zef
Center for
Development Research
University of Bonn

ZEF-Discussion Papers on Development Policy No. 316

Christoph Strupat and Emmanuel Nshakira-Rukundo

The Impact of Social Assistance Programmes in a Pandemic: Evidence from Kenya

Bonn, May 2022

Christoph Strupat and Emmanuel Nshakira-Rukundo, The Impact of Social Assistance Programmes in a Pandemic: Evidence from Kenya, ZEF – Discussion Papers on Development Policy No. 316, Center for Development Research, Bonn, May 2022, pp. 29.

ISSN: 1436-9931

Published by:
Zentrum für Entwicklungsforschung (ZEF)
Center for Development Research
Genscherallee 3
D – 53113 Bonn
Germany
Phone: +49-228-73-1861
Fax: +49-228-73-1869
E-Mail: zef@uni-bonn.de
www.zef.de

The author[s]:
Christoph Strupat, German Development Institute/Deutsches Institut für Entwicklungspolitik (DIE). Email: Christoph.Strupat@die-gdi.de

Emmanuel Nshakira-Rukundo, German Development Institute/ Deutsches Institut für Entwicklungspolitik (DIE), Apata Insights, Kampala & Institute for Food and Resource Economics, University of Bonn. Email: Emmanuel-Nshakira.Rukundo@die-gdi.de

Acknowledgements

This Paper is part DIE's research project "Social Cohesion in Africa". The project also established the Social Cohesion Hub, which provides a web-based, collaborative platform for exchange on social cohesion in research and development cooperation. The project is funded by Germany's Federal Ministry for Economic Cooperation and Development (BMZ).

The survey data used in this Discussion Paper was collected as part of a joint project between the Friedrich-Ebert-Stiftung (FES), the International Labour Office (ILO) and the German Development Institute (DIE). National survey institutes (NSIs) that are part of the AfroBarometer network were the implementing partners in the survey countries. Technical support, including data management, was provided by the Institute for Development Studies (IDS), University of Nairobi. Members of these institutions met on several occasions to jointly develop the questionnaire and agree on details of the survey protocol. The main objective of the survey was to gain a better understanding of the social and economic situation of households in the informal economy. The project was funded by the FES and the BMZ.

The authors would like to express his gratitude to Abel Oyuke, Sam Balongo, Rudolf Traub-Merz and all from the survey project team, who supported the survey in many important ways. Many thanks to IDS for their exceptional field work. The author would like to further thank Julia Leininger, Manfred Öhm and Henrik Maihack.

Abstract

This paper examines whether social protection – in the form of existing social assistance programmes - affects measures of household well-being such as poverty, food security and costly risk-coping behaviour during the COVID-19 pandemic. Using primary data from nationally representative, in-person surveys in Kenya allows the exploration of the impacts of major social assistance programmes. Our analysis employs the doubly robust difference-in-differences approach to estimate the impacts of social assistance programmes on common measures of household welfare. We find that social assistance programmes significantly reduce the prevalence of economic shocks and the further impoverishment of beneficiaries during the pandemic. Furthermore, households with social assistance coverage are less likely to sell assets as a coping strategy. Overall, the results suggest that, during a systematic crisis such as a pandemic, pre-existing social assistance schemes can deliver positive impacts in line with the primary goals of social safety nets and prevent households from falling deeper into poverty by preserving their asset base.

Keywords: cash transfers, COVID-19, Kenya

JEL Codes: I32, I38

1 Introduction

The COVID-19 pandemic is a major public health challenge that is generating negative economic and social impacts likely to persist for some time. Estimates of COVID-19 related poverty and inequality are alarming, suggesting that close to 600 million people will fall into poverty during the pandemic (Sumner, Hoy, & Ortiz-Juarez, 2020). The pandemic is like to roll back all the progress in poverty reduction achieved over the last few decades. To mitigate the adverse economic consequences of the pandemic and the related containment policies, social protection programmes have been adapted and expanded on a large scale in many countries (Gentilini et al., 2021).

Understanding the effects of social assistance on household welfare in the context of a pandemic is critical as they may differ from normal times. Even small cash transfers can have a sizeable impact on households in extreme poverty and those that are suffering from income, health, or consumption shocks might benefit from receiving social assistance (Londoño-Vélez & Querubín, 2022). In times of large covariate shocks such as pandemics, however, disruptions in markets and supply chains may dampen the effectiveness of money on households' consumption and food security (Hanna & Olken, 2018). This paper examines the impact of existing and partly adapted social assistance programmes during the pandemic, taking advantage of unique primary data from nationally representative in-person surveys before and after the first wave of the pandemic in Kenya.

Kenya is an ideal setting for examining the relationship between social assistance programmes and measures of household welfare in times of a pandemic. Over the past 10 years, the Kenyan social protection sector has evolved and expanded into a social protection system comprising various programmes and interventions (Government of Kenya, 2011). The Kenyan government has responded to the pandemic by continuing and adapting two national social assistance programmes: the National Safety Net Programme (NSNP) and the Hunger Safety Net Programme (HSNP) (Doyle & Ikutwa, 2021). Beneficiaries of the programmes received lump-sum payments and cash top-ups to the regular cash transfers (see Section 3 for more details on the adaptation). They received a lump sum of KES 8,000 (USD 74) to cover the period January to April 2020 and the second tranche of KES 4,000 (approx. USD 37) was disbursed as a lump sum at the end of June 2020 to cover May and June 2020. The two flagship programmes cover a combined 1.23 million vulnerable households (Government of Kenya, 2017). Kenya was severely impacted by the first wave of the pandemic that affected the country from March to October 2020 and the government has established one of the most stringent lockdowns among Sub-Saharan African countries (Hale et al., 2021; Leininger, Strupat, Adeto, & AbebeShimeles, 2021).

To examine the relationship between social assistance and household welfare in the pandemic context, we use unique primary data from two nationally representative, in-person surveys that were conducted before and after the first wave of the pandemic in Kenya. These repeated cross-sectional surveys include a total of 3,352 randomly selected households and were conducted as part of a joint project between the Friedrich-Ebert-Stiftung (FES), the International Labour Office (ILO), the German Development Institute (DIE) and the Institute for Development Studies at the University of Nairobi. The surveys are representative of the entire informal economy [1], which covers the majority of the Kenyan population, including households that receive benefits from the NSNP and HSNP.

Using both repeated cross-sectional surveys allows for the application of the doubly robust difference-in-differences approach (Sant'Anna & Zhao, 2020). As the NSNP and the HSNP have been continued during the pandemic and targeting criteria remained unchanged, one can compare households that are covered and not covered by these social assistance programmes before and after the first wave of the pandemic.[2] We find that social assistance programmes had statistically significant impacts on various measures of household welfare. Households of beneficiaries were 15 percentage points less likely to report experiencing economic shocks such as loss of income during the last 12 months as compared to non-beneficiary households, which is a relative decrease of 19 per cent. Beneficiary households were also 13 percentage points less likely to report income poor (a relative decrease of 20%) and also reported improved food access by 11 percentage points. Furthermore, households with social assistance coverage had

[1]The informal economy is defined as all economic activities by economic units that are – in law or in practice – not covered or insufficiently covered by formal arrangements (ILO, 2002).

[2]The social assistance programmes were not re-targeted due to the pandemic nor were new beneficiaries added to either programme (Doyle & Ikutwa, 2021). However, the size of the transfer has been increased. These cash top-ups to the regular cash transfers were provided by the United Nations Children's Fund (UNICEF) and an EU-funded consortium led by the Kenyan Red Cross Society and Oxfam (see more details in section 3).

a 7 percentage points lower probability of selling assets as a coping mechanism compared to non-beneficiary households during the pandemic. Overall, the results suggest that, during a systemic COVID-19 crisis, pre-existing social assistance schemes can deliver positive impacts in line with the primary goals of social safety nets and prevent a household from falling deeper into poverty by preserving their wealth and well-being.

Our findings contribute to the literature on the impacts of social protection (Bastagli et al., 2016; Brugh, Angeles, Mvula, Tsoka, & Handa, 2018; Garcia-Mandico, Reichert, & Strupat, 2021; Handa et al., 2015) and, more specifically, the effects of cash transfers in emergency settings in the developing world (Doocy & Tappis, 2017). Our study contributes to a small number of studies that have evaluated the effects of continued social assistance programmes during the pandemic. Banerjee, Faye, Krueger, Niehaus, and Suri (2020) study the effects of the Universal Basic Income (UBI) experiment during the COVID-19 pandemic in Kenya. They find that cash transfers significantly improved well-being on common measures such as more assets, lower prevalence of hunger and sickness and lower number of depression despite the pandemic. In Bolivia, Bottan, Hoffmann, and Vera-Cossio (2021) study how older individuals (around age 60) respond to additional cash delivered through the social pension system during the pandemic. They found an increase in food stocked and a lower probability of being hungry, in particular for low-income households. Londoño-Vélez and Querubín (2022) study the impacts of a new emergency social assistance programme in Colombia and find positive effects on measures of household well-being such as financial health or food access. We complement the findings of these studies in three ways. First, we present evidence on the effects of existing social assistance programmes that target vulnerable households, which is in contrast to Kenya's non-targeted UBI. Insofar our results inform about the returns of cash transfers through social assistance for poor and vulnerable households, which might be particularly relevant to governments in the developing world who may consider establishing social assistance programmes to protect the poor during future crises. Second, we explore the implications of the adaption and continuation of existing social assistance programmes during a pandemic. Unlike many of the new emergency social assistance programmes including the one in Colombia, which had been running just for a couple of months, Kenya has a long tradition in social protection, which allows for studying how adequate and comprehensive existing social assistance schemes are and to what extent their adaptation was sufficient to deal with the negative consequences of large covariate shocks such as pandemics. Third, our analysis reveals interesting heterogeneities between counties in Kenya that were exposed to more stringent lockdowns (lockdown counties) and those that had fairly relaxed measures.

The rest of this paper is organised as follows. Section 2 describes the spread of COVID-19 and the economic consequence of the pandemic in Kenya. Section 3 presents the national social assistance programmes and describes how they have been adapted during the pandemic. Section 4 introduces the data set, the definition of the outcome variables and presents the econometric model. Section 5 shows the estimation results and the robustness checks, and Section 6 concludes.

2 Spread of COVID-19, lockdown policies and economic consequences

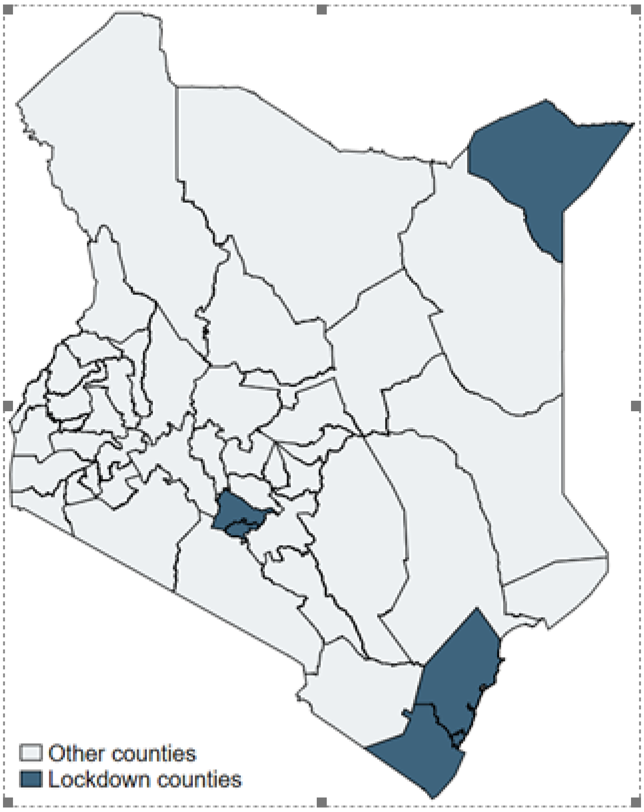
The first case of COVID-19 was confirmed in Kenya on 13 March 2020, and between then and February 2022, more than 322,541 cases and 5,631 deaths have been confirmed (or 10.7 deaths per 100,000 people). While COVID-19 cases have been confirmed across the country, in the early stages of the outbreak more than 82 per cent of the COVID-19 cases were found in Nairobi and 14 per cent in the coastal regions of Mombassa, Kwale and Kilifi (World Bank, 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, known as the "lockdown counties", was curtailed for three to four months. These were Kilifi and Kwale and four months in Nairobi, Kiambu, Mombasa and Mandera. Markets, restaurants and eateries were also closed in these counties (see Figure 1 for locations of lockdown counties) (Doyle & Ikutwa, 2021). Importantly, these specific measures did not include stay-at-home requirements during the daytime and were ended at the latest in July 2020. Further country-wide measures that were imposed in all 47 counties 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. Following this, all schools and learning institutions were closed until October 2020. A ban on international passenger flights lasted until August 2020 (Doyle & Ikutwa, 2021)). Kenya's economy contracted by 0.4 per cent between January and June 2020, a stark contrast with the growth of 5.4 per cent during the same period in 2019 (World Bank, 2020a), implying a net contraction of 5.8%. COVID-19 and the containment measures had the most severe socioeconomic impacts in Nairobi where, initially, cases were highest and lockdown measures were most stringent (The World Bank, 2022). Country-wide unemployment is almost double what it was before COVID-19, and the labour force participation rate has decreased. Close to half of the informal labour force in the lockdown counties and one-third of it in the other counties had to discontinue their labour activities for almost 12 weeks. Overall, The World Bank (2022) reports that earnings have significantly decreased for wage earners in the informal sector. Moreover, the reduction in earnings was found to be greater for informal workers in the lockdown counties (42 per cent) than in other counties (24 per cent). In addition, COVID-19 is estimated to increase poverty in Kenya by about 4 percentage points resulting in 2 million newly poor Kenyans (The World Bank, 2020).

3 Social protection in Kenya

Over the past 10 years, 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 is currently structured along the three main pillars of social assistance, social security and health insurance (Government of Kenya, 2017).[3] The most prominent programme under these pillars is the NSNP. It consists of three cash transfer programmes, namely; the Older Persons Cash Transfer (OP-CT), the Cash Transfer for Orphans and Vulnerable Children (CT-OVC) and the Persons with Severe Disabilities Cash Transfer (PWSD-CT). These three cash transfer pro-

[3]Coverage of social security programmes, such as social insurances, is limited. Only 3% of informal workers are covered (KNBS, 2019). 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).

Figure 1: Counties under different lockdown regimes



grammes give beneficiary households a transfer of KES 2,000 (USD 18) per month.[4] Target households are living in poverty and have at least one household member that falls under the categories covered by each programme (orphans and vulnerable children, elderly and people with severe disabilities). The HSNP is the fourth cash transfer programme; it is implemented by the National Drought Management Authority (NDMA). It targets households that cannot afford to meet basic expenses (regular nutritious food, adequate housing, sanitation, etc.) and are vulnerable to becoming poorer in times of shocks, for example, drought, livestock disease and floods. The programme provides KES 5,400 (USD 50) every two months.[5] The Government of Kenya directly finances 100 per cent of the four cash transfer programmes, which collectively reach 1.3 million households across all counties (Doyle & Ikutwa, 2021).

As a response to the COVID pandemic, the government announced on 25 March 2020 the continuation of NSNP/HSNP and that funds previously committed would be released so that the pandemic would not impact the timely delivery of benefits. Consequently, beneficiaries

[4] On 18 November 2021, the exchange rate for the Kenyan shilling was KES 1 = USD 0.0089 (Onvista, 2021).
[5] The targeting criteria of the NSNP and the HSNP have not changed during the COVID-19 pandemic.

received a lump sum of KES 8,000 (USD 74) to cover the period January to April 2020 (two regular payment cycles were pooled). The second tranche of KES 4,000 (approx. USD 37) was disbursed as a lump sum at the end of June 2020 to cover May and June 2020 (Doyle & Ikutwa, 2021). Vertical expansions that temporarily increased the level of support to NSNP beneficiaries by providing cash top-ups to the regular cash transfers were provided by the United Nations Children's Fund (UNICEF) and an EU-funded consortium led by the Kenyan Red Cross Society and Oxfam. UNICEF provided two monthly cash top-up payments of KES 2,000 per month to all NSNP beneficiaries with children under 10 years. The EU consortium provided monthly cash top-ups of KES 5,668 (approx. USD 52) for three months to all NSNP beneficiaries residing in informal settlements. The continuation and adaptations of the NSNP and HSNP were highlighted in public appeals of the government to "stand together" to cope with the pandemic (Government of Kenya, 2020).

The government also set up new short-term social assistance programmes to cushion some of the negative socioeconomic consequences of the pandemic. They target households that are not enrolled in the NSNP or HSNP. This short-term response consists of the multi-agency COVID-19 cash transfer and the National Council for Persons with Disabilities (NCPWD) cash transfer. Both programmes target 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) for a period of three to four months and reached 669,000 households (Doyle & Ikutwa, 2021).

4 Data and research design

4.1 Data

In this study, we assess the effect of the NSNP and the HSNP on economic shocks, lived poverty and coping mechanisms. The analysis is based on two primary cross-sectional surveys conducted before and during the pandemic in Kenya. In December 2018, 1,186 households were surveyed, and in December 2020 after lockdown measures were eased 2,166 households were surveyed, making a total sample of 3,352 households. The surveys were designed as repeated country-representative cross-sections of households in the informal economy. The data was collected through in-person interviews with the household head and one randomly selected household member over the age of 15.[6] One of the objectives 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 pandemic. The questionnaire included modules on household demographics, health, economic situation, social protection programmes, social cohesion and self-organisations. The selected sample was determined by random selection methods at every stage of sampling and the application of probability sampling was based on population data (see the detailed description of the sampling design and sampling process in the Appendix).[7]

The present study concentrates on outcomes related to the economic and social well-being of households. We are interested in three outcomes, namely prevalence of economic shocks, income poverty and lived poverty. Economic shocks are measured as whether a household member lost a job or lost income to a margin that seriously affected the household's ability to pay the most essential expenses. To assess income poverty, 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 (60 USD) we considered the household as 'income poor'. The third outcome 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. The concept of lived poverty emanates from the basic needs theories and has been developed and tested in the Afrobarometer surveys across various African countries (Meyer & Keyser, 2016). A standard question to assess lived poverty reads: "Over the past month, how often if ever have you or your family gone without —?" The interviewer then repeats the question about various basic necessities, including food, clean water, electricity, medical access, fuel, income, decent housing, decent clothing and education

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

[7]Random sampling with probability proportional to population size was applied at each stage. The sampling process was based on stratification of the country into regions. Regions were further classified into counties, and these were further divided into districts and villages. Primary sampling units (PSUs) are the smallest geographical unit for which reliable population data are obtainable. The primary sampling units were selected from each stratum based on its share of the national population, and further allocated based on the urban/rural divide. Twice as many primary sampling units were selected from lockdown counties to enable a detailed analysis. This oversampling was accounted for by applying sampling weights in the subsequent analysis.

amenities. The answer options range from “Never,” “Just Once or Twice,” “Several Times,” “Many Times,” or “Always”. We use a reduced version of the main Afrobarometor survey, capturing three of the nine questions. Thus our measure of lived poverty includes access to enough food to eat, enough clean water for home use and enough fuel to cook your food. We aggregated the three basic necessities and classified households as “lived poor” when they experience on average “several times”, “many times” or “always” a shortage of these items in the past month. Furthermore, we generated outcome indicators for each basic necessity calling “shortage of food”, “shortage of clean water” and “shortage of cooking fuel”.

A further set of outcome indicators is related to our indicator on the prevalence of economic shocks. Our secondary outcomes address coping strategies for economic shocks. We asked the respondent how the household coped with economic shocks. The responses were coded as selling assets, depleting e savings, taking a loan and borrowing money from family/other households. The responses were coded as binary outcomes. Finally, we assess if the cash transfers had an impact on assets. Our questionnaire also included questions concerning the household’s ownership of several assets such as a television, fridge, mobile phone, table, bed etc; each household asset for which information is collected 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 standardizes 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. The higher the score of the index, the wealthier the household.

Table 1 below shows the means of the outcome variables for the time before and after the first wave of the pandemic. Higher prevalence of economic shocks, income poverty and lived poverty can be detected. The prevalence of economic shocks increase by 17 percentages points, income poverty by 15 percentages points and lived poverty by 7 percentages points. All indicators show that households operating in the informal economy were largely affected by the negative consequences of the pandemic. Households experience also an increase in shortage of food and clean water, which might be due to loss of income and stop paying bills for water access. With regards to the coping strategies, we find an increase in selling assets and a decline in asset wealth. Furthermore, households increasingly deplete their savings and borrow money from family and friends.

Table 1: Means of the outcome variables before and after the first wave of the pandemic

	After first wave	Before pandemic	Difference
Economic shock (1/0)	0.79	0.62	0.17***
	(0.01)	(0.01)	(0.02)
Income poverty (1/0)	0.59	0.44	0.15***
	(0.01)	(0.02)	(0.02)
Lived poverty (1/0)	0.35	0.28	0.07***
	(0.01)	(0.01)	(0.02)
Shortage of food (1/0)	0.37	0.27	0.10***
	(0.01)	(0.01)	(0.02)
Shortage of clean water (1/0)	0.34	0.29	0.05***
	(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)	0.11	0.07	0.04***
	(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	0.19	0.03*
	(0.01)	(0.01)	(0.02)
Asset wealth index	1.45	1.56	-0.11***
	(0.01)	(0.02)	(0.02)
N	2,166	1,186	

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

With regards to our treatment variable, the survey team asked the household head whether the household is covered by the NSNP (including the three cash transfer programmes), the HSNP or any other existing social assistance programme. Enrolment status was checked by the enumerators using either identification documents or the NSNP card. To separate existing social assistance programmes from new short-term programmes (see Section 3), the enumerators first asked whether the respondents had 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 an employer. If it was from the national government, the respondents were asked to indicate the programme from which they received the cash transfers.

As the focus of the paper is to examine the effects of existing social assistance programmes (NSNP, HSNP) during the pandemic, Table 2 presents the mean coverage of these programmes before and after the first wave of the pandemic. As the government of Kenya managed to minimise disruptions to the routine delivery of benefits, 13 per cent of our sample were covered by social assistance programmes in 2020. This share is in line with the 1.3 million households that were covered by social assistance in 2020, which represents 13 per cent of the 10 million households that operate in the informal economy (KNBS, 2019).

Table 2: Enrolment in the national social protection programmes before and after the first wave of the pandemic

	After first wave of pandemic	Before pandemic	Difference
Social Assistance enrolment (%)	0.13	0.14	-0.01
	(0.01)	(0.01)	(0.01)
N	2,166	1,186	

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

4.2 Empirical specification

The estimation strategy used for this study exploits the effect of the national social assistance programmes (such as the NSNP and HSNP) 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 social assistance programmes are compared before and after the first wave of the pandemic using repeated cross-sectional data.[8] To employ the difference-in-differences strategy, the following specification is estimated.

$$Y_{ict} = \beta_0 + \beta_1 T_t * SA_{ict} + \beta_2 T_t + \beta_3 SA_{ict} + X_{ict}\beta_4 + v_c + \tau^{ipw\_rc} + \epsilon_{ict} \tag{1}$$

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

where Y_{ict} represents the outcome of interest (see Table 1) for household i residing in county c at the time of each survey t[9]. The variable T_t represents the before and after dummy which takes the value of 0 in the baseline and 1 in the round of data collected after the first wave of the pandemic. SA_{ict} is an indicator of social assistance in the household, taking the value 1 if the household i is covered by at least one of the two 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. The difference-in-differences estimator is then given by the interaction of the time dummy and the social assistance dummy hence $T_t * SA_{ict}$ with its corresponding β_1 coefficient.

Descriptive statistics of all household characteristics are in Table A1 of the Appendix. Tables A2 and A3 of the Appendix show further the means of all explanatory variables for each survey wave with and without social assistance coverage. Causal estimation with cross-sectional data requires that there are no compositional changes between the various cross-sections. As can be observed in Tables A2 and A3, no major compositional changes between and within repeated cross-sections surveys can be detected. To account for the different initial development levels of the Counties that are possibly related to the outcome variables and social assistance coverage, we include county fixed effects for the 47 Kenyan Counties shown by v_c. Furthermore, our data is only two survey rounds with one pre-pandemic data point. We are therefore unable to test for parallel trends. To alleviate concerns from this inability to test for parallel trends, we integrate inverse-probability weighting into the estimator. The term τ^{ipw_rc} represents the inverse-probability weights for repeated cross-sections derived from the doubly-robust difference-in-differences estimator (Sant'Anna & Zhao, 2020). The weight is calculated by considering the household characteristics in each cross-section and accounting for location fixed effects (county dummies). It ensures that the overlapping region of support is composed of the social assistance beneficiaries to whom a counterfactual is found, which

[9]Respondents are household members over the age of 15. They were randomly selected from the household after the screening of all household members. The random selection was done with the tablet computers that were used during the survey. As the analysis relies on cross-sectional surveys, respondents were not surveyed twice.

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)

The coefficient of interest is β_1. Interpreting these effects as causal depends critically on the identifying assumption. Conditional on the controls included in the specification (1), the identifying assumption is that respondents with and without coverage of the national social assistance programmes before the pandemic would continue with the same trends of the selected outcomes during the pandemic if the pandemic would not have happened. 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. We do not expect that the pandemic affects social assistance and non-social assistance beneficiaries differently. Therefore, controlling for observable socioeconomic household differences that partly explain social assistance coverage but are unrelated to the pandemic, we expect that the changes in the observed outcomes are due to the coverage of national social assistance programmes in times of the pandemic.

5 Results

5.1 Descriptive results

Table 3 shows the means of our outcome variables for the two groups across the two survey rounds. It seems that before the pandemic there were many statistically significant differences in levels of household well being between those with and without coverage of social assistance programmes. Households who receive social assistance are on average poorer, experience more economic shocks and are more often short of food, clean water and cooking fuel. If we compare both groups before and after the first wave of the pandemic, the difference-in-differences reveal statistical significant reductions in experiencing economic shocks, income poverty and lived poverty. Furthermore, the shortage of basic necessities (food, clean water and cooking fuel) is reduced and households are less likely to cope with the pandemic by selling their household assets. Consequently, we find an increase in household asset wealth. Most of these difference-in-differences findings are due to households who do not receive social assistance as they experience a large increase in the prevalence of economic shocks and income poverty and a more frequent shortage of basic necessities. In contrast, the rise of poverty and decline of well-being is modest for social assistance beneficiaries. These descriptive findings point to the potential preserving effect of social assistance on household welfare during the COVID-19 pandemic. However, it is important to consider household characteristics and time-invariant county characteristics to control for confounding factors, so the next subsection gives the estimation results of our econometric model.

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

	After first wave of pandemic			Before pandemic			
	Social assistance	No social assistance	Single diff (1-2)	Social assistance	No social assistance	Single diff (4-5)	Double diff. (1-2) –(4-5)
Economic shock	0.78	0.79	-0.01	0.72	0.63	0.09***	-0.10**
	(0.02)	(0.01)	(0.03)	(0.03)	(0.02)	(0.04)	(0.05)
Income poverty	0.84	0.58	0.15	0.73	0.41	0.21***	-0.06*
	(0.03)	(0.01)	(0.03)	(0.04)	(0.02)	(0.04)	(0.04)
Lived poverty	0.40	0.35	0.05	0.43	0.26	0.17***	-0.11**
	(0.03)	(0.01)	(0.03)	(0.04)	(0.01)	(0.04)	(0.05)
Shortage of food	0.43	0.36	0.07**	0.43	0.24	0.19***	-0.08*
	(0.03)	(0.01)	(0.03)	(0.04)	(0.01)	(0.04)	(0.05)
Shortage of clean water	0.35	0.32	0.03	0.39	0.27	0.12***	-0.12**
	(0.03)	(0.01)	(0.03)	(0.04)	(0.01)	(0.04)	(0.05)
Shortage of cooking fuel	0.21	0.21	0.00	0.26	0.19	0.07**	-0.07*
	(0.02)	(0.01)	(0.02)	(0.03)	(0.01)	(0.03)	(0.04)
Selling assets	0.11	0.10	0.01	0.14	0.06	0.07***	-0.06**
	(0.02)	(0.01)	(0.02)	(0.03)	(0.01)	(0.02)	(0.03)
Deplete savings	0.20	0.24	-0.03	0.14	0.18	-0.05	0.01
	(0.02)	(0.01)	(0.03)	(0.03)	(0.01)	(0.03)	(0.04)
Take loan	0.04	0.05	-0.01	0.02	0.04	-0.01	0.01
	(0.01)	(0.005)	(0.01)	(0.01)	(0.006)	(0.01)	(0.02)
Borrow money (family)	0.29	0.21	0.08**	0.24	0.19	0.05	0.03
	(0.03)	(0.01)	(0.03)	(0.03)	(0.01)	(0.03)	(0.04)
Asset wealth index	1.34	1.47	-0.13***	1.32	1.60	-0.27***	0.14**
	(0.04)	(0.01)	(0.03)	(0.05)	(0.02)	(0.05)	(0.06)
N	288	1,878		169	1,019		

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

5.2 Empirical results

We assess the effect of coverage by social assistance programmes on economic shocks and poverty. First, we look at the effect of reporting an economic shock on the household. Column 1 of Table 4 shows the results of the effect of social assistance on the probability of reporting economic shocks. We find that coverage by social assistance programmes reduced the probability of reporting an economic shock by 15.6 percentage points. Column 2 shows income poverty, defined as earning less than 7500 KES per month (equivalent to about US$ 75 per month of US$2.5 per day). We find that social assistance was associated with a reduction in the probability of income poverty by 14 percentage points. Thirdly, we consider the effect of social assistance programmes on lived poverty. We show that the probability of lived poverty is reduced by 11 percentages points. Our components of lived poverty include shortage of food, shortage of clean water and shortage of cooking fuel (column 4-6). We find that while a composite lived poverty reduces by 11 percentages points, significant at 10 per cent level, only one of the three items is significant. Households are 11 percentage points less likely to report food shortages when covered by social assistance programmes. We find that while there was a negative coefficient on access to clean water and cooking fuel, the results were not statistically significant.

Table 4: Effects of social assistance programmes on economic shocks and poverty

Variables	(1) Economic Shock	(2) Income Poverty	(3) Lived Poverty	(4) Not enough food	(5) No clean water	(6) No cooking fuel
Social assistance	-0.156**	-0.138*	-0.108*	-0.108*	-0.050	-0.059
	(0.073)	(0.070)	(0.062)	(0.058)	(0.064)	(0.056)
Baseline means	[0.72; 0.64]	[0.73; 0.44]	[0.43; 0.29]	[0.43; 0.28]	[0.39; 0.27]	[0.26; 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. Baseline means of outcomes for social assistance beneficiaries and the entire sample are in brackets. *** p<0.01, ** p<0.05, * p<0.1

Next, we look at the effect of social assistance programmes on coping strategies for economic shocks. As shown in Table 5 below, we consider four coping strategies, namely; selling off assets, depletion of savings, taking a consumption loan and borrowing money from friends and family. We find that social assistance reduced the probability of selling assets by 7 percentage points. In addition, we observe negative but non-significant coefficients on savings depletion and taking consumption loans. We did not observe any significant effect of social assistance on borrowing from friends and family. We further did not find any effect of social assistance on asset wealth. It, therefore, seems that social cash transfers provide some basic social safety nets that limit the probability of additional destitution through asset selling but were not able to effectively and significantly reduce the probability of other more transient and less adverse coping mechanisms. Moreover, social assistance during the pandemic did not have any noticeable effect on asset accumulation, implying that while there was some protection again asset depletion, households do not accumulate more assets.

Table 5: Effects of social assistance programmes on coping with economic shocks

	(1) Sell assets	(2) Use Savings	(3) Take Loan	(4) Family help	(5) Asset index
Social assistance	-0.069**	-0.052	-0.001	0.046	0.094
	(0.034)	(0.044)	(0.027)	(0.044)	(0.089)
Baseline means	[0.14; 0.07]	[0.14; 0.19]	[0.02; 0.05]	[0.24; 0.20]	[1.32; 1.56]
Observations	3,095	3,095	3,095	3,095	3,352

All regressions include household controls and county dummies. Standard errors are clustered at the county-survey round level and in parentheses. Baseline means of outcomes for social assistance beneficiaries and the entire sample are in brackets. *** p<0.01, ** p<0.05, * p<0.1

5.3 Heterogeneity analysis using lockdown counties

To explore whether the effect of social assistance programmes are heterogeneous between lockdown and non-lockdown counties, we split the sample and perform the analysis separately. Before turning to the results of the analysis it is important to consider that 80 per cent of the households in the 6 lockdown counties reside in urban areas, while it is only 20 per cent in non-lockdown counties. The main reason is that in the early stages of the outbreak the government curtailed lockdowns in counties where many COVID-19 cases have been detected. As more than 82 per cent of the COVID-19 cases were found in Nairobi and 14 per cent in the coastal regions around Mombasa (The World Bank, 2020), lockdown policies were mostly implemented in urban areas. Importantly, the lockdowns were curtailed for three to four months and include the closure of markets, restaurants and eateries, but did not include stay-at-home requirements during the daytime. Further country-wide measures were imposed in all 47 counties (see details in section 2). So non-lockdown counties experienced different types of restrictions that were less stringent and did not include the closure of markets, restaurants and eateries.

Table 6 shows the results of economic shocks and poverty for lockdown and non-lockdown counties. We find that social assistance programmes reduce the probability of reporting an economic shock in lockdown countries, but not in non-lockdown countries, which is in line with the higher prevalence of economic shocks in lockdown counties. Similar differences in the effects of social assistance programmes can be detected for income poverty. The coefficient for lockdown counties is statistically significant and we can observe that the effect size for lockdown counties is larger as compared to non-lockdown counties. The result of our measure of lived poverty which shows how frequently people go without basic necessities such as food, clean water or cooking fuel, shows that social assistance programmes reduce lived poverty only in non-lockdown counties. Households in non-lockdown counties mostly live in rural areas where the shortage of food and clean water is more prevalent. It seems that the social assistance programmes were effective in preventing households to become more deprived in these areas, while it has no effect in lockdown counties that have lower levels of pre-pandemic lived poverty (see baseline means of outcomes in Table 6). The result is in line with our findings looking at differences in the effects of the social assistance programme between urban and rural areas (see Table A4), where we find a reduction of lived poverty only in rural areas.

Table 7 shows the results for the four coping strategies for lockdown and non-lockdown counties. We found that social assistance reduced the probability of selling assets in non-lockdown counties, but not in lockdown counties. The rural-urban divide between both groups is the main reason for that result, as in non-lockdown counties, which are predominately rural, selling assets to cope with shocks is much more common than in lockdown counties (see base-

Table 6: Effects of social assistance programmes on economic shocks and poverty for lockdown and non-lockdown counties

	Lockdown			Non-lockdown		
	Economic Shock	Income Poverty	Lived Poverty	Economic Shock	Income Poverty	Lived Poverty
Social assistance	-0.251*	-0.174*	0.008	-0.085	-0.106	-0.230***
	(0.134)	(0.105)	(0.128)	(0.065)	(0.066)	(0.065)
Baseline means	[0.79; 0.66]	[0.75; 0.42]	[0.40; 0.26]	[0.69; 0.63]	[0.71; 0.45]	[0.49; 0.37]
Observations	1,025	951	1,025	2,327	2,204	2,328

All regressions include household controls and county dummies. Standard errors are clustered at the county-survey round level and in parentheses. Baseline means of outcomes for social assistance beneficiaries and the entire sample are in brackets. *** p<0.01, ** p<0.05, * p<0.1

line means of outcomes in Table 7). Results looking at differences between urban and rural areas confirm our findings (see Table A5). We observe non-significant coefficients on savings depletion and taking consumption loans, and borrowing from friends and family.

Table 7: Effects of social assistance programmes on coping with economic shocks for lockdown and non-lockdown counties

	Lockdown				Non-lockdown			
Variables	Sell assets	Savings	Take loan	Family help	Sell assets	Savings	Take loan	Family help
Social assistance	-0.023	-0.086	0.004	-0.016	-0.132***	0.031	0.003	0.069
	(0.053)	(0.085)	(0.072)	(0.069)	(0.039)	(0.048)	(0.017)	(0.064)
Baseline means	[0.05; 0.02]	[0.25; 0.21]	[0.08; 0.05]	[0.28; 0.23]	[0.16; 0.10]	[0.10; 0.16]	[0.01; 0.03]	[0.22; 0.19]
Observations	940	940	940	940	2,155	2,155	2,155	2,155

All regressions include household controls and county dummies. Standard errors are clustered at the county-survey round level and in parentheses. Baseline means of outcomes for social assistance beneficiaries and the entire sample are in brackets. *** p<0.01, ** p<0.05, * p<0.1

5.4 Robustness checks

Analysis of repeated cross-sectional data can have various threats in the estimation of causal effects. Two key threats are envisaged in our study. The first is the possibility of group compositional changes thereby suggesting that the effects observed are more likely driven by the changing sample rather than the treatment itself. The key remedy then is to provide evidence of no compositional changes. We compare between and within differences in the two cross-sectional and show results in supplementary tables A2 and A3. We can reject that in almost all the controls included in the models, there were no systematic differences between and within the samples.

Related to the above is a threat of regression to the mean. This simply implies that 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 hence introducing bias (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 include 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.

Another robustness check is related to the institutional setting of social assistance programmes in Kenya. The programmes are implemented by the national government (Government of Kenya, 2017) and their continuation during the pandemic was highlighted in public appeals (Government of Kenya, 2020). We use outcomes on institutional trust to check whether the programmes affect trust in the national government rather than in non-government institutions. If trust in non-government institutions such as traditional leaders has been affected by the social assistance programmes as well, this would raise concerns that the change in our outcome indicators is not entirely due to them. We show the results of this robustness check in Table A8. We find positive and significant effects of the programmes on trust in the president and the national government, while there have been no effects on trust in non-government institutions.

6 Conclusion

As it was unclear whether existing social assistance measures affect a household's well-being in times of large covariate shocks such as a pandemic, this study attempts to close this knowledge gap by focusing on the relationship between social assistance and common measures of household welfare in Kenya during the COVID-19 pandemic. The continuation and adaptation of existing social assistance programmes in response to the COVID-19 pandemic, coupled with the large impacts of the pandemic and lockdown policies, make Kenya an ideal setting for examining this relationship. Using unique primary data from repeated country-representative in-person surveys that were collected more than one year before and three months after the first wave of the pandemic and employing a doubly-robust difference-in-differences approach, shows that social protection in the form of existing social assistance programmes can be beneficial for vulnerable and poor households.

The findings suggest that social assistance has a preserving effect on household welfare. We find only modest increases in the prevalence of economic shocks and poverty for social assistance beneficiaries, while the increase is substantially larger for non-beneficiary households due to the pandemic. The coverage by social assistance helped vulnerable and poor households during the pandemic, especially with stabilizing household income and basics like food. This effect is pronounced in counties that were exposed to more stringent lockdowns (lockdown counties). The results strengthens the case for building the infrastructure for making social assistance programmes that can be continued during the pandemic and can be adapted to deliver additional cash in response to unanticipated crises like the one we are currently experiencing.

References

Afrobarometer Network. (2017). *Afrobarometer Round 7 Survey Manual* (Tech. Rep. No. Round 7). Retrieved from http://afrobarometer.org/sites/default/files/survey{_}manuals/ab{_}r7{_}survey{_}manual{_}en.pdf

Banerjee, A., Faye, M., Krueger, A., Niehaus, P., & Suri, T. (2020). Effects of a Universal Basic Income during the pandemic. *Working Paper*.

Bastagli, F., Hagen-zanker, J., Harman, L., Barca, V., Sturge, G., Schmidt, T., & Pellerano, L. (2016). *Cash transfers : what does the evidence say ? A rigorous review of programme impact and of the role of design and implementation features* (Tech. Rep. No. July). London: Overseas Development Institute. Retrieved from https://cdn.odi.org/media/documents/11316.pdf

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).

Brugh, K., Angeles, G., Mvula, P., Tsoka, M., & Handa, S. (2018). Impacts of the Malawi social cash transfer program on household food and nutrition security. *Food Policy*, *76*, 19–32.

Daw, J. R., & Hatfield, L. A. (2018). Matching in Difference-in-Differences: between a Rock and a Hard Place. *Health Services Research*, *53*(6), 4111–4117.

Doocy, S., & Tappis, H. (2017). Cash-based approaches in humanitarian emergencies: a systematic review. *Campbell Systematic Reviews*, *13*(1), 1–200.

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.

Garcia-Mandico, S., Reichert, A., & Strupat, C. (2021). The social value of health insurance results from Ghana. *Journal of Public Economics*, *194*, 104314.

Gentilini, U., Almenfi, M., Blomquist, J., Dale, P., De, L., Giuffra, F., ... Grun, R. (2021). *Social Protection and Jobs Responses to COVID-19 : A Real-Time Review of Country Measures.* Washington DC: The World Bank.

Government of Kenya. (2011). *Kenya National Social Protection Policy (2011).* Nairobi: Government of Kenya. Retrieved from https://socialprotection.or.ke/about-sps/kenya-national-social-protection-policy

Government of Kenya. (2017). *Kenya Social Protection Sector Review* (Tech. Rep.). Nairobi: Government of Kenya.

Government of Kenya. (2020). *Presidential Address on Enhanced Measures in Response to the Covid-19 Pandemic by H.E. Uhuru Kenyatta, C.G.H, President and Commander-In-Chief of Kenya Defence Forces on 6th April, 2020.* Nairobi: Government of Kenya. Retrieved from https://www.president.go.ke/2020/04/06/17505/

Hale, T., Angrist, N., Goldszmidt, R., Kira, B., Petherick, A., Phillips, T., ... Tatlow, H. (2021). A global panel database of pandemic policies (Oxford COVID-19 Government Response Tracker). *Nature Human Behaviour*, *5*(4), 529–538. Retrieved from http://dx.doi.org/10.1038/s41562-021-01079-8

Handa, S., Peterman, A., Huang, C., Halpern, C., Pettifor, A., & Thirumurthy, H. (2015). Impact of the Kenya Cash Transfer for Orphans and Vulnerable Children on early pregnancy and marriage of adolescent girls. *Social Science and Medicine*, *141*, 36–45. Retrieved from http://dx.doi.org/10.1016/j.socscimed.2015.07.024

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.

ILO. (2002). *Governing Body Record of decisions* (No. November). Geneva: International Labour Office.

KNBS. (2019). *Economic Survey 2019 - Highlights* (Tech. Rep. No. April). Nairobi: Kenya National Bureau of Statistics. Retrieved from https://www.knbs.or.ke/download/economic-survey-2019/

Leininger, J., Strupat, C., Adeto, Y., & AbebeShimeles, W. (2021). *The COVID-19 pandemic and structural transformation in Africa: Evidence for action* (Vol. Discussion) (No. No. 11/2021). Retrieved from http://dx.doi.org/10.23661/dp11.2021{%}0Ahttp://hdl.handle.net/10419/231451

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.

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.

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

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

Sumner, A., Hoy, C., & Ortiz-Juarez, E. (2020). *Estimates of the impact of COVID-19 on global poverty* (No. April). Helsinki. Retrieved from https://doi.org/10.35188/UNU-WIDER/2020/800-9

The World Bank. (2020). *Kenya Economic Update: Navigating the Pandemic COVID-19* (Tech. Rep.). Washington DC: The World Bank Group. Retrieved from https://documents1.worldbank.org/curated/en/957121606226133134/pdf/Kenya-Economic-Update-Navigating-the-Pandemic.pdf

The 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

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

Supplementary Materials

Sampling design and process

The sample universe associated with our survey includes all households in Kenya that operate in the informal economy on the day of the survey. We exclude households that are operating in the formal economy. To obtain a nationally representative cross-section of this target population, we use the most recent national census data from the Kenya National Bureau of Statistics (KNBS). We used a clustered, stratified, multi-stage, probability sample design. The objective of our sample design was to give every household that operate in the informal economy an equal chance of being chosen for inclusion in the sample. This ensures that the survey provides a representative estimate of the views of the target population. We reached this objective by (a) strictly applying random selection methods at every stage of sampling and by (b) applying sampling with probability proportionate to adult population size.

The sampling process was based on stratification of the country into regions. Regions were further classified into counties and these were further divided into districts and villages. Primary sampling units (PSUs) – sometimes referred to as enumeration areas – are the smallest geographical unit/cluster for which reliable population data were obtainable. The primary sampling units were selected from each stratum based on shares of the national population and number of households, and further allocated based on the urban/rural divide.

The sampling process was structured in four stages and follows largely the process of the Afrobarometer surveys (Afrobarometer Network, 2017): (i) selection of enumeration areas; (ii) selection of sampling start-points; (iii) selection of households; and (iv) identifying households that operate in the informal economy for interview.

- Selecting enumeration areas (EA): Based on the latest and updated population census Kenyan National Bureau of Statistics (KNBS) randomly select enumeration areas for each stratum and respective rural/urban divide, based on probability proportional to size of population and number of households.

- Selecting the sampling start-points (SSPs) for each enumeration area: As no complete lists of households of the informal economy were available from which the sample could be randomly drawn for each EA, we use physical maps of the enumeration areas that were provided by the KNBS. A random sampling start-point (SSP) is marked on the map and field teams travel as close as possible to it, or to housing settlements nearest to it. A second SSP is selected as a reserve or substitute in case the initial SSP is inappropriate or inaccessible. Random selection of a start-point uses a grid. A ruler is placed along the top of the map and another along the side. A table of random numbers is then used to select pairs of numbers, one for the top axis and one for the side axis, resulting in a random combination. A line is then drawn on the map horizontal to the number chosen on the side, and another line is drawn vertical to the number chosen on the top. The point on the map where these two lines intersect is the sampling start-point. Each x-Y pair of numbers from the random number table can be used only once.

- Selecting the household – walking pattern of interview teams: The interviewers start walking away from the physical start-point, with interviewer 1 walking towards the sun; interviewer 2 in the opposite direction; interviewers 3 and 4 at a 90-degree angle to the right and left. With this walking pattern, all four directions are covered. By counting households on both sides of the walking path, household No. 5 is selected as the first household for the interview and household No. 15 for the second interview. Special rules were applied in the case of multi-storey buildings, widely scattered households and settlements within commercial farms.If the interview cannot take place because nobody is at home, or the interview starts but cannot be finished, the walk continues to the next household on the same side of the road or opposite (household No. 6), while the second interview is done in household No. 16. If the interview is refused the walk continues in the same direction until household No. 15. The second interview would take place with household No. 25.

- Identifying households for the interview that operate in the informal economy: At the household level, each interview is done in two phases. Phase 1 of the interview is conducted with the household head living in the household. The household head provides demographic and employment information on each member of the household (15 or older).

Based on this screening a list is drawn up to include all household members who operate in the formal and informal economy. The interview was ended if at least one member (15 or older) is active in the formal economy and the household was replaced by another household.

For households were no member is active in the formal economy, the respondent for the main part of the interview (phase 2) is randomly selected from the list of persons that operate in the informal economy for interview. If the randomly selected respondent is unavailable the fieldworker makes an appointment for a later time in the day for a second attempt. If the interview is unsuccessful after the second attempt, the fieldworker randomly selects another respondent who qualifies within the same household for the interview. If the second respondent is unavailable or the interview is unsuccessful for whatever reason, the household is dropped and the fieldworker replaces it with another household.

To identify activities within the informal economy, the survey used the following operational definitions: i) Informal farming, raising animals or fishing: economic activities whose products have been produced for sale were grouped as informal. ii) Informal employees: paid job with no reference to an employer's tax contribution or contribution to a public or private pension scheme. If employers did not pay contributions, employees were grouped as informal. iii) Informal employers and own-account workers: informality is defined by non-registration in the national registry, which is used for company taxation. iv) Contributing family workers: defined, by default, as having an informal job because of the informal nature of jobs held by contributing family workers that also can include unemployed or students.

Supplementary Tables

Table A1: Means of the explanatory variables

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

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

Table A2: Means of the explanatory variables for social assistance beneficiaries

	After first wave	Before pandemic	Difference	Std. Error
Age 15-29	0.2639	0.3254	-0.0616	0.0438
Age 30-39	0.2118	0.2604	-0.0485	0.0408
Age 40-49	0.2674	0.2775	0.0098	0.0409
Age 50-49	0.1319	0.1361	-0.0042	0.033
Age >60	0.1250	0.1006	0.0244	0.0311
No education	0.1701	0.1657	0.0045	0.0363
Some primary education	0.1979	0.2189	-0.021	0.0392
Primary education	0.3507	0.3373	0.0134	0.0462
Secondary education	0.2604	0.2663	-0.0059	0.0427
University education	0.0108	0.0118	0.001	0.0127
Female	0.4306	0.4207	0.010	0.0482
Household size	4.4722	4.5858	-0.1136	0.2149
Share of children (age<15) in household	0.336	0.3306	0.0053	0.0250
Share of elderly (age>60) in household	0.0798	0.0764	0.0034	0.019
Disability in the household	0.0802	0.0809	-0.0008	0.0095
Household resides in rural areas	0.5968	0.6509	-0.0541	0.0473
Number of observations	288	169		

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

Table A3: Means of the explanatory variables for non-social assistance beneficiaries

	After first wave	Before pandemic	Difference	Std. Error
Age 15-29	0.3323	0.3550	-0.0227	0.0184
Age 30-39	0.2668	0.2783	-0.0115	0.0173
Age 40-49	0.1853	0.1819	0.0034	0.0151
Age 50-49	0.1177	0.1003	0.0174	0.0123
Age >60	0.0980	0.0846	0.0134	0.0113
No education	0.0820	0.0718	0.0102	0.0105
Some primary education	0.1933	0.1967	-0.0034	0.0154
Primary education	0.3477	0.3402	0.0075	0.0185
Secondary education	0.3317	0.3402	-0.0085	0.0184
University education	0.0453	0.0511	-0.0059	0.0083
Female	0.4694	0.4730	-0.0235	0.0194
Household size	4.3775	4.1927	0.1848**	0.0848
Share of children (age<15) in household	0.3055	0.3069	-0.0014	0.0098
Share of elderly (age>60) in household	0.0379	0.0492	-0.0113**	0.0055
Disability in the household	0.0692	0.0757	-0.0065	0.0100
Household resides in rural areas	0.6715	0.6608	0.0107	0.0183
Number of observations	1,878	1,017		

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

Table A4: economic shock, income and lived poverty for urban and rural areas

Variables	Urban			Rural		
	Economic Shock	Income Poverty	Lived Poverty	Economic Shock	Income Poverty	Lived Poverty
Social assistance	-0.295*	-0.143	-0.058	-0.085	-0.017	-0.125*
	(0.162)	(0.131)	(0.151)	(0.076)	(0.091)	(0.076)
Observations	1,140	1,059	1,140	2,212	2,096	2,212

Regressions include household controls and 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 A5: coping mechanisms for urban and rural areas

	Urban	Urban	Urban	Urban	Rural	Rural	Rural	Rural
	Sell assets	Savings	Take loan	Family help	Sell assets	Savings	Take loan	Family help
Social assistance	-0.118	-0.133	0.014	0.007	-0.104**	0.058	-0.023	-0.012
	(0.072)	(0.099)	(0.109)	(0.093)	(0.043)	(0.047)	(0.022)	(0.076)
Observations	1,046	1,046	1,046	1,046	2,049	2,049	2,049	2,049

Regressions include household controls and 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 A6: Robustness check: economic shock, income and lived poverty with only time invariant controls

Variables	(1) Economic shock	(2) Income poverty	(3) Lived poverty	(4) Not enough food	(5) No clean water	(6) No cooking fuel
Social assistance	-0.141**	-0.100	-0.087*	-0.065	-0.056	-0.071
	(0.057)	(0.065)	(0.049)	(0.048)	(0.047)	(0.044)
Observations	3,352	3,155	3,352	3,352	3,352	3,352

Regressions include household controls and 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 mechanisms with only time invariant controls

Variables	(1) Sell assets	(2) Savings	(3) Loan	(4) Family help	(5) Asset index
Social assistance	-0.070***	-0.058*	-0.019	0.048	0.005
	(0.025)	(0.034)	(0.026)	(0.040)	(0.081)
Observations	3,095	3,095	3,095	3,095	3,352

Regressions include household controls and 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: Robustness check: institutional trust

Variables	(1) Trust in president	(2) Trust in national government	(3) Trust in traditional. leaders	(4) Trust in local leaders	(5) Trust in religious. leaders
Social assistance	0.183*	0.295***	0.014	0.002	0.219
	(0.110)	(0.107)	(0.118)	(0.125)	(0.136)
Observations	3,324	3,319	3,320	3,318	3,302

Regressions include household controls and county dummies. Standard errors are clustered at the county-survey round level and in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Trust is measured as categorical variable that ranges from “not at all” (coded “0”) to “a lot” (coded “4”).