (2017). Conflict-sensitive cash transfers: social cohesion.

Idris, I. (2024). Humanitarian Digital Transfers in Challenging Contexts.

IFPRI and UNDP (2024). The socio-economic impact of armed conflict on sudanese urban households. Technical report, Working paper.

Jaroszewicz, A., Jachimowicz, J., Hauser, O., and Jamison, J. (2022). How effective is (more) money? Randomizing unconditional cash transfer amounts in the US. Technical report.

Jaspars, S., Murdoch, C., and Majid, N. (2022). Digital feast and famine.

Jeong, D. and Trako, I. (2022). Cash and in-kind transfers in Humanitarian settings. *World Bank Development Impact Evaluation Group, Policy Research Working Paper*, 10026.

Keen, D. (1991). III A disaster for whom? Local interests and international donors during famine among the Dinka of Sudan. *Disasters*, 15(2):150–165.

Kipchumba, E. and Sulaiman, M. (2021). Digital finance and intra-household decision-making: Evidence from mobile money use in Kenya. Technical report, Working paper.

Kirui, O. K., Siddig, K., Abushama, H., and Taffesse, A. S. (2023). *Armed conflict and business operations in Sudan: Survey evidence from agri-food processing firms*. International Food Policy Research Institute.

Kondylis, F. and Loeser, J. (2021). Intervention size and persistence. Policy Research Working Paper No. 9725, World Bank.

Kosec, K. and Mo, C. H. (2025). The unintended consequences of social transfer programs: Effects on conflict, governance, and social cohesion. *Annual Review of Resource Economics*, 17.

Lee, S., Abay, K. A., Barrett, C. B., and Hoddinott, J. (2025). Estimating multidimensional development resilience. *Journal of Development Economics*, page 103583.

Lind, J., Sabates-Wheeler, R., and Szyp, C. (2022). Cash and livelihoods in contexts of conflict and fragility: Implications for social assistance programming.

Lischer, S. K. (2003). Collateral damage: Humanitarian assistance as a cause of conflict. *International Security*, 28(1):79–109.

Maghsoudi, A., Harpring, R., Piotrowicz, W. D., and Kedziora, D. (2023). Digital technologies for cash and voucher assistance in disasters: A cross-case analysis of benefits and risks. *International Journal of Disaster Risk Reduction*, 96:103827.

Manley, J., Balarajan, Y., Malm, S., Harman, L., Owens, J., Murthy, S., Stewart, D., Winder-Rossi, N. E., and Khurshid, A. (2020). Cash transfers and child nutritional outcomes: A systematic review and meta-analysis. *BMJ Global Health*, 5(12):e003621.

McKenzie, D. (2012). Beyond baseline and follow-up: The case for more T in experiments. *Journal of Development Economics*, 99(2):210–221.

Mehrabi, Z., McDowell, M. J., Ricciardi, V., Levers, C., Martinez, J. D., Mehrabi, N., Wittman, H., Ramankutty, N., and Jarvis, A. (2021). The global divide in data-driven farming. *Nature Sustainability*, 4(2):154–160.

Mercy Corps (2023a). Sudan Conflict Response: CVA Case Study Series. Alternative Approaches to Multi-Purpose Cash Assistance Delivery in Active Conflict Contexts. https://www.calpnetwork.org/wp-content/uploads/2023/08/MC_MPCA__MFI_casestudy_Published.pdf. Accessed August 2025.

Mercy Corps (2023b). Sudan conflict response: CVA case study series: Piloting Mobile Money Cash assistance in Sudan. https://www.calpnetwork.org/publication/sudan-conflict-response-piloting-mobile-money-cash-assistance-in-sudan-cva-case-study-series/.

Mercy Corps and CALP Network (2023). Multipurpose cash assistance and microfinance institutions: Case study. https://www.calpnetwork.org/wp-content/uploads/2023/08/MC_MPCA__MFI_casestudy_Published.pdf. Accessed August 2025.

Ongudi, S., Thiam, D., Miranda, M. J., and Abdoul, S. (2024). The direct and indirect effects of cash transfer program on the consumption of nutrients: Evidence from Kenya. *Agricultural Economics*, 55(3):454–478.

Premand, P. and Rohner, D. (2024). Cash and conflict: Large-scale experimental evidence from Niger. *American Economic Review: Insights*, 6(1):137–153.

Raleigh, C., Linke, R., Hegre, H., and Karlsen, J. (2010). Introducing ACLED: An armed conflict location and event dataset. *Journal of Peace Research*, 47(5):651–660.

Riley, E. (2024). Resisting social pressure in the household using mobile money: Experimental evidence on microenterprise investment in Uganda. *American Economic Review*, 114(5):1415–1447.

Rohner, D. and Thoenig, M. (2021). The elusive peace dividend of development policy: From war traps to macro complementarities. *Annual Review of Economics*, 13:111–131.

Sabates-Wheeler, R., Lind, J., and Holland-Szyp, C. (2025). The limits to cash-plus provision in protracted crises. *Development Policy Review*, 43(4):e70020.

Sarwar, M. B., Diepeveen, S., and Moreno, D. B. (2023). Cash transfers and digital financial inclusion: Regional evidence from Asia Pacific with a focus on Bangladesh, Cambodia, and Nepal. Technical report, ODI Report.

Shimada, H. (2025). Aid paradox for unrecognized governments: The Taliban and aid. *Development Policy Review*, 43(3):e70008.

Siddig, K., Nigus, H. Y., Abushama, H., Mohamed, S., and Rakhy, T. (2025). Essential commodities prices, availability, and market actors' perceptions: February 2025. Technical report.

Smith, G. (2025). Maintaining and strengthening social assistance systems in conflict settings: Sudan case study.

SPARC (2024). Darfur's long-distance trade: The impact of war and the rapid support forces on trade. https://www.sparc-knowledge.org/publications-resources/darfurs-long-distance-trade-impact-war-and-rapid-support-forces-trade. Accessed August 2025.

Suri, T. (2017). Mobile money. *Annual Review of Economics*, 9(1):497–520.

Suri, T., Aker, J., Batista, C., Callen, M., Ghani, T., Jack, W., Klapper, L., Riley, E., Schaner, S., and Sukhtankar, S. (2023). Mobile money. *VoxDevLit*, 2(2):3.

Tappis, H. and Doocy, S. (2018). The effectiveness and value for money of cash-based humanitarian assistance: A systematic review. *Journal of Development Effectiveness*, 10(1):121–144.

Telecommunications, S. and Authority, P. R. (2018). Annual report 2017/2018. Accessed: 28 August 2025.

Thomas, E. and De Waal, A. (2022). Hunger in Sudan's political marketplace. *World Peace Foundation*.

UN OCHA (2023). Global Humanitarian Overview 2023, October Update (Snapshot as of 31 October 2023). https://www.unocha.org/publications/report/world/global-humanitarian-overview-2023-october-update-snapshot-31-october-2023.

UNHCR (2024). How Do People Use Cash Assistance from UNHCR? https://dataviz.unhcr.org/product-gallery/2024/05/how-do-people-use-cash-assistance-from-unhcr/. Accessed August 2025.

UNHCR (2025). Sudan Situation: Regional Refugee Response Plan – Mid-Year Update (January - June 2024). https://data.unhcr.org/en/documents/details/117796. Accessed August 2025.

World Bank (2020). Project Information Document - Sudan Family Support Program. https://documents.worldbank.org/pt/publication/documents-reports/documentdetail/221631600765395284/project-information-document-sudan-family-support-program-sfsp-p173521. Accessed August 31, 2025.

World Bank (2024). Implementation Completion and Results Report on a Grant to the World Food Programme for the Sudan Emergency Safety Nets Project. World Bank document. Accessed on 28 August 2025.

World Food Programme (2008). Food Consumption Analysis: Calculation and Use of the Food Consumption Score in Food Security Analysis. Technical report, World Food Programme.

World Food Programme (2020). Comprehensive Food Security and Vulnerability Assessment (CFSVA) Summary Report, Q1 2020. WFP. Accessed on 31 August 2025.

World Food Programme (2021). Digital Cash Transfers in Lao PDR 2021. https://www.wfp.org/publications/digital-cash-transfers-lao-pdr-2021. Accessed August 2025.

World Food Programme (2024). Annual country reports: Sudan. https://www.wfp.org/publications/annual-country-reports-sudan. Accessed August 2025.

Wormald, A., Agarwal, R., Braguinsky, S., and Shah, S. K. (2021). David overshadows Goliath: Specializing in generality for internationalization in the global mobile money industry. *Strategic Management Journal*, 42(8):1459–1489.

A. Supplementary Tables

Table A1: Balance test between treatment and control groups - full sample

	Pre - Ramadan	Ramadan	Pairwise t-test(P-value)
Main outcome variables			
FCS (0 - 112)	68.96	69.07	0.91
	(1.10)	(1.19)	
DDS (0 - 8)	7.04	6.98	0.25
	(0.06)	(0.08)	
FIES (0 - 8)	3.22	3.24	0.81
	(0.12)	(0.10)	
No food stock (No stock=1)	0.34	0.35	0.68
	(0.02)	(0.02)	
Stress (0 - 40)	21.95	22.13	0.61
	(0.24)	(0.26)	
Moderate stress (moderate=1)	0.91	0.93	0.39
	(0.01)	(0.01)	
severe stress (severe=1)	0.25	0.23	0.49
	(0.02)	(0.02)	
Household characteristics			
Respondent gender (male=1)	0.38	0.38	0.74
	(0.01)	(0.01)	
Head gender (male=1)	0.89	0.87	0.09*
	(0.01)	(0.01)	
Head age	44.55	43.76	0.08*
	(0.31)	(0.42)	
Head education: low	0.21	0.20	0.36
	(0.02)	(0.02)	
Head education: medium	0.50	0.51	0.52
	(0.01)	(0.02)	
Head education: high	0.29	0.29	0.91
	(0.02)	(0.03)	
Household size	8.80	8.79	0.97
	(0.17)	(0.22)	
Married	0.83	0.84	0.73
	(0.01)	(0.01)	
Poor or poorer than many	0.55	0.56	0.69
	(0.02)	(0.02)	
Exposure to street violence	0.29	0.30	0.52
	(0.02)	(0.02)	
Exposure to intrahousehold violence	0.01	0.02	0.69
	(0.00)	(0.00)	
Exposure to sexual violence	0.01	0.01	0.84
	(0.00)	(0.00)	
Exposure to SAF RSF	0.13	0.14	0.90
	(0.02)	(0.03)	
Feeling insecure	0.19	0.20	0.56
	(0.02)	(0.03)	
Have electricity	0.89	0.88	0.33
	(0.02)	(0.02)	
Able to visit market	0.86	0.87	0.51
	(0.01)	(0.02)	
Received assistance	0.46	0.46	0.96
	(0.01)	(0.02)	
House material: brick	0.50	0.50	0.98
	(0.03)	(0.03)	
House material: mud	0.25	0.22	0.08*
	(0.02)	(0.02)	
Have bank account	0.58	0.58	0.75
	(0.02)	(0.03)	
Modality of transfer (Bangak=1)	0.49	0.52	0.12
	(0.01)	(0.01)	
Modality of transfer (Fawry/cashi=1)	0.04	0.04	0.69
	(0.00)	(0.01)	
Modality of transfer (Airtime=1)	0.47	0.44	0.07*
	(0.01)	(0.01)	
RSF controlled areas	0.04	0.06	0.03**
	(0.01)	(0.01)	
Number of battle events	0.02	0.02	0.99
	(0.12)	(0.12)	
Observations	1549	1033	

Notes. This table compares baseline household characteristics and associated outcomes across the control and two treatment arms. Columns (1) and (2) report mean values and standard errors. The last column report p-values from pairwise comparisons and t-tests. Standard errors are clustered at locality level, *** p<0.01, ** p<0.05, * p<0.1.

Table A2: The impact of digital transfer is higher among states controlled by RSF

	FCS	DDS	FIES	Food insecurity	SWB index (std)	Stress	Anxiety
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment: 50 USD	2.839*	0.361***	-0.711***	-0.052	0.256***	-0.970**	-0.323
	(1.506)	(0.084)	(0.190)	(0.035)	(0.076)	(0.421)	(0.468)
Treatment: 75 USD	1.961	0.180	-0.169	-0.012	0.067	0.046	0.450
	(1.970)	(0.136)	(0.222)	(0.031)	(0.086)	(0.527)	(0.464)
50 USD # RSF areas	-2.173	-0.232	0.438	0.034	-0.128	0.321	-0.021
	(2.169)	(0.149)	(0.279)	(0.043)	(0.110)	(0.703)	(0.608)
75 USD # RSF areas	2.508	-0.046	-0.918***	-0.125***	0.181	-1.776*	-1.942**
	(2.941)	(0.179)	(0.317)	(0.045)	(0.117)	(0.908)	(0.819)
R-squared	0.017	0.081	0.037	0.025	0.090	0.027	0.029
Observations	1,509	1,495	1,489	1,509	1,486	1,475	1,486

Notes. The dependent variables in columns (1) through (4) are food (in) security indicators - FCS, DDS, FIES Food insecurity, respectively. In column 5, the dependent variable is a standardized subjective well-being index. In columns 6 and 7, the dependent variables measures of mental health problems - symptoms of stress and GAD score, respectively. Treatment 50 USD and 75 USD are binary indicators taking a value of 1 for those households assigned to the digital cash transfer intervention and 0 otherwise. RSF areas is a binary variable taking a value of 1 for those households living in the RSF controlled areas, 0 otherwise. Standard errors, clustered at locality level, are given in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A3: The impact of digital transfer is lower for those relatively poor or poorest

	FCS	DDS	FIES	Food insecurity	SWB index (std)	Stress	Anxiety
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment: 50 USD	3.196*	0.461***	-0.860***	-0.071**	0.276***	-2.161***	-1.015**
	(1.786)	(0.097)	(0.226)	(0.031)	(0.101)	(0.609)	(0.474)
Treatment: 75 USD	5.085**	0.453***	-0.894***	-0.094**	0.194*	-1.762**	-0.852
	(2.086)	(0.117)	(0.286)	(0.040)	(0.100)	(0.712)	(0.568)
Relatively poor	-1.160	0.038	0.045	0.005	-0.086	-0.417	0.162
	(1.965)	(0.120)	(0.233)	(0.030)	(0.078)	(0.517)	(0.450)
50 USD # relatively poor	-2.541	-0.375**	0.673*	0.066	-0.152	2.422***	1.271**
	(2.702)	(0.146)	(0.365)	(0.042)	(0.144)	(0.832)	(0.630)
75 USD # relatively poor	-3.452	-0.415**	0.464	0.034	0.000	1.661**	0.572
	(3.023)	(0.182)	(0.403)	(0.050)	(0.131)	(0.800)	(0.687)
Observations	1,496	1,496	1,476	1,496	1,486	1,462	1,473
R-squared	0.021	0.017	0.035	0.022	0.026	0.033	0.008

Notes. The dependent variables in columns (1) through (4) are food (in) security indicators - FCS, DDS, FIES Food insecurity, respectively. In column 5, the dependent variable is a standardized subjective well-being index. In columns 6 and 7, the dependent variables measure mental health problems - symptoms of stress and anxiety, respectively. Treatment 50 USD and 75 USD are binary indicators taking a value of 1 for those households assigned to the digital cash transfer intervention and 0 otherwise. Relative poverty is a binary variable taking a value of 1 for poor or poorest households, 0 otherwise. Standard errors, clustered at locality level, are given in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A4: The impact of digital transfer is lower for those relatively large households

	FCS	DDS	FIES	Food insecurity	SWB index (std)	Stress	Anxiety
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment: 50 USD	2.847	0.391***	-0.816***	-0.041	0.326***	-1.676***	-1.404***
	(1.890)	(0.129)	(0.244)	(0.036)	(0.095)	(0.440)	(0.464)
Treatment: 75 USD	4.378**	0.376***	-1.002***	-0.105**	0.337***	-1.171	-1.003
	(2.197)	(0.139)	(0.271)	(0.044)	(0.121)	(0.778)	(0.814)
Large HH size	1.487	0.143	-0.403*	-0.043	0.131	-1.277***	-1.065*
	(1.779)	(0.114)	(0.228)	(0.031)	(0.105)	(0.483)	(0.546)
50USD # Large HH size	-1.950	-0.247	0.571	0.014	-0.220*	1.513**	1.814***
	(2.484)	(0.170)	(0.347)	(0.044)	(0.124)	(0.662)	(0.658)
75USD # Large HH size	-1.914	-0.269	0.605*	0.050	-0.239	0.564	0.808
	(2.633)	(0.163)	(0.362)	(0.060)	(0.145)	(0.839)	(0.845)
Constant	57.614***	6.678***	4.666***	0.862***	-0.197***	22.263***	9.324***
	(2.491)	(0.249)	(0.178)	(0.025)	(0.068)	(0.830)	(0.421)
R-squared	0.016	0.024	0.030	0.020	0.023	0.026	0.006
Observations	1,509	1,509	1,489	1,509	1,499	1,475	1,486

Notes. The dependent variables in columns (1) through (4) are food (in) security indicators - FCS, DDS, FIES Food insecurity, respectively. In column 5, the dependent variable is a standardized subjective well-being index. In columns 6 and 7, the dependent variables measures of mental health problems - symptoms of stress and GAD score, respectively. Treatment 50 USD and 75 USD are binary indicators taking a value of 1 for those households assigned to the digital cash transfer intervention and 0 otherwise. Large household size is a binary variable taking a value of 1 for those households with eight members and above, 0 otherwise. Standard errors, clustered at locality level, are given in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A5: The impact of digital transfer is lower for those without additional income

	FCS	DDS	FIES	Food insecurity	SWB index (std)	Stress	Anxiety
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treatment:50 USD	-0.011	-0.002	0.007	0.021	0.134	-0.328	1.194*
	(2.388)	(0.168)	(0.287)	(0.033)	(0.116)	(0.618)	(0.687)
Treatment:75 USD	-0.987	0.021	-0.183	-0.019	-0.053	0.356	1.191
	(2.534)	(0.213)	(0.336)	(0.034)	(0.115)	(0.602)	(0.779)
Have income source	9.129***	0.564***	-1.195***	-0.095***	0.290***	-2.997***	-1.689***
	(1.955)	(0.156)	(0.297)	(0.031)	(0.103)	(0.600)	(0.523)
50 USD # Have income source	2.173	0.324*	-0.635*	-0.073	0.080	-0.590	-2.040**
	(2.960)	(0.180)	(0.363)	(0.045)	(0.144)	(0.803)	(0.829)
75 USD # Have income source	5.505**	0.253	-0.600*	-0.074*	0.330**	-1.605**	-2.266***
	(2.632)	(0.220)	(0.338)	(0.038)	(0.139)	(0.755)	(0.759)
R-squared	0.067	0.077	0.087	0.043	0.057	0.086	0.063
Observations	1,509	1,509	1,489	1,509	1,499	1,475	1,486

Notes. The dependent variables in columns (1)-(4) are food (in) security indicators - FCS, DDS, FIES, and Food insecurity, respectively. In column 5, the dependent variable is a standardized subjective well-being index. In columns 6 and 7, the dependent variables measure mental health problems - symptoms of stress and anxiety, respectively. Treatment 50 USD and 75 USD are binary indicators taking a value of 1 for those households assigned to the digital cash transfer intervention and 0 otherwise. Have income source is a binary variable taking a value of 1 for those households who have alternative income sources and 0 otherwise. Standard errors, clustered at locality level, are given in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A6: Impact of digital cash transfer on food security: food consumption and dietary diversity score - full sample

	Food Consumption Score				Dietary Diversity Score			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	2.227***	2.184***			0.200***	0.197***		
	(0.842)	(0.826)			(0.057)	(0.056)		
Treatment:50 USD			1.715*	1.700*			0.208***	0.206***
			(1.000)	(0.994)			(0.063)	(0.062)
Treatment:75 USD			2.730**	2.661**			0.193**	0.187**
			(1.113)	(1.082)			(0.075)	(0.073)
R-squared	0.011	0.019	0.012	0.019	0.013	0.019	0.013	0.019
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Mean of control	60.55	60.55	60.55	60.55	6.75	6.75	6.75	6.75
P-value (50 vs 75 USD)			0.43	0.45			0.85	0.81
Observations	2,509	2,509	2,509	2,509	2,509	2,509	2,509	2,509

Notes. This table reports results from ANCOVA regressions characterizing food consumption score (FCS) (columns 1-4) and dietary diversity score (DDS) (columns 5-8). Treatment is a binary variable taking a value of 1 for those households assigned to the digital cash transfer intervention and 0 otherwise. Controls include: respondent gender, respondent age, education level of the household head, household size, access to electricity, marital status, housing condition, and having a bank account. Standard errors, clustered at locality level, are given in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A7: Impact of digital cash transfer on food security: food insecurity experience scale - full sample

	Food Insecurity Experience Scale (FIES)				Food Insecurity (FIES>1)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	-0.329***	-0.329***			-0.001	-0.001		
	(0.114)	(0.113)			(0.015)	(0.015)		
Treatment:50 USD			-0.200	-0.204			0.021	0.020
			(0.134)	(0.135)			(0.016)	(0.016)
Treatment:75 USD			-0.456***	-0.452***			-0.023	-0.022
			(0.149)	(0.147)			(0.021)	(0.021)
R-squared	0.012	0.018	0.013	0.019	0.007	0.016	0.009	0.018
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes	No	Yes	No	Yes
Mean of control	4.21	4.21	4.21	4.21	0.79	0.79	0.79	0.79
P-value (50 vs 75 USD)			0.12	0.13			0.04	0.05
Observations	2,477	2,477	2,477	2,477	2,509	2,509	2,509	2,509

Notes. The dependent variable in columns (1)-(4) is Food Insecurity Experience Scale (FIES) while the dependent variable in columns (1)-(4) is a binary indicator capturing experience of food insecurity (FIES>=1). Treatment is a binary variable taking a value of 1 for those households assigned to the digital cash transfer intervention and 0 otherwise. Controls include: respondent gender, respondent age, education level of the household head, household size, access to electricity, marital status, housing condition, and having a bank account. Standard errors, clustered at locality level, are given in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A8: Impact of digital cash transfer on subjective well-being - full sample

	Happy or very happy		Satisfied		Good economic condition		SWB index (std)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	0.056***		0.026		0.025		0.084*	
	(0.021)		(0.019)		(0.019)		(0.046)	
Treatment:50 USD		0.062**		0.031		0.011		0.091**
		(0.025)		(0.020)		(0.019)		(0.045)
Treatment:75 USD		0.050**		0.021		0.039*		0.078
		(0.023)		(0.025)		(0.023)		(0.059)
R-squared	0.019	0.019	0.026	0.026	0.020	0.020	0.020	0.020
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Mean of control	0.70	0.70	0.59	0.59	0.23	0.23		
50 USD vs 75 USD		0.57		0.68		0.15		0.79
Observations	2,509	2,509	2,509	2,509	2,509	2,509	2,495	2,495

Notes. This table reports results from ANCOVA regressions characterizing self-reported happiness (columns 1–2), life satisfaction (columns 3–4), perceived economic condition (columns 5–6), and standardized subjective well-being index (columns 7-8). Happiness is measured as a binary indicator equal to 1 if the respondent reports being "happy" or "very happy." Life satisfaction is a binary indicator equal to 1 if the respondent rates their overall life satisfaction above 5 on a 0–10 scale. Perceived economic condition is a binary indicator equal to 1 if the respondent reports their economic situation as "good" or "very good." Treatment is a binary variable assuming a value of 1 for those households assigned to the digital cash transfer intervention and 0 otherwise. Controls include: respondent gender, respondent age, education level of the household head, household size, access to electricity, marital status, housing condition, and having a bank account. Standard errors, clustered at locality level, are given in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A9: Impact of digital cash transfer on mental health - full sample

	Stress		Severe stress		GAD score		Severe anxiety	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Treatment	-0.059		-0.010		0.099		0.003	
	(0.307)		(0.018)		(0.243)		(0.008)	
Treatment:50 USD		-0.073		-0.006		0.176		0.006
		(0.289)		(0.018)		(0.261)		(0.010)
Treatment:75 USD		-0.046		-0.014		0.023		-0.000
		(0.410)		(0.023)		(0.346)		(0.011)
Constant	23.818***	23.819***	0.509**	0.509**	11.152**	11.143**	0.251*	0.250*
	(4.052)	(4.053)	(0.247)	(0.247)	(4.735)	(4.737)	(0.128)	(0.129)
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R-squared	0.017	0.017	0.013	0.013	0.019	0.019	0.005	0.005
Mean of control	21.23	21.23	0.21	0.21	8.36	8.36	0.09	0.09
50 USD vs 75 USD		0.93		0.29		0.67		0.53
Observations	2,462	2,462	2,462	2,462	2,480	2,480	5,018	5,018

Notes. The dependent variables in columns (1)-(4) are continuous and binary indicators of stress while the dependent variables in columns (5)-(6) capture continuous and binary indicators of anxiety. Stress is measured using the 10-item Perceived Stress Scale, with responses ranging from 0 (low stress) to 40 (high stress). Severe stress is defined as PSS $\geq$ 27 (binary indicator). Anxiety is measured using the Generalized Anxiety Disorder (GAD-7) scale, ranging from 0 to 21, with severe anxiety defined as GAD $\geq$ 15 (binary indicator). Treatment is a binary variable taking a value of 1 for those households assigned to the digital cash transfer intervention and 0 otherwise. Controls include: respondent gender, respondent age, education level of the household head, household size, access to electricity, marital status, housing condition, and having a bank account. Standard errors, clustered at locality level, are given in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

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