RUHR ECONOMIC PAPERS

Christoph Strupat
Emmanuel Nshakira-Rukundo
Arndt Reichert

The Impact of Shock-Responsive Social Cash Transfers: Evidence from an Aggregate Shock in Kenya

rwi #1073

Imprint

Ruhr Economic Papers

Published by

RWI – Leibniz-Institut für Wirtschaftsforschung
Hohenzollernstr. 1-3, 45128 Essen, Germany

Ruhr-Universität Bochum (RUB), Department of Economics
Universitätsstr. 150, 44801 Bochum, Germany

Technische Universität Dortmund, Department of Economic and Social Sciences
Vogelpothsweg 87, 44227 Dortmund, Germany

Universität Duisburg-Essen, Department of Economics
Universitätsstr. 12, 45117 Essen, Germany

Editors

Editorial Office

Ruhr Economic Papers #1073

Responsible Editor: Manuel Frondel

ISSN 1864-4872 (online) – ISBN 978-3-96973-246-5

Ruhr Economic Papers #1073

Christoph Strupat, Emmanuel Nshakira-Rukundo, and Arndt Reichert

The Impact of Shock-Responsive Social Cash Transfers: Evidence from an Aggregate Shock in Kenya

Bibliografische Informationen der Deutschen Nationalbibliothek

The Deutsche Nationalbibliothek lists this publication in the Deutsche Nationalbibliografie; detailed bibliographic data are available on the Internet at **http://dnb.dnb.de**

RWI is funded by the Federal Government and the federal state of North Rhine-Westphalia.

http://dx.doi.org/10.4419/96973246
ISSN 1864-4872 (online)
ISBN 978-3-96973-246-5

Christoph Strupat, Emmanuel Nshakira-Rukundo, and Arndt Reichert*

The Impact of Shock-Responsive Social Cash Transfers: Evidence from an Aggregate Shock in Kenya

Abstract

This study examines the effects of a nationwide shock-responsive social cash transfer scheme during an aggregate shock, with a focus on highly risk susceptible informal sector households in Kenya. Leveraging primary in-person survey data in a doubly robust difference-in-differences framework, we find that households receiving shock-responsive cash transfers were less likely to encounter income loss, poverty, and food scarcity compared to households not receiving them. The scheme also reduced the likelihood of engaging in costly risk coping such as selling productive assets. When comparing different pillars of the scheme with varying degrees of shock-responsiveness, we observe that the impacts were statistically significant only when payment cycles were pooled and the transfers were vertically scaled. The study adds to the global policy discussion on developing effective shock-responsive interventions, underscoring the merits of (adapted) social cash transfers during crises.

JEL-Codes: I13, I15, I18, J01

Keywords: Cash transfers; shock-responsiveness; COVID-19; Kenya

March 2024

* *Christoph Strupat, German Institute of Development and Sustainability (IDOS); Emmanuel Nshakira-Rukundo, RWI, University of Bonn/Germany and Apata Insights, Kampala/Uganda; Arndt Reichert, Leibniz University Hannover.* *– The authors would like to express their gratitude to Abel Oyuke, Sam Balongo, Rudolf Traub-Merz, and all members of the survey project team. Many thanks to the Institute of Development Studies of the University of Nairobi for their exceptional fieldwork. The author would like to further thank Prof. Dr. Matin Qaim and Prof. Dr. Matthias Rieger for giving feedback on earlier versions of this study.* *– All correspondence to: Christoph Strupat, German Institute of Development and Sustainability (IDOS), Tulpenfeld 6, 53113 Bonn Germany, e-mail: christoph.strupat@idos-research.de*

Introduction

Insurance markets in low and middle-income countries often fall short in coverage and benefits. These limitations particularly apply to the large population group of informal sector households which are also among those most vulnerable to idiosyncratic economic shocks (Fink, Jack, & Masiye, 2020).[1] They can receive (partial) protection through informal local insurance networks (Ambrus, Mobius, & Szeidl, 2014; Jack & Suri, 2014; Robinson, 2012; Strupat & Klohn, 2018) and financial support from social protection programs such as cash transfer schemes (e.g., Daidone, Davis, Handa, and Winters (2019), Lawlor, Handa, and Seidenfeld (2019), de Janvry, Finan, Sadoulet, and Vakis (2006)).

Aggregate shocks such as pandemics, natural disasters, floods due to climate change, and conflict challenge traditional and informal risk-pooling systems by affecting a large number of households at once on both the income and expenditure side (Banerjee, Hanna, Olken, & Lisker, 2024). In addition, the typical emergency relief responses face several challenges, ranging from difficulties in promptly identifying and meeting the needs of the affected populations (e.g., Clarke and Dercon (2016)).[2] This can lead to severe (food) consumption cuts and harmful coping strategies, such as selling off assets, which can trap households in a cycle of poverty (Andrabi, Daniels, & Das, 2023; Dercon & Porter, 2014).

With the rise in the frequency and severity of aggregate shocks World Economic Forum (2023), a vital global policy discourse on the conceptualization and design of shock-responsive programs that effectively protect households from the devastating consequences has emerged (Banerjee et al., 2024). We aim to inform this debate by presenting empirical evidence of the effects of a large social cash transfer scheme among informal sector households experiencing a large aggregate shock. Development practitioners particularly value three features of shock-responsive cash transfer schemes that are deemed to be especially important in the presence of aggregate shocks. First, a registry of hard-to-target informal sector

[1] Some of the challenges of social insurance programs associated with a large informal sector in developing countries are carefully examined by Banerjee et al. (2021) in the context of universal health insurance in India.

[2] To expedite aid, emergency relief could issue universal payments to everyone in a crisis zone, akin to a basic income approach. Yet, a significant drawback is the modest amount distributed to each individual, which may be insufficient for their needs (Hanna & Olken, 2018)

households is readily available. Second, developed delivery mechanisms can be leveraged for a speedy provision of financial support. Third, the administrative financing architecture is in place that allows the pooling of domestic and international funds for program expansion, which can be both vertical (scaling up financial support to current recipients) and horizontal (extending coverage to new informal sector households). Thus, shock-responsive social cash transfer programs have several inherent characteristics that make them particularly appealing to leverage for an adaptive response to aggregate shocks.[3] The degree of shock responsiveness is arguably a function of the combination of adapted features to provide the greatest population protection against aggregate shocks.

We study the value of Kenya's shock-responsive social cash transfer scheme using own primary in-person repeated cross-sectional survey data of informal sector households that were exposed to the adverse economic consequences of the COVID-19 pandemic and associated containment measures. Just like most emerging economies, Kenya experienced a large negative economic shock with a net contraction of more than five percentage points due to the outbreak of the coronavirus (Decerf, Ferreira, Mahler, & Sterck, 2021). To mitigate economic hardship, the two pillars of the scheme – the National Safety Net Program (NSNP) and the Hunger Safety Net Programme (HSNP) that cover in total between 1.0 and 1.5 million informal sector participants and tend to be comparable in terms of the size of the social cash transfer and targeting strategies – responded to the pandemic in a manner that makes them unique for both our research objectives and crafting of future policies.

Participants of either program received cash transfers via mobile money to respect containment policies. Participants of the NSNP received a lump sum of KES 8,000 (USD 78) in the month the first coronavirus cases were detected nationally, i.e., March 2020. A second tranche of KES 4,000 (USD 40) was disbursed as a lump sum at the end of June 2020. The total of these two lump sums is equivalent to the monetary value of the standard cash transfer of KES 2,000 (20 USD) that was delivered every month before the pandemic and after

[3] The same three operational dimensions indeed appear to have received particular attention at the design phase of all explicit shock-responsive programs that were systematically recorded: (i) identification of households in need, (ii) dynamic delivery of support, (iii) and expansion financing (e.g., FAO (2023)).

June 2020. By temporarily diverting from periodic payments through the pooling of payment cycles, relatively large payments were made during an arguably very critical time. Additional monthly cash top-ups of up to roughly KES 6,000 (USD 60) were provided during the same period, i.e., between March and June 2020, to participating households by the United Nations Children's Fund (UNICEF), the World Food Programme (WFP), and an EU-funded consortium led by the Kenyan Red Cross Society and Oxfam. Hence, the NSNP was vertically expanded during the pandemic. By and large, the HSNP adapted to the pandemic in the same way, except that the there was no pooling of payment cycles of the bi-monthly transfer of KES 5,400 (USD 50) and no vertically expansion of the cash transfer size. While we primarily evaluate the overall impact of the two-pillared scheme in this paper, we also estimate the distinct effects of each program in a detailed heterogeneity analysis. This allows us to elucidate the relevance of pooling of payment cycles and vertically scaling the social cash transfer during an aggregate shock.

The effectiveness of shock-responsive social cash transfer schemes in terms of protecting informal sector households from (food) poverty as well as employing costly means of consumption smoothing in times of aggregate shocks is far from certain for various reasons. First, informal-sector households pre-identified to receive cash transfers may not be those suffering most from an aggregate shock, causing the program to fail to provide effective protection (Banerjee et al., 2024). Second, despite possible timing advantages over alternative social protection measures during aggregate shocks, it is unclear whether the cash transfer arrives before the depletion of precautionary savings and the use of costly means of risk coping such as selling assets (Bazzi, Sumarto, & Suryahadi, 2015). As the timing of payments of transfers depends on many logistical aspects, especially amid an aggregate shock, it may be less likely that they will arrive when they are most needed. This raises the empirical question of whether (shock-responsive) social cash transfer schemes protect households from (food) poverty and costly means of consumption smoothing. Third, disruptions in markets may dampen the effects of shock-responsive social cash transfer schemes on households' (food) consumption (Banerjee, Faye, Krueger, Niehaus, & Suri, 2020). For example, their efficacy may be compromised by disruptions in supply chains.

We first descriptively show that informal sector households in Kenya had hardly any access to loans to cope with the financial implications of the pandemic using own survey data covering a total of almost three and a half thousand observations across waves. These data are representative of the entire informal economy, accounting for the majority of the Kenyan population.[4] They further suggest that informal insurance networks were largely unable to support Kenyan households during the pandemic. We then present novel descriptive statistics revealing important coverage limitations of the typical emergency response, which consisted of separate COVID-19 relief programs by the Kenyan government. The negligible number of self-reported recipients of these programs in our nationally representative survey of the informal economy, on the one hand, and increased levels of (food) poverty as well as depleted assets among the average informal sector household, on the other hand, suggest that the new relief programs did not provide sufficient protection.

The main part of the paper consists of the estimation of the causal effects of the shock-responsive social cash transfer scheme. The difference in the estimated impacts of its two pillars is examined in an effect heterogeneity section. We utilise own data from in-person surveys conducted among informal sector households before and after the first wave of the pandemic in Kenya. Following a doubly robust difference-in-differences approach (Sant'Anna & Zhao, 2020), we compare informal sector households which are recipients of the social cash transfers with informal sector households not receiving these transfers before and after the onset of the pandemic. Abay, Berhane, Hoddinott, and Tafere (2021) adopt a comparable methodology, utilising a difference-in-differences approach in their examination of the effectiveness of a predominantly stable cash and in-kind rural transfer program in mitigating food insecurity during the COVID-19 pandemic in Ethiopia.

The identifying assumption underlying the estimation strategy is that the difference between recipients and non-recipients would be constant if the economic shock resulting from the pandemic and associated containment measures had not happened. To illuminate the validity of this assumption, we differentiate the effects on Kenyan counties based on their COVID-19 impact levels as per

[4] The sampling was purposely done for the informal sector as this population segment is most vulnerable to aggregate shocks.

data on lockdowns and infection transmission that are provided in Brand et al. (2021) and adjusted for differences in testing capacity as well as reporting errors. We anticipate that if our assumption is correct, the discrepancy in economic outcomes between participants and non-participants in the social cash transfer scheme will be marginal between our two data points collected about three months before and about three months after the first wave of the pandemic in counties with insignificant pandemic exposure. We specifically utilize the curated data regarding lockdowns and the spread of infections to distinguish among three types of counties: (1) those with a high number of COVID-19 cases that enacted significant lockdown measures, (2) those with a high number of COVID-19 cases but did not implement lockdown measures, and (3) those with a relatively low number of COVID-19 cases and no lockdown measures. With counties of the third category, we can arguably explore the change in potential outcomes in the absence of the major aggregate shock. First, in these counties, the infection risk was minimal, and only broad, national containment policies were enforced, affecting workers in the informal sector only slightly. Therefore, it appears unlikely that the economic activities in these counties were significantly disrupted by the aggregate shock (Goolsbee & Syverson, 2021).

Descriptive statistics show that there was indeed no major shift in the economic situation over time in the control group in counties with a relatively low number of COVID-19 cases and no lockdown measures. According to our data, respective households experienced, if at all, a relatively small economic shock that did not significantly affect, for instance, the propensities of becoming poor and depleting productive assets. Second, the social cash transfer scheme was operational in these counties throughout our observation period such that the average informal sector household participating in the social cash transfer program before the pandemic received either roughly the same (in case of the HSNP) or an even large amount of financial support (in case of the NSNP) during the pandemic even though the county of residence was minimally affected. In support of this argumentation, we document that in our data COVID-19 impact levels in a county are unrelated to its social cash transfer prevalence.

Kenya offers a pertinent case for examining the responsiveness of social safety nets to aggregate shocks, having prioritised this area for over a decade. Within global discussions on crafting shock-responsive programs, Kenya's social cash transfer scheme stands out, noted for its innovative features Banerjee et al. (2024). The government's prior experience proved invaluable in addressing the recent aggregate shock. For example, the HSNP is designed to flexibly modify cash grants during droughts Gardener et al. (2017). More recent efforts have rather focused on the NSNP and its adaptation capacities. In particular, a social registry aimed to cover half the population is currently developed, which will enable targeting vulnerable groups in both normal and crisis times. Yet, this registry was not established when the pandemic commenced, leading to an emphasis on increasing the amounts in the existing social cash transfer scheme (vertical expansion) rather than expanding its reach (horizontal expansion). Fortunately, this focus in the expansion aligns with our methodological approach, as it means the selection criteria remained the same during the pandemic, avoiding the addition of new recipients to either program (Doyle & Ikutwa, 2021) . Hence, we can effectively consider pre-pandemic differences between the two groups in our analyses.

Our findings indicate that households enrolled in the shock-responsive social cash transfer scheme were 11 percentage points less likely to report a decline in income over the past year, compared to non-participating households. This corresponds to a 17 percent lower probability of income reduction. Similarly, participating households were also 11 percentage points less likely to report being poor (a relative decrease of about 22 percent) and 10 percentage points less likely of being short of food. Importantly, relative to non-participants, they also had a 7 percentage points lower probability of selling assets during the pandemic.

In addition, we find evidence that the statistically significant effects are confirmed only in the case of the NSPN, which pooled payment cycles and provided vertically scaled transfers. This suggests that these design adaptations were an important aspect of the response to the pandemic. Our findings, hence, indicate that amid the systemic COVID-19 crisis, shock-responsive social cash transfer programs can offer effective safeguards against the dangers of temporarily slipping below subsistence levels and facing heightened threats of irreversible productivity losses.

Our estimation approach passes several checks. First, we show that the observed effects of the shock-responsive schemes are driven by counties that experienced a relatively large aggregate shock. Moreover, in line with our identifying assumption, we do not observe any effects among counties without lockdown measures and low COVID-19 incidence but where cash transfer recipients continued to receive at least the same level of financial support. Second, we show that there were no systematic differences between and within the cross-sectional samples, suggesting that the effects observed are driven by the treatment and not by compositional changes in the samples. Eventually, we show that our findings are not subject to regression-to-the-mean bias. For this, we use only time-invariant controls in our standard estimations (Zeldow & Hatfield, 2021) reporting that our results remain robust.

Our paper is most closely connected with studies estimating the effects of social assistance programmes during the pandemic and other aggregate shocks. Previous evidence relates to social transfer programs that remained largely unchanged during aggregate shocks (Abay et al., 2021; Alloush, Bloem, & Malacarne, 2023; Banerjee et al., 2020; Bottan, Hoffmann, & Vera-Cossio, 2021; Premand & Stoeffler, 2022) and emergency relief programs (Brooks, Donovan, Johnson, & Oluoch-Aridi, 2020; del Valle, 2021; Londoño-Vélez & Querubín, 2022; Stein et al., 2022). Our empirical perspective on country-wide targeted social cash transfer programs of varying degrees of shock-responsiveness for informal sector households is new. To further improve our understanding of the value of shock-responsive social cash transfers, we compare magnitudes of the effects reported in this paper with those reported in other studies focusing on social transfer programs without shock-responsiveness. In terms of effects on food shortage, our point estimate falls in the range of studies estimating the effect of social cash transfers during aggregate shocks (Abay et al., 2021; Alloush et al., 2023; Bottan et al., 2021). Similarly, our estimated effects on poverty is in the same range as Premand and Stoeffler (2022) who report the effects of social cash transfers in times of a drought shock. Significant differences emerge in the adoption of risk-coping strategies, particularly in the context of selling off assets. Our research indicates that the shock-responsive social cash transfer decreased the likelihood of asset sales by 7 percentage points. This contrasts with the findings of Abay et al. (2021) and Premand and Stoeffler (2022), who observe no significant impact on risk-coping strategies. All in all, this comparison to studies without shock-responsiveness suggests that shock responsive social cash transfers (i.e., pooling of payment cycles and vertically scaling the cash transfer) can prevent households from using harmful coping strategies such as selling assets, while at the same time it stabilises household income and consumption levels of basic necessities including food.

The rest of this paper is organised as follows. Section 2 describes the spread of COVID-19 and the economic consequences of the pandemic in Kenya. Section 3 presents the social cash transfer programmes and describes how they have been adapted during the pandemic. Section 4 introduces the dataset, defines the outcome variables, and presents the econometric model. Section 5 reports the estimation results, the robustness checks, and findings concerning effect heterogeneity. Section 6 concludes.

Covid-19, Lockdown Policies and Economic Consequences

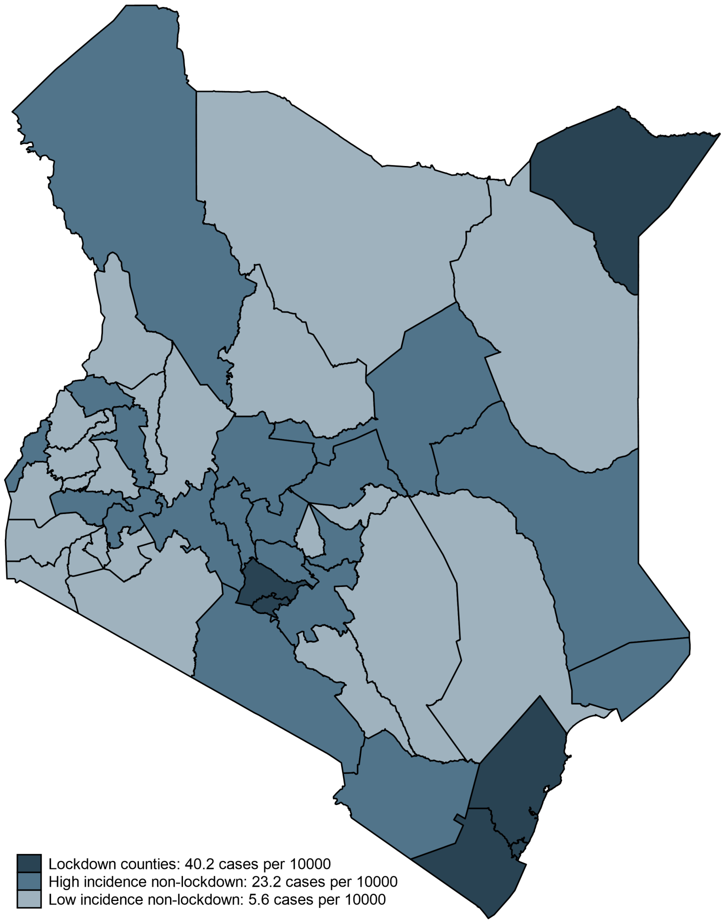
The first case of COVID-19 was confirmed in Kenya on 13 March 2020. In total, about 344,100 cases and 5,689 deaths have been confirmed (or 10.7 deaths per 100,000 people) as of November 2023 (Mathieu et al., 2020). In response to the outbreak, on 15 March 2020, the Government of Kenya declared a state of emergency and implemented a range of containment measures. Movement in and out of the six most affected counties was restricted. These lockdown measures were implemented for three months in Kilifi and Kwale and for four months in Nairobi, Kiambu, Mombasa, and Mandera. Markets, restaurants, and eateries were also closed in these counties (Doyle & Ikutwa, 2021). We refer to these counties as "lockdown counties".

Although COVID-19 containment measures in both lockdown and non-lockdown counties did not include any stay-at-home requirements, our data show that half of the informal labour force in the lockdown counties had to discontinue their labour activities with an average duration of 12 weeks. In the other counties, only one third of the informal labour force had to discontinue their activities and the average number of weeks without labour activities amounted to only two. These average statistics are largely driven by those non-lockdown counties with a relatively high number of COVID-19 cases. Some containment measures were implemented in all 47 counties between March and June 2020. These included instructing non-essential public and private sector workers to work from home, banning large social gatherings, including weddings, church gatherings, and congregating at malls, and a nationwide night curfew from 7.00 p.m. to 5.00 a.m. Also, all schools and learning institutions were closed. A ban on international passenger flights lasted until August 2020 (Doyle & Ikutwa, 2021).

In order to make inferences of the penetration of SARS-CoV-2 transmission into each Kenyan county, we used data provided by Brand et al. (2021) that consist of line-list information about confirmed cases and PCR swab tests performed from the Kenyan Ministry of Health. To improve the quality of the PCR datasets regarding, for instance, the test date, symptoms, and location, the authors implemented a cleansing process including spelling checks, string distance calculations, and an automated geo-search of addresses using different combinations of the available spatial data per record.

Figure 1 depicts the spatial distribution of the cumulative number of confirmed COVID-19 cases per 10,000 inhabitants by the end of 2020. Lockdown counties had the highest COVID-19 incidence with, on average, 40.2 confirmed cases per 10,000 inhabitants. They are followed by high incidence non-lockdown counties which experienced, on average, 23.2 cases per 10,000 inhabitants and a group of non-lockdown counties with low COVID-19 incidence (5.6 cases per 10,000 inhabitants, on average). Following from this, three groups of counties are classified: (i) counties with lockdown measures (lockdown counties, N=6), (ii) counties without lockdowns, but high COVID-19 incidence (high incidence non-lockdown counties, N=19), and (iii) counties with low COVID-19 incidence (low incidence non-lockdown counties, N=22).

Figure 1: Cumulative number of COVID-19 cases per 10,000 inhabitants in a county, by COVID-19 impact levels



Source: Authors construction using curated data from Brand et al. (2021).

According to World Bank estimates, the Kenyan economy contracted by 0.4 percent between January and June 2020, in stark contrast with the growth of 5.4 percent during the same period in 2019 (World Bank, 2020), implying a net contraction of 5.8 percent. COVID-19 and containment measures had the most severe socioeconomic impacts in Nairobi where, initially, cases were highest and lockdown measures were most stringent (Pape & Delius, 2021). Country-wide unemployment was almost double what it had been before the COVID-19 pandemic. The labour force participation rate simultaneously decreased. Overall, the World Bank reports that earnings have significantly decreased for wage earners in the informal sector (Pape & Delius, 2021). In addition, COVID-19 is estimated to have contributed to the increase of poverty by about 4 percentage points, resulting in 2 million newly poor Kenyans (World Bank, 2022). Our descriptive analyses of the informal economy presented in Section 4 also confirm these overall patterns.

Social Protection in Kenya

Over the past two decades, the Kenyan social protection sector has evolved and expanded into a social protection system. The 2011 National Social Protection Policy (NSPP) introduced a vision of increasing coverage, improving coordination, and bringing about greater integration of programmes and services (Government of Kenya, 2011). Social protection in Kenya currently consists of social assistance, social security, and health insurance (Government of Kenya, 2017).[5]

The most prominent social protection programme is the NSNP, which delivers participating households a social cash transfer of KES 2,000 (USD 20) per month.[6] Target households are living in poverty and have at least one household member that falls under the following categories: orphans and vulnerable children (Cash Transfer for Orphans and Vulnerable Children), the elderly (Old Age Cash Transfer), people with severe disabilities (People with Severe Disabilities Cash Transfer) and urban severely food insecure (Urban Food Subsidy Programme). While NSNP integragtes different targeting strategies, payments have the same financial value and follow similar schedules (Mwasiaji, Tesliuc, Mistiaen, Sandford, & Munavu, 2016).

The other large pillar is the HSNP, which also consists of a social cash transfer. Similar to the NSNP, it targets households that are living in poverty, cannot afford to meet basic expenses (regular nutritious food, adequate housing, sanitation, etc.), and are vulnerable to becoming poorer in times of shocks such as droughts,

[5] Coverage of social security programmes, such as social insurances, is limited. Only 3% of informal workers are covered (KNBS, 2019b). In terms of health insurance, 7.7 million members are covered, but most members are from the formal sector where membership is compulsory (Government of Kenya, 2017)

[6] On 1 January 2020, the exchange rate for the Kenyan shilling was KES 1 = USD 0.0098 (Onvista, 2021)

livestock diseases, and floods. The programme provides KES 5,400 (USD 48) every two months.[7] It responds to drought shocks by explicitly relaxing eligibility rules to make it more responsive Gardener et al. (2017). The Government of Kenya directly finances 100 percent of both cash transfer programmes, which collectively reach 1.3 million households across all counties (Doyle & Ikutwa, 2021). Overall, the Kenya National Social Protection Programme covers about 4.7 million individuals, equivalent to about 9% of the population (Gentilini et al., 2021).

As a response to the COVID-19 pandemic, the government announced on 25 March 2020 the continuation of the NSNP and HSNP (Doyle & Ikutwa, 2021). Previously committed funds were quickly released. While HSNP households received their regular transfers throughout the timeframe of our study, the NSNP shifted from periodic payements to lump sum payments for a period of four months. In particular, participating households of the NSNP received a lump sum of KES 8,000 (USD 78) to cover the period from January to April 2020. The second tranche of KES 4,000 (approx. USD 40) was disbursed as a lump sum at the end of June 2020 to cover May and June 2020 (Doyle & Ikutwa, 2021). From July 2020 onwards, the NSNP reverted back to the original format, i.e., monthly payment of KES 2,000 (USD 20).

Between March and June 2020, vertical expansions increased the level of support to NSNP households through the provision of cash top-ups by non-government actors. UNICEF provided two monthly cash top-up payments of KES 2,000 to 9,700 NSNP households with children under 10 years. An EU consortium provided monthly cash top-ups of KES 5,668 (approx. USD 55) for three months to 32,000 NSNP households residing in informal settlements in two lockdown counties, i.e., Nairobi and Mombasa. The World Food programme (WFP) provided cash top-ups to 94,500 NSNP households in informal settlements in the same lockdown counties for three months. Each household received KES 4,000 (40 USD) each month – an amount intended to cover half of the total food and nutrition needs for a family of four. Hence, much of the vertical expansion of the program was concentrated in lockdown counties.

[7]The targeting criteria of the NSNP and the HSNP have not changed during the COVID-19 pandemic.

The government set up new short-term cash-based emergency relief programmes, which targeted households that were not enrolled in the NSNP or HSNP. This short-term response consisted of the multi-agency COVID-19 cash transfer and the National Council for Persons with Disabilities (NCPWD) cash transfer. Both programmes targeted the chronically sick, widowers, the elderly, and persons with disabilities. The response took the form of a weekly cash transfer of KES 1,000 (approx. USD 10) between March and June 2020 (Doyle & Ikutwa, 2021). Instead of utilising established mechanisms from the NSNP and HSNP, these new programmes conducted new registration activities for households without adequate verification to ensure only eligible households were enrolled. Discretion by registration teams was unchecked, leading to potential inaccuracies in eligibility determination. Furthermore, reliance on paper-based registration introduced errors and delayed the process since the data had to be sent to Nairobi for manual digitization, and the poor quality of data collected hindered the registration of many households. Data on the final number of cash transfer recipients were neither publicly available nor known by key informants within the implementing Ministry of Labour and Social Protection (MLSP) (Doyle & Ikutwa, 2021).

Data and Research Design

Data

Our analysis is based on nationally representative in-person surveys among informal sector households conducted before and after the first wave of the pandemic. In December 2018, 1,186 informal sector households were surveyed. In December 2020, after lockdown measures were eased, 2,166 households were surveyed. Our sample therefore consists in total of 3,352 households. The surveys were designed as repeated nationally representative cross-sectional surveys to study the socioeconomic conditions of households in the informal economy. An important objective of the second round of the surveys was to obtain an understanding of the economic and social situation of the informal economy before and after the first wave of the COVID-19 pandemic. The data were collected through in-person interviews with the household head and one randomly selected household member over the age of 15.[8] The questionnaire included modules on household demographics, health, economic situation, social protection programmes, social cohesion, and self-organisations. The overall sample and sampling design are similar to Strupat (2022).

Our survey data allow us to assess which informal sector households are covered by the NSNP, the HSNP, and the new COVID-19 emergency relief programmes before and after the first wave of the COVID-19 pandemic. The respondent was asked whether the household was covered by the NSNP, the HSNP, or any of the new programmes. Enrolment status was checked by the enumerators using either identification documents or the NSNP card. To separate existing cash transfer programmes from new short-term programmes (see Section 3), the enumerators first asked whether the respondents received any support in cash since the COVID-19 outbreak. If yes, they were asked if it was received from the national government, the local government, or the employer. If it was from the national government, the respondents were asked to indicate the programme from which they received the cash transfers.

Table 1 presents the mean coverage of the old and new cash transfer programmes before and after the first wave of the pandemic. As the government of Kenya managed to minimise disruptions to the routine delivery of cash transfers, 11 percent of informal sector households in our sample continued to be covered by the NSNP and 5 percent by the HSNP in 2020. Importantly, only 3 percent of households in the informal sector were covered by the COVID-19 emergency programs suggesting that the new registration activities for households without adequate verification and poor quality of data collected indeed hindered the registration of many households, especially in the informal sector (Doyle & Ikutwa, 2021; Gardener et al., 2017)

[8]The random selection of the household member was done after screening all household members with the tablet computers that were used during the survey.

Table 1: Enrolment in cash transfer programmes before and after the first wave of the pandemic (in percent)

	Pandemic		
	Before	After first wave	Difference
NSNP: Pooling of payment cycles	0.11	0.11	-0.005
and vertical expansion	(0.01)	(0.01)	(0.01)
HSNP: Neither pooling of payment	0.05	0.05	0.006
cycles nor vertical expansion	(0.01)	(0.01)	(0.01)
COVID-19 emergency	-	0.03	-
		(0.15)	
Observations	1,186	2,166	

Notes: In Column 3, standard errors are in parentheses. Significance levels correspond with *** $p<0.01$ for 1 %, ** $p<0.05$ for 5% and * $p<0.1$ for 10%.

For our analysis, we concentrate on outcomes related to, on the one hand, the economic and social well-being of households and, on the other hand, costly risk-coping measures used by households. As to the former, we are mainly interested in three outcomes: loss of income, poverty, and basic consumption shortfall. A household is defined as experiencing a loss of income if at least one household member lost a job or lost income to a margin that seriously affected the household's ability to pay the most essential expenses. For our poverty measure, we collected information about the earnings of all household members to calculate the per capita household income. If the per capita household income was less than the monthly minimum wage of 7,500 KES (73 USD), we considered the household to be poor. The outcome "basic consumption shortfall" is an experiential measure of lived poverty which shows how frequently people go without basic necessities such as food, clean water, or cooking fuel during the past month (Meyer & Keyser, 2016). We asked respondents: "Over the past month, how often if ever have you or your family gone without ... ?" The interviewer then repeats the question about the necessities of food, clean water, and cooking fuel. The answer options range from "Never," "Just Once or Twice," "Several Times," "Many Times," or "Always". Thus, our measure of basic consumption shortfall includes shortages of food to eat, clean water for home use, and fuel to cook food. We aggregated the three basic necessities and classified households to experience a shortfall of basic consumption when they reported “several times”, “many times”, or “always” a shortage of these three items in the past month. Furthermore, we generated outcome indicators for shortfalls of each basic necessity: “shortage of food”, “shortage of clean water” and “shortage of cooking fuel”.

Another important set of outcome indicators addresses coping strategies for aggregate shocks. We asked the respondent how the household coped with economic shocks. The responses were coded as selling productive assets, depleting savings, taking a loan, and borrowing money from family or other households. The responses for the first two response categories were coded as binary outcome variables. Finally, to assess whether the cash transfers had an impact on assets, we included questions concerning the household’s ownership of several assets such as a television, fridge, mobile phone, table, bed and more productive assets such as tools, animal drawn cart, plough etc into the questionnaire. Each household asset is assigned a weight or factor score generated through principal components analysis. The first principal component explains the largest proportion of the total variance and it is used as the asset wealth index to represent the household’s asset wealth. The factor analysis procedure is used to calculate the principal component. This procedure first standardised the indicator variables by calculating the Z-scores. Then the factor coefficient scores which are also the factor loadings are generated. The indicator values are multiplied by the loadings and summed to the household asset wealth index. The wealth index as created is a continuous variable. A reduction in the score of the index indicates that assets were sold.

Table 2 shows the means of the outcome variables for the time before and after the first wave of the pandemic. We observe a higher prevalence of income losses, poverty, and basic consumption shortfalls. The prevalence of loss of income increased by 15 percentage points, poverty by 15 percentage points, and basic consumption shortfall by 6 percentage points. All indicators show that the average household operating in the informal economy was largely affected by the negative consequences of the pandemic. Households also experienced an increase in the shortage of food and clean water. The latter might be due to loss of income and stop paying bills for water access. Concerning the risk-coping strategies, we find an increase in the likelihood of households reporting to sell assets and a decline in asset wealth. Furthermore, households increasingly report the depletion of their savings.

Table 2: Means of the outcome variables before and after the first wave of the pandemic

	After first wave of pandemic	Before pandemic	Difference
Loss of income (1/0)	0.79	0.64	0.15***
	(0.01)	(0.01)	(0.02)
Poverty (1/0)	0.65	0.50	0.15***
	(0.01)	(0.02)	(0.02)
Basic consumption shortfall (1/0)	0.26	0.20	0.06***
	(0.01)	(0.01)	(0.02)
Shortage of food (1/0)	0.28	0.21	0.07***
	(0.01)	(0.01)	(0.02)
Shortage of clean water (1/0)	0.37	0.27	0.10***
	(0.01)	(0.01)	(0.02)
Shortage of cooking fuel (1/0)	0.21	0.20	0.01
	(0.01)	(0.009)	(0.01)
Selling assets (1/0)	0.10	0.07	0.03***
	(0.007)	(0.007)	(0.01)
Deplete savings (1/0)	0.23	0.18	0.05***
	(0.01)	(0.01)	(0.02)
Take loan (1/0)	0.04	0.03	0.01
	(0.004)	(0.005)	(0.01)
Borrow money family/friends (1/0)	0.22	0.20	0.02*
	(0.01)	(0.01)	(0.02)
Asset wealth index	1.45	1.56	-0.10***
	(0.01)	(0.02)	(0.02)
Observations	2,166	1,186	

Notes: Standard errors are in parentheses. Significance levels correspond with *** p<0.01 for 1 %, ** p<0.05 for 5% and * p<0.1 for 10%.

Empirical Specification

We aim to estimate the effect of the shock-responsive social cash transfer scheme during the COVID-19 pandemic in a doubly robust difference-in-differences setting (Sant'Anna & Zhao, 2020) More specifically, households with and without coverage of the cash transfer programmes are compared before and after the first wave of the pandemic using repeated cross-sectional data. [9] For this purpose, we combine NSNP and HSNP into one single indicator. [10] To employ the difference-in-differences strategy, the following specification is estimated:

$$Y_{ict} = \beta_0 + \beta_1 POST_t * CT_{ict} + \beta_2 POST_t + \beta_3 CT_{ict} + X_{ict}\beta_4 + \nu_c + \tau^{pw\_rc} + \varepsilon_{ict} \quad (1)$$

where Y_{ict} represents the outcome of interest for household i residing in county c at the time of each survey t. The variable $POST_t$ is a dummy variable that takes the value of 0 in the baseline and 1 in the round of data collected after the first wave of the pandemic. The variable CT_{ict} indicates recipients of the shock-responsive social cash transfer, taking the value 1 if the household i is covered by at least one of the two social cash transfer programmes at the time of the survey t. X_{ict} is a set of household characteristics observed at the time of each survey, including age and sex of the household head, education level of the household head, disability in the household, household size, the household's share of elderly and children, and whether the household resides in rural areas (for the full list of covariates, see Table A1 in the Appendix). To account for the different initial development levels of the counties that are possibly related to the outcome variables and shock-responsive social cash transfer coverage, we include county-level fixed effects shown by ν_c.

The difference-in-differences estimator is then given by the interaction of the time dummy and the social cash transfer dummy (i.e., $POST_t * CT_{ict}$) with its corresponding β_1 coefficient. The coefficient yields intention-to-treat estimates because a (small) fraction of non-participants of the social cash transfer scheme received the typical emergency response that occurred in parallel to the shock-responsive social cash transfer scheme. The resulting partial compliance in the control group is likely to imply that our results represent conservative estimates of the treatment effects (Duflo, Glennerster, & Kremer, 2007)

[9] NSNP and the HSNP have been continued during the pandemic and their targeting criteria have not been changed

[10] We also provide a separate analysis in Section 5.4 to explore how each programme might have had different effects on recipients.

Causally interpreting the estimated effects of the shock-responsive social cash transfer requires the main identifying assumption to hold, that is, conditional on the vector X_{ict} the difference in economic outcomes between recipients and non-recipients of the social cash transfer scheme would remain constant over time without the economic shock from the pandemic and its containment measures. Given the repeated cross-sectional nature, we make comparisons not with the same units before and after the first wave of the pandemic but with units of similar characteristics before and after the first wave of the pandemic. This is possible because the economic shock resulting from the pandemic and associated containment measures did not lead to a change in the prevalence of the social cash transfer such that surveyed transfer (non-) recipients after the first wave of the pandemic are representative of the surveyed transfer (non-) recipients before the first wave of the pandemic and vice versa see Table A2 in the Appendix). Therefore, conditional on the covariates, we expect that the changes in the differences in the observed outcomes between the two groups in our survey data are due to the cash transfer protecting from the adverse economic consequences of the pandemic and associated containment measures.

Our data comprise two survey rounds with one pre-pandemic data point and one post-pandemic data point. In the absence of pre-trend data, one of the options is balancing out the probability of receiving cash transfers between cash transfer recipients and non-recipients based on observed characteristics before estimating the difference-in-differences (McKenzie, 2023). For this purpose, we integrate inverse-probability weighting into the estimator. The term τ^{ipw_rc} represents the inverse probability weights (IPW) for repeated cross-sections derived from the doubly-robust difference-in-differences estimator (Sant'Anna & Zhao, 2020). The IPW weight is calculated by considering the household characteristics in each cross-section and accounting for county dummies. It ensures that the overlapping region of support is composed of the participants of the shock-responsive social cash transfer scheme to whom a counterfactual is found. This grants a high degree of homogeneity between the treatment and control groups in terms of observable characteristics. ε_{ict} is the usual error term. We conduct all the regressions through the *drdid* command in Stata, specifying inverse probability weights with repeated cross-sections (Sant'Anna & Zhao, 2020) In the robustness section, we aim to illuminate on the validity of the identifying assumption of our estimation approach.

Results

Descriptive Results

Table 3 displays the means of our outcome variables for the two groups across the two survey rounds.

Table 3: Means of the outcome variables by cash transfer coverage before and after the first wave of the pandemic

	After first wave			Before pandemic			Differences	
	Cash transfer (1)	No cash transfer (2)	Single diff. (3)	Cash transfer (4)	No cash transfer (5)	Single diff. (6)	Single diff. (7)	Double diff. (8)
Income loss	0.78	0.79	-0.01	0.72	0.63	0.09**	0.16***	-0.10**
	(0.02)	(0.01)	(0.03)	(0.03)	(0.02)	(0.04)	(0.02)	(0.04)
Poverty	0.68	0.65	0.03	0.68	0.47	0.21**	0.18***	-0.18**
	(0.03)	(0.01)	(0.03)	(0.04)	(0.02)	(0.04)	(0.02)	(0.05)
Consumption	0.30	0.26	0.04	0.31	0.18	0.13**	0.08***	-0.09**
	(0.03)	(0.01)	(0.03)	(0.04)	(0.01)	(0.03)	(0.02)	(0.04)
Food Shortage	0.29	0.28	0.01	0.32	0.20	0.12**	0.08***	-0.11**
	(0.03)	(0.01)	(0.03)	(0.04)	(0.01)	(0.03)	(0.02)	(0.04)
Clean water	0.43	0.36	0.07**	0.43	0.24	0.19**	0.12***	-0.12**
	(0.03)	(0.01)	(0.03)	(0.04)	(0.01)	(0.02)	(0.02)	(0.04)
Cooking fuel	0.21	0.21	0.00	0.26	0.19	0.07**	0.04*	-0.05
	(0.02)	(0.01)	(0.02)	(0.03)	(0.01)	(0.02)	(0.02)	(0.04)
Sale of assets	0.10	0.10	0.00	0.14	0.06	0.08**	0.04***	-0.07**
	(0.02)	(0.01)	(0.02)	(0.03)	(0.01)	(0.02)	(0.01)	(0.03)
Asset wealth	1.34	1.47	-0.13	1.32	1.60	-0.27**	-0.13**	0.14**
	(0.04)	(0.03)	(0.05)	(0.05)	(0.02)	(0.06)	(0.02)	(0.06)
Use savings	0.20	0.24	-0.03	0.14	0.18	-0.05	0.06***	0.01
	(0.02)	(0.01)	(0.03)	(0.03)	(0.01)	(0.02)	(0.02)	(0.04)
Take loan	0.04	0.04	-0.00	0.02	0.04	-0.01	0.00	0.00
	(0.01)	(0.005)	(0.01)	(0.01)	(0.005)	(0.01)	(0.01)	(0.02)
Borrow money (family)	0.29	0.21	0.08**	0.24	0.19	0.05	0.02	0.03
	(0.03)	(0.01)	(0.03)	(0.03)	(0.01)	(0.03)	(0.02)	(0.04)
Observations	288	1,878			1,017			

Notes: Standard errors are in parentheses. Significance levels correspond with *** p<0.01 for 1 %, ** p<0.05 for 5% and * p<0.1 for 10%.

It seems that before the pandemic there were many statistically significant outcome differences between those with and without coverage of the shock-responsive social cash transfer programmes (Column 6). On average, households that receive cash transfers are more likely to be poor, have a higher (idiosyncratic) risk of substantive income losses, and are more often short of food, clean water, and cooking fuel (Columns 4 and 5). When comparing both groups before and after the first wave of the pandemic, the displayed difference-in-differences are statistically significant for the risk of experiencing an income loss, the propensity of being poor, and the likelihood of basic consumption shortfalls (Column 8). Furthermore, we observe less devastating changes in the likelihood of shortages of basic necessities (food, clean water, and cooking fuel) and utilisation of costly risk-coping measures (in particular, selling household assets) between the two survey rounds. Participants and non-participants of the shock-responsive social transfer scheme had hardly any access to loans to cope with the financial implications of the pandemic. Informal insurance networks such as borrowing money from family were not expanded during the pandemic.

Importantly, consistent with strong limitations in the emergency relief measures targeted to the non-recipients of the shock-responsive social cash transfer schemes, about all of the observed difference-in-differences are driven by households that do not receive cash transfers through the studied scheme. These non-participating households experience a particularly large economic decline and increased rates of shortage of basic necessities (see Column 7). In contrast, the rise of poverty and the decline of well-being are modest for the social cash transfer recipients (compare Columns 1 and 4).

These descriptive results point to the potential preserving effect of the treatment during the COVID-19 pandemic. However, it is important to consider household characteristics and time-invariant county characteristics, which could represent confounding factors. Below, we assess the extent to which the associations presented in this section have a causal interpretation.

Empirical Results

We assess the effect of participation in the shock-responsive social cash transfer scheme on household well-being and risk-coping behaviour with likely adverse long-term economic consequences. First, we estimate the intention-to-treat effect on the propensity to report a significant income loss. Column 1 of Table 4 displays the respective estimated treatment effect. We find that the shock-responsive social cash transfer reduced the probability of reporting an income drop by 11 percentage points. Column 2 shows the results of our poverty measure. We find the treatment to yield a reduction in the probability of being poor by 11 percentage points. Thirdly, we consider the effect on basic consumption shortfall. We find a reduced probability of a household report experiencing a shortage in basic necessities of 9 percentage points due to the shock-responsive social cash transfer scheme (Column 3). We find that this latter result is driven by one of the three items. In particular, households are 10 percentage points less likely to report food shortages when receiving the treatment. On the contrary, we observe statistically insignificant negative coefficients on access to clean water and cooking fuel.

Table 4: Effects of cash transfers on income loss, poverty, basic consumption shortfall, and shortage

Variables	Income loss (1)	Poverty (2)	Basic Consumption Shortfall (3)	Food Shortage (4)	Clean Water Water Shortage (5)	Cooking Fuel Fuel Shortage (6)
Cash transfer	-0.114**	-0.109**	-0.091*	-0.104*	-0.049	-0.018
	(0.057)	(0.050)	(0.051)	(0.056)	(0.058)	(0.043)
Baseline means (cash transfer)	0.72	0.68	0.31	0.32	0.43	0.26
Baseline means	0.64	0.50	0.20	0.21	0.27	0.20
Observations	3,352	3,155	3,352	3,352	3,352	3,352

All regressions include household controls and county dummies. Standard errors are clustered at the county-survey round level and in parentheses. Significance levels correspond with *** $p<0.01$ for 1 %, ** $p<0.05$ for 5% and * $p<0.1$ for 10%.

Next, we estimate the effect of the shock-responsive social cash transfers on the use of risk-coping strategies. Table 5 displays the result for two coping strategies, namely selling off assets and depleting savings. We find that the social cash transfer reduced the probability of selling assets by 9 percentage points. In addition, we observe a positive but non-significant coefficient on the asset wealth index and a negative but non-significant coefficient on savings depletion. [11] It seems therefore, that shock-responsive social cash transfers provide some basic social protection against potentially irreversible loss of the economic foundation of households.

Table 5: Effects of cash transfers on coping with the aggregate shock

Variables	Sale of assets (1)	Asset wealth index (2)	Use savings (3)
Cash transfer	-0.067** (0.031)	0.050 (0.057)	-0.022 (0.037)
Baseline means (cash transfer recipients)	0.14	1.32	0.14
Baseline means (entire sample)	0.07	1.56	0.17
Observations	3,095	3,352	3,095

All regressions include household controls and county dummies. Standard errors are clustered at the county-survey round level and in parentheses. Significance levels correspond with *** $p<0.01$ for 1 %, ** $p<0.05$ for 5% and * $p<0.1$ for 10%.

Robustness Checks

To illuminate the validity of our main identifying assumption, we split the sample by the county-level COVID-19 impact and perform the analysis separately according to the three county groups (Figure 1), i.e., lockdown counties, non-lockdown counties with high COVID-19 incidence, and non-lockdown counties with low COVID-19 incidence. We would expect no effects in counties less impacted by the pandemic, meaning that changes in the outcomes of those with and without social cash transfers would have been the same. Thus, if our identification assumption is correct, the difference in the change of the outcomes between participants and non-participants in the social cash transfer scheme will be marginal in the non-lockdown counties with low COVID-19 incidence. The point estimates of this heterogeneity analysis therefore allow us to shed light

[11] Consistent with the very limited ability of households to access loans and the difficulty of relying on the social network during times of an aggregate shock, we do not observe any significant effects on these risk coping measures (results are available upon request).

on the validity of our main identifying assumption of parallel trends. Moreover, consistent with the assumed link between the pandemic impact and the difference in the changes of the outcome variables over time among recipients and non-recipients, we anticipate the magnitudes of the absolute effects to increase with the size of the aggregate shock.

Descriptive statistics show a concentration of the adverse changes in our indicators of economic activity among lockdown counties and non-lockdown high-incidence counties. Specifically, non-participants in these counties experienced substantive rates of income loss, poverty, and basic consumption shortfall. On the contrary, among non-participants in counties not subjected to a lockdown and with low COVID-19 incidence rates, the economic situation remained largely stable, with only minor, rather insignificant fluctuations noted (Table A3 in the Appendix).

Table 6 shows the results for the effects on income loss and poverty among the three types of counties. We find that the social cash transfer scheme reduces the probability of reporting a loss of income only in lockdown countries. The coefficients corresponding to counties without lockdown measures are statistically insignificant. The coefficient for counties without lockdown measures and a low COVID-19 incidence exhibits a significantly smaller magnitude relative to that for counties with lockdown measures. Similar heterogeneity in the estimated effects can be observed for our poverty measure.

Table 6: Effects of cash transfers on income loss, poverty, basic consumption shortfall, by pandemic impact

	Income loss			Poverty			Consumption		
Variables	Lockdown	Non Lockdown		Lockdown	Non Lockdown		Lockdown	Non Lockdown	
		High incide	Low incide		High incide	Low incide		High incide	Low incide
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Cash transfer	-0.17	-0.130	0.007	-0.17	-0.117	-0.071	-0.02	-0.231	-0.05
	(0.08)	(0.094)	(0.107)	(0.09)	(0.092)	(0.083)	(0.113)	(0.094)	(0.06)
Baseline means (cash transfer)	0.80	0.73	0.64	0.68	0.71	0.65	0.20	0.49	0.38
Baseline mean (overall mean)	0.67	0.64	0.61	0.48	0.45	0.55	0.16	0.32	0.26
Observations	1,167	1,164	1,021	1,084	949	1,122	1,167	1,021	1,164

Regressions include household controls and county dummies. Standard errors are clustered at the county-survey round level and in parentheses. Significance levels correspond with *** $p<0.01$ for 1 %, ** $p<0.05$ for 5% and * $p<0.1$ for 10%.

The coefficient for lockdown counties is statistically significant and tends to be larger, in absolute terms, compared with the respective coefficient for non-lockdown counties. The differences between coefficients of non-lockdown counties are not statistically significant. The smallest (and insignificant) point estimates, in absolute terms, are observed in counties experiencing low COVID-19 incidence rates. The result of our measure of basic consumption shortfalls shows a negative impact only in non-lockdown counties with a high COVID-19 incidence. The coefficient for counties with a low COVID-19 incidence rate is small and statistically insignificant. This finding is in line with our expectations because households in lockdown counties mostly live in urban areas where the consumption shortfall of food and clean water is generally less prevalent (see baseline means of outcomes in Table 6), i.e., point estimates are anticipated to be relatively less pronounced.

Table 7 shows the results for the coping strategies among the three groups of counties. We only find the shock-responsive cash transfer scheme to reduce the probability of selling assets in lockdown counties. The smallest point estimates, in absolute terms, are observed in non-lockdown counties experiencing low COVID-19 incidence rates. We find non-significant coefficients on the asset wealth index and savings depletion in all three county groups.

Table 7: Effects of cash transfers on coping with the aggregate shock, by pandemic impact

Variables	Sale of assets			Asset wealth index			Use of savings		
	Lockdown	Non Lockdown		Lockdown	Non Lockdown		Lockdown	Non Lockdown	
		High incidence	Low incidence		High incidence	Low incidence		High incidence	Low incidence
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Cash transfer	-0.060	-0.108	-0.05	0.113	0.036	0.076	-0.06	0.041	0.031
	(0.029)	(0.071)	(0.06)	(0.105)	(0.081)	(0.109)	(0.10)	(0.067)	(0.059)
Baseline means (cash transfer)	0.09	0.14	0.16	1.30	1.31	1.34	0.24	0.09	0.10
Baseline mean (overall mean)	0.05	0.07	0.10	1.62	1.61	1.47	0.20	0.17	0.16
Observations	1,072	921	1,102	1,167	921	1,102	1,072	921	1,102

Regressions include household controls and county dummies. Standard errors are clustered at the county-survey round level and in parentheses. Significance levels correspond with *** p<0.01 for 1 %, ** p<0.05 for 5% and * p<0.1 for 10%.

Besides elucidating the validity of the parallel trend assumption, we analyse a threat that can be pertinent to repeated cross-sectional data. We assess the occurrence of group compositional changes which potentially drive our estimation results. We provide evidence of no compositional changes. We compare between and within differences in the two cross-sections and show results in supplementary Tables A4 and A5. We can reject that in almost all the controls included in the models, there were no systematic differences between and within the samples.

Eventually, while differences in baseline controls might be removed through weighting, the sample in the subsequent rounds might reverse to a mean of relatively different characteristics than the previous sample. This can introduce biases (Daw & Hatfield, 2018). Recent methods of estimation achieve continuous weighting in each cross-section. However, it is also recommended to use only time-invariant controls in standard estimations (Zeldow & Hatfield, 2021). We, therefore, implement all the regressions with only county dummies. Between 2018 and 2020, there was no reclassification of urban regions, so we also included a rural/urban dummy as a time-invariant control. We show these results in Tables A6 and A7 that even with only time-invariant controls, our results are robust.

Heterogeneity Analysis

In this subsection, we analyse which of the two social cash transfer pillars is driving our main findings. While both pillars were comparable in terms of size of the transfer before the start of the pandemic, they differed concerning the degree of shock responsiveness between March and June 2022. In particular, only the NSNP pooled payment cycles and was vertically expanded. Table 8 displays the separate intention-to-treat effects of the two programs on income loss, poverty, and basic consumption. We observe that the effects tend to be, in absolute terms, larger for the vertically scaled social cash transfer program (NSNP). In addition, the estimated impacts are all statistically insignificant for the other program (HSNP). However, our sample is not large enough to allow testing for the statistical significance of the difference in the estimated effects of the two programs.

Table 8: Effects of cash transfers on income loss, poverty, basic consumption shortfall, by degree of shock-responsiveness

Variables	Income loss	Poverty	Consumption	Food Shortage	Clean Water	Cooking Fuel
	(1)	(2)	(3)	(4)	(5)	(6)
NSNP: Pooling of payment cycles and vertical expansion						
Cash transfer	-0.139**	-0.095*	-0.113**	-0.106**	-0.020	-0.025
	(0.056)	(0.055)	(0.053)	(0.052)	(0.067)	(0.052)
Observations	3,194	3,008	3,194	3,194	3,194	3,194
HSNP: Neither pooling of payment cycles nor vertical expansion						
Cash transfer	-0.064	-0.124	-0.046	-0.021	-0.103	-0.003
	(0.099)	(0.081)	(0.083)	(0.085)	(0.091)	(0.083)
Observations	3,053	2,874	3,053	3,053	3,053	3,053

Regressions include household controls and county dummies. Standard errors are clustered at the county-survey round level and in parentheses. Significance levels correspond with *** p<0.01 for 1 %, ** p<0.05 for 5% and * p<0.1 for 10%.

Table 9 displays the results for the use of risk coping strategies. We observe qualitatively the same results as for the other outcome variables, which suggests that the adaptations to the social cash transfer program were an important aspect of the response to the aggregate shock. As much of the vertical expansion of the NSNP was concentrated in Nairobi and Mombasa, we also provide an additional heterogeneity analysis by focusing on both counties. Tables A8 and A9 show that the magnitude of the NSNP effects are much larger for Nairobi and Mombasa in comparison to the remaining counties, however, due the limited sample size, the results are not statistical significant.

Conclusion

This study attempts to close an important knowledge gap concerning the ability of shock-responsive social cash transfer schemes to protect well-being and the economic foundation of vulnerable households in times of aggregate shocks. We focus on the relationship between Kenya's shock-responsive social cash transfers and household welfare as well as risk-coping measures during the COVID-19 pandemic. Kenya's social protection agenda has been frequently used as a leading

Table 9: Effects of cash transfers on coping with the aggregate shock, by degree of shock-responsiveness

Variables	Sell assets	Asset wealth index	Use of savings
	(1)	(2)	(3)
NSNP: Pooling of payment cycles and vertical expansion			
Cash transfer	-0.089**	0.036	-0.015
	(0.042)	(0.067)	(0.046)
Observations	2,941	3,194	2,941
HSNP: Neither pooling of payment cycle nor vertical expansion			
Cash transfer	-0.029	0.096	-0.043
	(0.055)	(0.079)	(0.057)
Observations	2,814	3,053	2,814

Regressions include household controls and county dummies. Standard errors are clustered at the county-survey round level and in parentheses. *Significance levels correspond with *** $p<0.01$ for 1 %, ** $p<0.05$ for 5% and * $p<0.1$ for 10%.

example in the global discourse on conceptualising shock-responsive programs. Coupled with the large impacts of the pandemic and lockdown policies, this makes Kenya a very relevant setting for examining this relationship.

Using unique primary data from repeated country-representative in-person surveys for the informal economy that were collected more than one year before and ten months after the start of the pandemic, the intention-to-treat results from our doubly-robust difference-in-differences approach show that the analysed shock-responsive social cash transfer scheme was highly beneficial for vulnerable and poor informal sector households. Specifically, we find only modest increases in the prevalence of income losses, poverty, and basic consumption shortfalls among program participants. On the contrary, the respective prevalence rates sharply rose among non-participants during the pandemic, even though the government aimed at providing financial support to these households through more traditional emergency relief programs. Thus, the social cash transfer scheme helped vulnerable and poor households during the pandemic, especially in stabilising household income and consumption levels of basic necessities including food. Importantly, it also prevented households from selling productive assets that otherwise arguably would have threatened them to slide into chronic poverty, marked by an enduring decline in income and fundamental consumption levels. The estimated effects are driven by counties that were exposed to more stringent lockdowns and a high COVID-19 incidence.

Turning to policy implications, the results strengthen the case for investing in adaptive and shock-responsive social cash transfers. Three features of shock-responsive cash transfer schemes have attracted much attention of policymakers when faced with aggregate shocks. First, a registry of hard-to-target informal sector households is readily available. Second, developed delivery mechanisms can be leveraged for a speedy provision of financial support. Third, the administrative financing architecture is in place that allows the pooling of domestic and international funds for vertical as well as horizontal program expansion. For instance, the ability to pool payment cycles in order to provide lump sums and quickly provide top-up payments (i.e., vertical scaling of the program) as observed in the studied shock-responsive social cash transfer scheme allows policymakers to adapt the program to the needs of poor and vulnerable households during the pandemic.

Data availability statement The data underlying this article will be shared on request to the corresponding author.

Funding This work was supported by Germany's Federal Ministry for Economic Cooperation and Development (BMZ).

Appendix

Table A1: Means of the explanatory variables

	After first wave	Before pandemic	Difference	Std. Err	p-value
Cash transfer	0.1330	0.1425	-0.0095	0.0124	0.442
Age 15-29	0.3232	0.3508	-0.0276	0.0170	0.115
Age 30-39	0.2595	0.2757	-0.0163	0.0159	0.308
Age 40-49	0.1962	0.1813	0.0149	0.0142	0.293
Age 50-49	0.1196	0.1054	0.0142	0.0115	0.218
Age >60	0.1016	0.0868	0.0147	0.0107	0.167
No education	0.0937	0.0852	0.0086	0.0104	0.409
Some primary education	0.1939	0.1998	-0.0059	0.0143	0.679
Primary education	0.3481	0.3398	0.0083	0.0172	0.629
Secondary education	0.3223	0.3297	-0.0074	0.0169	0.661
University education	0.0420	0.0455	-0.0035	0.0074	0.632
Female	0.4469	0.4798	-0.0329*	0.0180	0.068
Household size	4.3901	4.2487	0.1414*	0.0790	0.083
Share of children (age<15) in household	0.3095	0.3103	-0.0008	0.0091	0.934
Share of elderly (age>60) in household	0.0434	0.0530	-0.0096*	0.0054	0.078
Disability in the household	0.0702	0.0809	-0.0108	0.0095	0.255
Household resides in rural areas	0.6602	0.6594	0.0008	0.0171	0.961
Number of observations	2,166	1,186			

Note: *, ** and *** denote $p < 0.10$, $p < 0.05$ and $p < 0.01$, respectively.

Table A2: Effects of economic shock from pandemic and associated containment measures on social cash transfer prevalence

	Cash transfer (1)	NSNP (2)	HSNP (3)
Lockdown counties	0.054	0.014	0.052
(Reference group: Low incidence non-lockdown counties)	(0.0680)	(0.053)	(0.037)
High incidence non-lockdown (Reference group: Low incidence non-lockdown counties)	0.023 (0.041)	0.037 (0.030)	-0.015 (0.028)
Number of Observations	3,352	3,194	3,053

NSNP included pooling of payment cycles. HSNP neither implemented pooling of cycles nor vertical expansion. We regress pandemic impact (three groups: lockdown counties, high incidence non-lockdown counties and low incidence non-lockdown counties) on receiving cash transfers either from NSNP, HSNP or both). Regressions include household controls, county, and survey wave dummies. Standard errors are clustered at the county level and in parentheses. Note: *, ** and *** denote $p < 0.10$, $p < 0.05$ and $p < 0.01$, respectively.

Table A3: Descriptive statistics for non-recipients of cash transfers before and after the first wave of the pandemic, by pandemic impact

	After first wave of pandemic			Before pandemic			Difference		
	Lockdown county No cash transfer (1)	High Incidence No cash transfer (2)	Low Incidence No cash transfer (3)	Lockdown County No cash transfer (4)	High Incidence No cash transfer (5)	Low Incidence No chash transfer (6)	Diff. (1-4) (7)	Diff. (2-5) (8)	Diff (3-6) (9)
Income	0.8421	0.7939	0.7093	0.6493	0.6111	0.6272	0.1928	0.1822	0.0822
	(0.374)	(0.405)	(0.455)	(0.478)	(0.488)	(0.484)	(0.0285)	(0.030)	(0.030)
Poverty	0.5764	0.6402	0.5893	0.4570	0.4125	0.5285	0.1194	0.2277	0.0600
	(0.480)	(0.494)	(0.493)	(0.493)	(0.499)	(0.499)	(0.0365)	(0.030)	(0.030)
Consumption shortfall	0.2726	0.1989	0.1488	0.2465	0.1296	0.1654	0.0261	0.0693	-0.0166
	(0.446)	(0.399)	(0.356)	(0.432)	(0.336)	(0.372)	(0.0309)	(0.020)	(0.020)
Sale of Asset	0.0927	0.0946	0.0849	0.0383	0.0557	0.0871	0.0544	0.0389	-0.0020
	(0.290)	(0.293)	(0.279)	(0.192)	(0.229)	(0.282)	(0.0188)	(0.010)	(0.020)
Asset	1.4292	1.5649	1.5632	1.6624	1.6650	1.4953	-0.2332	-0.1001	0.0678
	(0.605)	(0.644)	(0.562)	(0.606)	(0.685)	(0.554)	(0.0424)	(0.040)	(0.040)
Use	0.2878	0.2237	0.2317	0.1882	0.1858	0.1741	0.0997	0.0378	0.0577
	(0.453)	(0.417)	(0.423)	(0.391)	(0.389)	(0.380)	(0.0311)	(0.020)	(0.030)
Take loan	0.0325	0.0495	0.0386	0.0523	0.0310	0.0323	-0.0197	0.0185	0.0063
	(0.177)	(0.217)	(0.193)	(0.222)	(0.173)	(0.177)	(0.0138)	(0.001)	(0.001)
Borrow (family)	0.2537	0.1957	0.1776	0.2056	0.2012	0.1716	0.0481	-0.0055	0.0060
	(0.435)	(0.397)	(0.383)	(0.405)	(0.401)	(0.377)	(0.0305)	(0.020)	(0.030)

Standard errors are in parentheses. * p < 0.10, ** p < 0.05, *** p <0.01

Table A4: Means of the explanatory variables for recipients of cash transfers

	After first wave	Before pandemic	Diff.	Std. Error	P-Value
Age 15-29	0.2639	0.3254	-0.061	0.0438	0.161
Age 30-39	0.2118	0.2604	-0.048	0.0408	0.235
Age 40-49	0.2674	0.1775	0.0898	0.0409	0.086
Age 50-49	0.1319	0.1361	-0.004	0.033	0.900
Age 60	0.1250	0.1006	0.0244	0.0311	0.433
No education	0.1701	0.1657	0.0045	0.0363	0.902
Some primary education	0.1979	0.2189	-0.021	0.0392	0.592
Primary education	0.3507	0.3373	0.0134	0.0462	0.772
Secondary education	0.2604	0.2663	-0.005	0.0427	0.891
University education	0.0108	0.0118	0.001	0.0127	0.480
Female	0.4306	0.5207	0.0902	0.0482	0.062
Household size	4.4722	4.5858	-0.113	0.2149	0.597
Share of children (age<15)	0.336	0.3306	0.0053	0.0250	0.831
Share of elderly (age 60)	0.0798	0.0764	0.0034	0.019	0.860
Disability in the household	0.0802	0.0809	-0.000	0.0095	0.950
Household resides in rural areas	0.6068	0.6509	-0.044	0.0473	0.179
Number of observations	288	169			

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A5: Means of the explanatory variables for non-recipients of cash transfers

	After first wave of	Before pandemic	Diff.	Std. Error	P-Value
Age 15-29	0.3323	0.3550	-0.0227	0.0184	0.219
Age 30-39	0.2668	0.2783	-0.0115	0.0173	0.506
Age 40-49	0.1853	0.1819	0.0034	0.0151	0.822
Age 50-49	0.1177	0.1003	0.0174	0.0123	0.156
Age >60	0.0980	0.0846	0.0134	0.0113	0.236
No education	0.0820	0.0718	0.0102	0.0105	0.329
Some primary education	0.1933	0.1967	-0.0034	0.0154	0.827
Primary education	0.3477	0.3402	0.0075	0.0185	0.686
Secondary education	0.3317	0.3402	-0.0085	0.0184	0.644
University education	0.0453	0.0511	-0.0059	0.0083	0.478
Female	0.4694	0.4730	-0.0235	0.0194	0.225
Household size	4.3775	4.1927	0.1848*	0.0848	0.029
Share of children (age<15)	0.3055	0.3069	-0.0014	0.0098	0.883
Share of elderly (age>60)	0.0379	0.0492	-0.0113*	0.0055	0.041
Disability in the household	0.0592	0.0657	-0.0065	0.0100	0.518
Household resides in rural	0.6715	0.6608	0.0107	0.0183	0.560
Number of observations	1,878	1,017			

Note: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A6: Robustness check: income loss, poverty, basic consumption shortfall using only time-invariant controls

	Income loss	Poverty	Basic consumption shortfall	Food Shortage	Clean Water Shortage	Cooking Fuel Shortage
Cash transfer	-0.111**	-0.088*	-0.076	-0.087*	-0.039	-0.029
	(0.055)	(0.052)	(0.052)	(0.050)	(0.058)	(0.043)
Baseline means (cash transfer recipients)	0.72	0.68	0.31	0.32	0.43	0.26
Baseline mean (overall mean)	0.64	0.50	0.20	0.21	0.27	0.20
Observations	3,354	3,157	3,354	3,354	3,354	3,354

Regressions only include county dummies. Standard errors are clustered at the county-survey round level and in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A7: Robustness check: coping with aggregate shock using only time-invariant controls

	Sale of assets (1)	Asset wealth index (2)	Use of savings (3)
Cash transfer	-0.064**	0.012	-0.037
	(0.031)	(0.057)	(0.036)
Baseline means (cash transfer recipients)	0.14	1.32	0.14
Baseline mean (overall mean)	0.07	1.56	0.17
Observations	3,097	3,354	3,097

Regressions only include county dummies. Standard errors are clustered at the county-survey round level and in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A8: Effects of cash transfers on income loss, poverty, basic consumption shortfall, by different county groups

	Income loss			Poverty			Consumption		
	Nairobi & Mombasa	Other counties	Only lockdown	Nairobi & Mombasa	Other counties	Only lockdown	Nairobi & Mombasa	Other counties	Only lockdown
NSNP: Pooling of payment cycles and	-0.202 (0.19)	-0.103* (0.059)	-0.111 (0.095)	-0.194 (0.27)	-0.111** (0.055)	-0.154* (0.091)	-0.282 (0.21)	-0.111** (0.055)	-0.143 (0.13)
Observations	448	2,746	652	420	2,588	603	448	2,746	652

Regressions include household controls and county dummies. The sub-sample 'Nairobi & Mombasa' includes households from Nairobi and Mombasa. The sub-sample 'Other counties' includes households from all counties except Nairobi and Mombasa. The sub-sample 'Only lockdown counties' includes households from all lockdown counties except Nairobi and Mombasa. Standard errors are clustered at the county-survey round level and in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table A9: Effects of cash transfers on coping with the aggregate shock, by different county groups

	Sale of assets			Asset wealth index			Use of savings		
	Nairobi & Mombasa	Other counties	Only lockdown	Nairobi & Mombasa	Other counties	Only lockdown	Nairobi & Mombasa	Other counties	Only lockdown
NSNP: Pooling of payment cycles and of payment cycles and	-0.033** (0.01)	-0.083* (0.046)	-0.024 (0.049)	0.387* (0.20)	-0.021 (0.064)	0.065 (0.102)	-0.145 (0.16)	0.018 (0.048)	-0.134 (0.15)
Observations	402	2,539	604	448	2,746	652	402	2,539	604

Regressions include household controls and county dummies. The sub-sample 'Nairobi & Mombasa' includes households from Nairobi and Mombasa. The sub-sample 'Other counties' includes households from all counties except Nairobi and Mombasa. The sub-sample 'Only lockdown counties' includes households from all lockdown counties except Nairobi and Mombasa. Standard errors are clustered at the county-survey round level and in parentheses. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

References

Abay, K. A. ., Berhane, G., Hoddinott, J., & Tafere, K. (2021). COVID-19 and Food Security in Ethiopia : Do Social Protection Programs Protect? *Economic Development and Cultural Change*, Forthcoming.

Alloush, M., Bloem, J. R., & Malacarne, J. G. (2023). Social Protection amid a Crisis : New Evidence from South Africa ' s Older Person ' s Grant. *The World Bank Economic Review*, *00*(0), 1–23.

Ambrus, B. A., Mobius, M., & Szeidl, A. (2014). Consumption Risk-Sharing in Social Networks. *American Economic Review*, *104*(1), 149–182.

Andrabi, T., Daniels, B., & Das, J. (2023). Human Capital Accumulation and Disasters Evidence from the Pakistan Earthquake of 2005. *Journal of Human Resources*, *58*(4), 1057–1096.

Banerjee, A., Faye, M., Krueger, A., Niehaus, P., & Suri, T. (2020). Effects of a Universal Basic Income during the pandemic. *Working Paper*. Retrieved from https://econweb.ucsd.edu/{~}pniehaus/papers/ubi{_}covid.pdf

Banerjee, A., Finkelstein, A., Hanna, R., Olken, B. A., Ornaghi, A., & Sumarto, S. (2021). The challenges of universal health insurance in developing countries: Experimental evidence from indonesia's national health insurance. *American Economic Review*, *111*(9), 3035–3063.

Banerjee, A., Hanna, R., Olken, B. A., & Lisker, D. S. (2024). Social Protection in the Developing World. *Unpublished Working Paper*. Retrieved from https://economics.mit.edu/sites/default/files/2023-08/Social{_}Protection{_}paper{_}manuscript.pdf

Bazzi, S., Sumarto, S., & Suryahadi, A. (2015). It's all in the timing: Cash transfers and consumption smoothing in a developing country. *Journal of Economic Behavior and Organization*, *119*, 267–288. Retrieved from http://dx.doi.org/10.1016/j.jebo.2015.08.010

Bottan, N., Hoffmann, B., & Vera-Cossio, D. A. (2021). Stepping up during a crisis: The unintended effects of a noncontributory pension program during the Covid-19 pandemic. *Journal of Development Economics*, *150*(January), 102635. Retrieved from https://doi.org/10.1016/j.jdeveco.2021.102635

Brand, S. P., Ojal, J., Aziza, R., Were, V., Okiro, E. A., Kombe, I. K., ... Barasa, E. (2021). COVID-19 transmission dynamics underlying epidemic waves in Kenya. *Science*, *374*(6570), 989–994.

Brooks, W., Donovan, K., Johnson, T., & Oluoch-Aridi, J. (2020). *Cash transfers as a response to COVID-19: A randomized experiment in Kenya*. Retrieved from https://elischolar.library.yale.edu/egcenter-discussion-paper-series/1082/{%}0Ahttps://elischolar.library.yale.edu/cgi/viewcontent.cgi?article=2081{&}context=egcenter-discussion-paper-series

Clarke, D. J., & Dercon, S. (2016). *Dull Disasters: How Planning Ahead Will Make a Difference*. Oxford: Oxford University Press.

Daidone, S., Davis, B., Handa, S., & Winters, P. (2019). The Household and Individual-Level Productive Impacts of Cash Transfer Programs in Sub-Saharan Africa. *American Journal of Agricultural Economics*, *101*(5), 1401–1431.

Daw, J. R., & Hatfield, L. A. (2018). Matching and Regression to the Mean in Difference-in-Differences Analysis. *Health Services Research*, *53*(6), 4138–4156.

Decerf, B., Ferreira, F. H., Mahler, D. G., & Sterck, O. (2021). Lives and livelihoods: Estimates of the global mortality and poverty effects of the Covid-19 pandemic. *World Development*, *146*, 105561. Retrieved from https://doi.org/10.1016/j.worlddev.2021.105561

de Janvry, A., Finan, F., Sadoulet, E., & 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.

del Valle, A. (2021). The effects of public health insurance in labor markets with informal jobs: Evidence from Mexico. *Journal of Health Economics*, *77*, 102454.

Dercon, S., & Porter, C. (2014). Live aid revisited: Long-term impacts of the 1984 Ethiopian famine on children. *Journal of the European Economic Association*, *12*(4), 927–948.

Doyle, A., & Ikutwa, N. (2021). *Towards shock-responsive social protection: lessons from the COVID-19 response in Kenya* (Tech. Rep. No. March). Oxford: Oxford Policy Management. Retrieved from https://www.opml.co.uk/files/Publications/A2241-maintains/maintains-covid-19-srsp-responses-kenya-case-study-final.pdf?noredirect=1

Duflo, E., Glennerster, R., & Kremer, M. (2007). Chapter 61 Using Randomization in Development Economics Research: A Toolkit. *Handbook of Development Economics*, *4*(07), 3895–3962.

FAO. (2023). *Social Protection and Anticipatory Action to Protect Agricultural Livelihoods*. Rome: Food and Agriculture Organisation.

Fink, G., Jack, B. K., & Masiye, F. (2020). Seasonal liquidity, rural labor markets, and agricultural production. *American Economic Review*, *110*(11), 3351–3392.

Gardener, C., Pearson, R., Riungu, C., Hurrell, A., O'Brien, C., Hill, V., ... Davila, D. (2017). *Evaluation of the Hunger Safety Net Programme Phase 2: The Legacy of HSNP Phase 2: systems, practices and lessons learned* (Tech. Rep.). Oxford: Oxford Policy Management. Retrieved from https://www.opml.co.uk/files/Publications/a0013-evaluation-kenya-hunger-safety-net-programme/hsnp-legacy-systems-practices-lessons-learned.pdf

Gentilini, U., Almenfi, M., Blomquist, J., Dale, P., De la Flor Guiffra, L., Desai, V., ... Weber, M. (2021). *Social Protection and Jobs Responses to COVID-19 : A Real-Time Review of Country Measures.* Washington DC: The World Bank. Retrieved from https://documents.worldbank.org/en/publication/documents-reports/documentdetail/281531621024684216/social-protection-and-jobs-responses-to-covid-19-a-real-time-review-of-country-measures-may-14-2021

Goolsbee, A., & Syverson, C. (2021). Fear, lockdown, and diversion: Comparing drivers of pandemic economic decline 2020. *Journal of Public Economics*, *193*, 104311. Retrieved from https://doi.org/10.1016/j.jpubeco.2020.104311

Government of Kenya. (2017). *Kenya Social Protection Sector Review* (Tech. Rep.). Nairobi: Government of Kenya. Retrieved from www.developmentpathways.co.uk/publications/kenya-socialprotection-sector-review-2017

Hanna, R., & Olken, B. A. (2018). Universal basic incomes versus targeted transfers: Anti-poverty programs in developing countries. *Journal of Economic Perspectives*, *32*(4), 201–226.

Jack, W., & Suri, T. (2014). Risk Sharing and Transactions Costs : Evidence from Kenya's Mobile Money Revolution. *American Economic Review*, *104*(1), 183–223.

Lawlor, K., Handa, S., & Seidenfeld, D. (2019). Cash Transfers Enable Households to Cope with Agricultural Production and Price Shocks: Evidence from Zambia. *Journal of Development Studies*, *55*(2), 209–226. Retrieved from https://doi.org/10.1080/00220388.2017.1393519

Londoño-Vélez, J., & Querubín, P. (2022). The Impact of Emergency Cash Assistance in a Pandemic: Experimental Evidence From Colombia. *Review of Economics and Statistics*, *104*(1), 157–165.

Mathieu, E., Ritchie, H., Rodés-Guirao, L., Appel, C., Giattino, C., Hasell, J., ... Roser, M. (2020). *Coronavirus Pandemic (COVID-19)*.

McKenzie, D. (2023). *What to do about parallel trends when you only have baseline data?* Retrieved from https://blogs.worldbank.org/impactevaluations/what-do-about-parallel-trends-when-you-only-have-baseline-data

Meyer, D. F., & Keyser, E. (2016). Validation and Testing of the Lived Poverty Index Scale (LPI) in a Poor South African Community. *Social Indicators Research*, *129*(1), 147–159.

Mwasiaji, W., Tesliuc, C., Mistiaen, E., Sandford, J., & Munavu, M. M. (2016). *Inua Jamii: Towards a More Effective National Safety Net for Kenya* (Tech. Rep. No. March). Washington DC: The World Bank. Retrieved from http://documents.worldbank.org/curated/en/949781468198008332/pdf/105760-WP-P131305-PUBLIC.pdf

Onvista. (2021). *Onvista Kenya Shilling-United States Dollar Exchange Rates.* Retrieved 2022-03-20, from https://www.onvista.de/devisen/Kenia-Schilling-US-Dollar-KES-USD

Pape, U., & Delius, A. (2021). *Livelihoods of Kenyan households bear the brunt of the COVID-19 pandemic.* Retrieved 2022-07-21, from https://blogs.worldbank.org/africacan/livelihoods-kenyan-households-bear-brunt-covid-19-pandemic

Premand, P., & Stoeffler, Q. (2022). Cash transfers, climatic shocks and resilience in the Sahel. *Journal of Environmental Economics and Management*, *116*(September), 102744. Retrieved from https://doi.org/10.1016/j.jeem.2022.102744

Robinson, J. (2012). Limited insurance within the household: Evidence from a field experiment in Kenya. *American Economic Journal: Applied Economics*, *4*(4), 140–164.

Sant'Anna, P. H., & Zhao, J. (2020). Doubly robust difference-in-differences estimators. *Journal of Econometrics*, *219*(1), 101–122.

Stein, D., Bergemann, R., Lanthorn, H., Kimani, E., Nshakira-Rukundo, E., & Li, Y. (2022). Cash, COVID-19 and aid cuts: a mixed-method impact evaluation among South Sudanese refugees registered in Kiryandongo settlement, Uganda. *BMJ Global Health*, *7*(5), e007747.

Strupat, C. (2022). Social Protection and Social Cohesion in Times of the COVID-19 Pandemic: Evidence from Kenya. *European Journal of Development Research*, *34*(3), 1320–1357.

Strupat, C., & Klohn, F. (2018). Crowding out of solidarity? Public health insurance versus informal transfer networks in Ghana. *World Development*, *104*, 212–221.

World Bank. (2022). *Monitoring COVID-19 Impact on Households in Kenya.* Retrieved 2022-04-20, from https://www.worldbank.org/en/country/kenya/brief/monitoring-covid-19-impact-on-households-and-firms-in-kenya

World Economic Forum. (2023). *The Global Risks Report 2023*. Geneva: The World Economic Forum. Retrieved from https://www.weforum.org/reports/global-risks-report-2023

Zeldow, B., & Hatfield, L. A. (2021). Confounding and regression adjustment in difference-in-differences studies. *Health Services Research*, 1–10.