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COVID-19, Poverty, and Social Safety Net Response in Zambia

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Abstract

What has the impact of the COVID-19 pandemic been on poverty in Zambia, and how can social protection programs mitigate these effects? This paper estimates the pre-pandemic poverty level in Zambia and then simulates the distributional impact of COVID-19 in the country. The paper also estimates the impact of a social cash transfer program that led the COVID response, on poverty levels. In the absence of recent nationally representative household survey data, this is done by updating the consumption distribution in the 2015 Living Conditions Monitoring Survey using annual real per capita gross domestic product growth rates for specific sectors. The study shows that the national poverty headcount rate increased from 54.4 percent in 2015 to 55.8 percent in 2019, and this change was driven entirely by rural areas. By contrast, the economic impact of COVID-19 has disproportionately impacted urban areas and exacerbated the already high poverty levels, with the poverty headcount increasing to 57.6 percent in 2020. Expanding and enhancing cash transfers have been a key policy lever that many countries have used to mitigate the negative economic consequences of the pandemic. Simulations in Zambia suggest that a fully operational social cash transfer program with the current and proposed enhanced transfer amounts has the potential to reduce poverty significantly—by four and six percentage points, respectively. Beyond this specific analysis, the paper makes a case for the innovative use of existing data to inform adaptive or shock responsive social protection, even in largely data poor environments.

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Introduction

The COVID-19 pandemic and ensuing lockdowns and travel restrictions have resulted in an unprecedented health and economic crisis. The combination of demand- and supply-side shocks is expected to lead to a sharp increase in the number of people around the world living below the extreme poverty line. World Bank estimates suggest that the number of people living in extreme poverty[2] is expected to increase by between 88 million (baseline estimate) and 115 million (downside estimate) in 2020 (PovcalNet, World bank Global Economic Prospects 2021). The potential increase in extreme poverty due to COVID-19 would be equivalent to reversing almost a decade of progress in global poverty reduction, as the projected headcount rates, ceteris paribus, would return back to the levels observed in the first half of the 2010s (Sumner, Hoy, and Ortiz-Juarez, 2020).

The global response to the pandemic has been swift and widespread. A total of 212 countries and territories have introduced or plan to introduce 1,179 social protection measures. A total of $789 billion is being spent on social protection responses in 119 countries for which the data was available. Social assistance programs, in the form of cash transfers, in-kind transfers, waiving utility fees and public works, account for the majority of responses. COVID-19 related cash transfer responses are deemed to be relatively adequate, representing about 26 percent of the average monthly GDP per capita and in some low-income countries as high as 52 percent. The duration of cash transfers ranges from one to twelve months with a global average of 3.3 months. (Gentilini et.al. 2020).

In Zambia, the first two cases of COVID-19 were recorded on March 18, 2020 and the spread of confirmed cases was slow in the months that followed. However, swift and deep disruptions to international trade and global supply chains resulted in an immediate negative economic impact (WFP, 2020). Zambia's economy is expected to have contracted by 3.5 percent in 2020, in contrast to a projected growth of 3.6% before the pandemic (IMF, June 2020). This comes at a time when the country also faces a serious macroeconomic crisis because of rising inflation, a high fiscal deficit, a depreciating kwacha, and pressing external debt obligations.

High and chronic poverty have been features of Zambian society over the last decade, with the national poverty headcount rate holding steady at around 54 percent since 2010 (Zamstats LCMS Report, 2010, 2015). With a Gini index of 57.1, Zambia is also among the most unequal countries in the world, ranking alongside South Africa and Namibia in the region.[3] Developments since 2015

[2] The World Bank defines extreme poverty as the state of living on or less than $1.90 per day in 2011 PPP terms.
[3] World Bank World Development Indicators.

have contributed to the stubbornly high poverty rate. A slump in the price of copper, consecutive years of severe drought and an escalating debt crisis have all caused a deceleration in economic growth, with GDP per capita growing by only 0.26 percent between 2016 and 2019. The COVID-19 pandemic will exacerbate these negative developments by pushing vulnerable households into poverty and increasing the poverty gap further for chronically poor households.

The recent data from the phone survey conducted by the World Bank in Zambia in June 2020 provides important insights on the impact of COVID-19 (Finn and Zadel, 2020). While the findings from the survey can at best only be representative of the population in Zambia that has access to a cellphone and lives in an area with cellphone reception (therefore by construction missing out on the poorest households), the results are still concerning: (a) less than half of children who were in school before the pandemic were engaging in any learning after school closures; (b) 4 in 5 households reported a drop in income from non-farm businesses, and one-third reported a drop in or disappearance of wages; (c) there was a considerable reduction in employment, with the hardest hit sectors being tourism, manufacturing and services; and (d) food insecurity was already high, and this has been further exacerbated with a high proportion of households reporting skipping meals or running out of food. These findings are consistent across urban and rural households. Furthermore, the first-round results from Innovation for Poverty Action's RECOVER[4] survey conducted in July 2020 in Zambia corroborated the findings from the World Bank Phone Survey: (a) over 50% of respondents say they have had to deplete savings to pay for food, health care, or other expenses since February 2020; (b) more than 50% of employed individuals have earned less pay than they did in a typical week before the government closed schools; (c) over 35% of respondents say they have had to limit portion sizes at mealtimes or reduce the number of meals at least once in the past week; and (d) almost no households received food/cash from the government in response to COVID-19.

In this context, a social assistance response should be at the forefront to mitigate the economic impact of COVID-19, by providing immediate consumption support to poor and vulnerable households. In the early 2010s, the Government of Zambia acknowledged the need for a sophisticated and scaled up social assistance sector and took steps to develop one. The flagship Social Cash Transfer (SCT) program that began in 2003 as a small pilot in Kalomo district today has a caseload of 616,000 households, representing 30 percent of the national poor.[5]

As highlighted in Bowen, et. al. 2020, data and information are a key building block for adapting existing social protection programs to respond to crises or shocks. In this context, post-shock assessments are critical even in countries with strong early warning systems or good pre-shock predictors of impact, given the unpredictable nature of shocks. The phone survey highlighted earlier provides a useful first indication of the impact of COVID-19 on Zambian households but

[4] In Zambia, the survey is being conducted in partnership with the Ministry of General Education (MoGE) and the Ministry of Health to inform the government's policy responses. Dates of survey: June 15-July 6, 2020.
[5] Findings from the upcoming Zambia Social Protection and Jobs Public Expenditure Review 2021.

as described above has limitations due to network connectivity and hides heterogeneity of impact that is important for policy makers to prioritize responses.

In order to assess the sufficiency of the SCT program to address the needs of the poor and vulnerable households in Zambia, it is necessary to first understand the distributional impact of COVID-19. The first major challenge is the age of the data available – Zambia last had a nationally representative household survey in 2015. Since then there have been substantial changes in the labor market, the broader economy and in the country's overall debt situation. Moreover, the SCT program has scaled up substantively from 180,000 beneficiaries in 2015.

The age of the LCMS data means that the welfare aggregate used to estimate poverty[6] needs to be adjusted in order to bring it to a reasonable current equivalent. In our analysis this means using real sector-level growth and forecasts, and modeled population growth rates to arrive at reasonable consumption and population levels respectively. Although these can be viewed as rather blunt methods for adjusting the welfare aggregate, we believe that the simulations offer a reasonable narrative of developments in household welfare in the country over the last five years. This analysis is limited to understanding the direct and short-term impact of the crisis and does not assess other indirect or long-term impacts such as that on education and health services or outcomes. Moreover, it is uncertain whether the medium or long-term impacts of COVID-19 will continue to show the same trends observed in this analysis.

The rest of the paper is structured as follows. Section 1 briefly reviews the methodologies that have been employed in other contexts to estimate the poverty and distributional impacts of COVID-19. Section 2 lays out the data sources and empirical strategy to estimate the impact of COVID-19 in Zambia and then to simulate potential social assistance responses. This is followed by a presentation of key results in Section 3 and a discussion of these findings and policy implications in Section 4.

1. Overview of methodologies to assess the impact of COVID-19 in other contexts

Broadly, there are three categories[7] of methods being used across the World Bank to assess the distributional impact of COVID-19. The ***Micro Simulations*** model use ad-hoc assumptions on income/employment/consumption by sectors/occupation based on either the country knowledge of the most affected industries and/or government classification of essential jobs, or the literature with information from previous pandemics or economic crisis. In these simulations, the magnitude of the shock varies by sector, informality status, firm size, region, and type of employment and

[6] Adult equivalent monthly consumption expenditure.

[7] These approaches are being used by different country and research teams at the World Bank to inform its operations and responses to COVID-19.

either income/consumption is assumed to be impacted by a percentage amount and/or an amount of time. The Micro Simulations have been employed to estimate the impact in Afghanistan, Armenia, Azerbaijan, Bulgaria, Belarus, Botswana, Colombia, Croatia, Georgia, the Islamic Republic of Iran, Iraq, Kenya, Lesotho, Moldova, Mozambique, Namibia, Panama, Peru, the Russian Federation, South Africa, Thailand, Ukraine, and the Western Balkans. Cuesta and Pico (2020) developed an ex-ante simulation exercise in Colombia using a static micro-simulation model to estimate the poverty level with and without COVID-19. The micro-data used for the exercise comes from a recently conducted random-sample income survey and focuses on partial equilibrium analysis by simulating changes in labor supply and holding other general equilibrium effects of the pandemic constant.

The second category is ***Macro-Microsimulation*** approaches which use sectoral GDP-to-consumption/income-growth models focused on annual impacts. Consumption growth is based on the household head's sector of employment and sectoral GDP growth determines real income growth, while changes in employment composition are assumed. Some of the Macro-Microsimulation models use the World Bank's ADePT software to model the impact of sectoral GDP growth on employment and relies on a GDP-to-employment elasticity to estimate the impact of the pandemic across sectors. These relatively sophisticated models have been used to estimate the impact of COVID-19 in Mauritius, the Seychelles, Ecuador, Chile, Indonesia, Mexico, and Sri Lanka. Additionally, Goshu et.al. (2020) introduce a range of scenarios for growth in real consumption per capita to estimate the differentiated welfare effects in rural and urban areas in Ethiopia. The mild and severe scenarios are broken down further into sub-scenarios based on assumptions on how long the pandemic will last and the severity of its effects on the economy. In Indonesia, Suryahadi, Izzati, and Suryadarma (2020) apply a historical pattern of shocks (Asian Financial Crisis (1997-98) and a large increase in fuel prices (2005-06)) which adversely affected the economy to estimate the distributional impact of the pandemic on household expenditure. Similarly, in Tunisia, Kokas et.al. (2020) use a hybrid approach which combines sectoral GDP projections and microsimulation techniques to simulate price shocks as a result of COVID-19. The paper evaluates the impact on welfare under two different scenarios: an optimistic scenario where the economy contracts in the first half of the year 2020 and recovers in the second, and a pessimistic scenario where the economy contracts throughout the pandemic year at a constant rate.

The third bucket of approaches are ***Nowcasting Models*** which require high frequency income or employment data as an input and therefore are employed in a very few countries. Recently in Argentina, an autoregressive Nowcasting model used quarterly income distribution data to estimate the impact of COVID-19. Additionally, researchers have relied on high frequency phone surveys in low income countries to estimate the socio-economic impacts of the pandemic. Josephson, Kilic and Michler (2020) use longitudinal data from high frequency phone surveys in Ethiopia, Malawi, Nigeria, and Uganda. The authors use reduced form equations to estimate heterogeneity in effects across countries, regions (urban/rural), gender, and time. Over the last one-year the World Bank and partners have also conducted high frequency phone surveys in 44 developing countries to estimate the economic and welfare impacts of the pandemic and inform policy responses. These surveys are harmonized, and data have been uploaded to a public dashboard in which users can explore the socioeconomic impact of the pandemic on households and individuals for 90 indicators on 14 topics. Even though the findings from phone-based surveys are limited to understanding the concurrent impacts and the coping strategies of households and are unable to estimate the impact on poverty and distribution, they complement macroeconomic projections and provide a basis for policy responses.

A study in the Philippines uses phone surveys to estimate the effect of the pandemic on low income households' employment, earnings, and food security and investigated the effect of cash transfer programs in mitigating the impact of COVID-19 (Cho et.al. 2021). However, instead of creating a fresh representative sample, the study took advantage of previously conducted impact evaluations to construct a representative treatment group (households that received cash transfers) and a control group (non-cash transfer households). While the labor market impact due to COVID-19 was equally large for both cash transfer and non-cash transfer households, the results suggest that the timely delivery of cash transfers enabled households to better cope with food insecurity.

Simulations in advanced economies have used nowcasting models with greater precision due to their generally better access to a variety of high-quality data sources. In Italy, high frequency electricity market data have been used to estimate the short-term impact of the pandemic on the economy (Fezzi and Fangela, 2020). A study in Ireland has used a nowcasting methodology to estimate the differential impact of COVID-19 on the population. This micro-simulation model simulates the real-time income distribution of the population as a function of the available data on personal and household characteristics, and generates counterfactual income distribution scenarios which mirror price and labor force survey data (Donoghue et.al. 2020). In the United States, Chetty et.al. (2020) use anonymized data from multiple private companies to track economic activity and analyze the impact of the pandemic on employment and spending. In another study from the United States (Han, Meyer, and Sullivan, 2020) the authors constructed new measures of the income distribution and poverty with a lag of only a few weeks using high frequency data from the Basic Monthly Current Population Survey which collects income information for a large, representative sample of U.S. families. Khamis et.al., (2020) reviews a large number of studies from high-income countries examining the labor market impact of COVID-19 using rich data from labor force surveys.

2. Data and methodology

The methodology used in this paper corresponds to the Macro-Microsimulations approach discussed above.

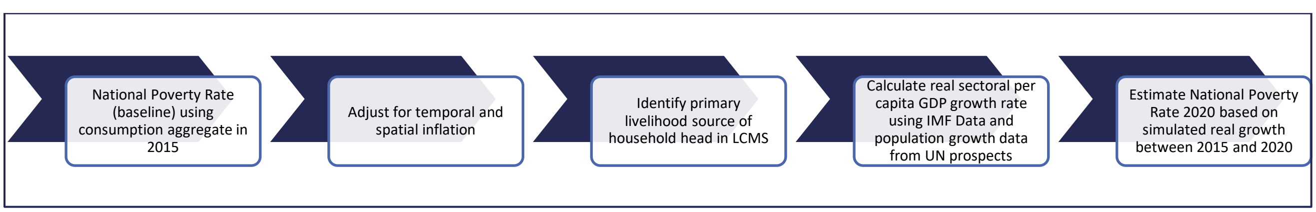
Assessing welfare and poverty impacts

The key data set used in this analysis is the Zambia Living Conditions Monitoring Survey (LCMS) of 2015. This is Zambia's most recent nationally representative household survey data set, and the poverty estimate at the national poverty line in 2015 serves as the baseline for the simulations. The data set also contains key socio-economic and demographic indicators that are used in the simulations and presentation of results. All poverty estimates are at the national poverty line, which is ZMW 214.26 per adult equivalent in 2015 terms.[8]

The primary, secondary and tertiary sectors in Zambia experienced widely different fortunes over the 2015 to 2020 period. Because these differences were so large, the next step of the simulation involved adjusting each household's consumption based on the main sector of livelihood for the household head as identified in the 2015 LCMS. This was done using the IMF's real sectoral GDP growth estimates for 2015 to 2019, and forecasts for 2020. A similar approach has been taken in Ajwad, Aran, Azam and Hentschel (2013), Ajwad, Haimovich, and Azam (2009), and Aran (2013) to estimate the distributional impact of economic shocks as a result of the 2008 financial crisis and help policy makers estimate the impact of safety nets on the poverty level and inequality. More recently Kokas et.al (2020) employed a similar approach to assess the welfare impact of COVID-19 in Tunisia.

The sectoral real GDP growth rates used in our analysis are those published by the IMF in its quarterly World Economic Outlook released in June 2020. Kindly note that there is an updated forecast for 2020 available in October 2020 but which was not used to update the results presented in this paper for three reasons: (a) there is no substantial difference between the two estimates in terms of poverty impacts; (b) the June 2020 forecast contributed to the government discussions around social protection responses; and (c) the broader message of this paper is that 'quick and dirty' simulations, even using best guess estimates in the immediate aftermath of shocks, can provide useful information to design responses.

Figure 1. Methodological Framework



The aim of the microsimulation exercise is to estimate the consumption distribution in Zambia in pre and post COVID-19 scenarios. Table 1 shows the estimated sectoral-level changes in real GDP per capita for the primary sector (agriculture and mining), secondary sector (manufacturing) and

[8] Zambia's national poverty line is slightly lower than the World Bank's $1.90 international poverty line.

tertiary sector (all services) in Zambia over the period in question. The effect of the severe drought is immediately evident, with real per capita growth in the primary sector falling by 8.3 percent in both 2018 and 2019. The secondary sector grew in real per capita terms between 2015 and 2018, before falling significantly in 2019. Forecasts for 2020 show that real per capita GDP in this sector contracted by 10.3 percent, a similar number to that seen in the tertiary sector.

Table 1 Real per capita growth estimates by sector, 2016 to 2020

	Real GDP growth estimate				Forecast	Real GDP per capita				
	2016	**2017**	**2018**	**2019**	**2020**	**2016**	**2017**	**2018**	**2019**	**2020**
Primary	5.8	5.8	-5.4	-5.4	3.0	2.9	2.9	-8.3	-8.3	0.1
Secondary	4.7	6.7	3.8	-1.7	-7.4	1.8	3.8	0.9	-4.6	-10.3
Tertiary	2.8	1.7	7.3	4.6	-6.9	-0.1	-1.2	4.4	1.7	-9.8

Source: Real GDP growth estimates and forecasts from IMF's World Economic Outlook Forecast, June 2020. Population growth rates from UN population prospects.
Note: The modeled national population growth rate is 2.9 percent in each of the years between 2015 and 2020.

The consumption projections are relatively broad, and although they capture overall trends in Zambia's economy between 2015 and 2020, there are nevertheless some important caveats to bear in mind when interpreting the results that follow. These include the following: (a) the analysis is undertaken in real terms as accurate spatial price information has been difficult to obtain; (b) the simulations do not factor in additional health expenditures that may have been met by households because of COVID-19; (c) categorizing households as being primarily dependent on one of three mutually exclusive groups does not take into account the fact that many households may have members employed in different sectors; (d) the simulations use the employment categorization in 2015, however, it is possible that households have switched employment sectors between 2015 and 2020; (e) the deleterious effects of two years of severe drought may not be fully captured in the sector-level adjustments. This is particularly true if certain parts of the country were hit harder by the drought than others; and (f) the simulations and results on the urban-rural divide do not account for urbanization that has occurred in Zambia over the last five years.[9]

Simulating the social assistance response

Since the 2015 LCMS did not explicitly identify beneficiaries of the SCT program, we need to construct a distribution of coverage using eligibility criteria and overlay it on the existing data. A further complication is that the program changed significantly between 2015 and 2019. The

[9] Please refer to Annex 1 for additional details on caveats and future considerations.

caseload was scaled up by a factor of 3, and new categories of eligible households were added (for example female-headed households with 3 or more children). Therefore, we first simulate SCT eligibility based on household characteristics using the actual categorical criteria that were used to target the SCT program. This is consistent with De La Fuente, Rosales, and Jellema (2017) who use a similar approach to assess the redistributive impact of fiscal policy in Zambia.

SCT targeting follows a two-step approach. It first identifies households that meet one or more of four criteria are identified – female headed households with three or more children; households with a disabled head; households headed by a child; households headed by a senior (more than 64 years). It then applies a proxy means test (PMT) to identify, out of those households that fall into one of the four categories, which ones are likely to be extremely poor. Our simulations follow a similar approach by first identifying all households that are categorically eligible and then assigning the benefits to match the actual total caseload by district. To perform robustness checks, the program caseload was assigned in three different ways within each district.

The first - "assignment to the poorest i.e. households below national poverty line" - distributes in each of the districts, the caseload to the poorest (based on 2019 poverty estimate described above) among the households that fall under the categorical targeting. However, since the PMT can be measured imprecisely, there will be both inclusion and exclusion errors. Alternative approaches simulate two scenarios that attempt to address these potential errors.

The second set of results - "random assignment" - represents the opposite of the first approach by assuming that the PMT is not effective in identifying the poor. Within each district the caseload is distributed randomly among the households under the categorical targeting. As it is shown in the results below, even with a random assignment, the program still reaches households in all quintiles of the consumption distribution with a majority of caseload in the bottom three quintiles, given the categorical targeting and the regional distribution of the caseload.

The third and final approach - "mixed assignment" - assumes that the PMT works partially in that the extreme poor have a higher chance of being program beneficiaries. To simulate this scenario, we assign half the caseload of each district randomly among the households that are eligible, and the other half to those eligible and poor. As the weight of the first and second approaches in arriving at the third 'mixed' approach is not known from other empirical analysis, we assume that they have an equal probability of occurrence.

Some districts fall short in terms of number of households that fall into the categorical eligibility criteria. This could be a result of significant changes to the composition of the population – either by the increase of this type of households, or by migration – and by extrapolating the 2015 population structure using the overall population growth we may be underestimating the number of households that belong to that criteria. In other words, the administrative caseload is larger than the eligible population in those districts. In districts with a deficit of categorically eligible households we assigned half of the remaining caseload to poor households in that district, and the other half randomly to any household in the district that did not already receive the benefit. We find that all the three approaches are effective in terms of targeting and are able to match the real caseload. However, we use mix assignment in our simulations to account for targeting errors in the absence of data showing otherwise.

Finally, for social assistance response simulations, we use two scenarios. The first, the status quo scenario, keeps nominal transfer amounts constant from 2017.[10] The second, the enhanced scenario, increases transfer amounts so that the 2021 transfer value adjusted for inflation is equivalent to the 2017 transfer value.[11] The simulations are undertaken on the current program caseload and do not include further expansion of the program, in the absence of clear government directives on eligibility criteria for additional households.[12] The Government of Zambia, though, has already adopted the enhanced scenario for SCT transfer amounts, and an expansion of the SCT caseload to 994,000 households, and both are now part of the 2021 budget and its medium-term expenditure framework.

3. Results

Pre-pandemic changes in the household consumption distribution from 2015 to 2019

Between 2015 and 2019, growth appears to have benefited wealthier urban households, with the poorest rural households being left behind. The curves in Figure 2 represent the average change in consumption at each point of the 2015 distribution for urban and rural households. This can be thought of as something akin to a growth incidence curve, though of course these results use a single consumption distribution with projections, rather than two different distributions.

The poorest urban households did not experience any real growth in consumption over the 2015 to 2019 period. Even for the best-off urban households (the right-hand side of the blue curve below), consumption growth was sluggish at around 2.5 percent over the period. The results for rural households closely reflect the poor performance of the agriculture sector between 2015 and

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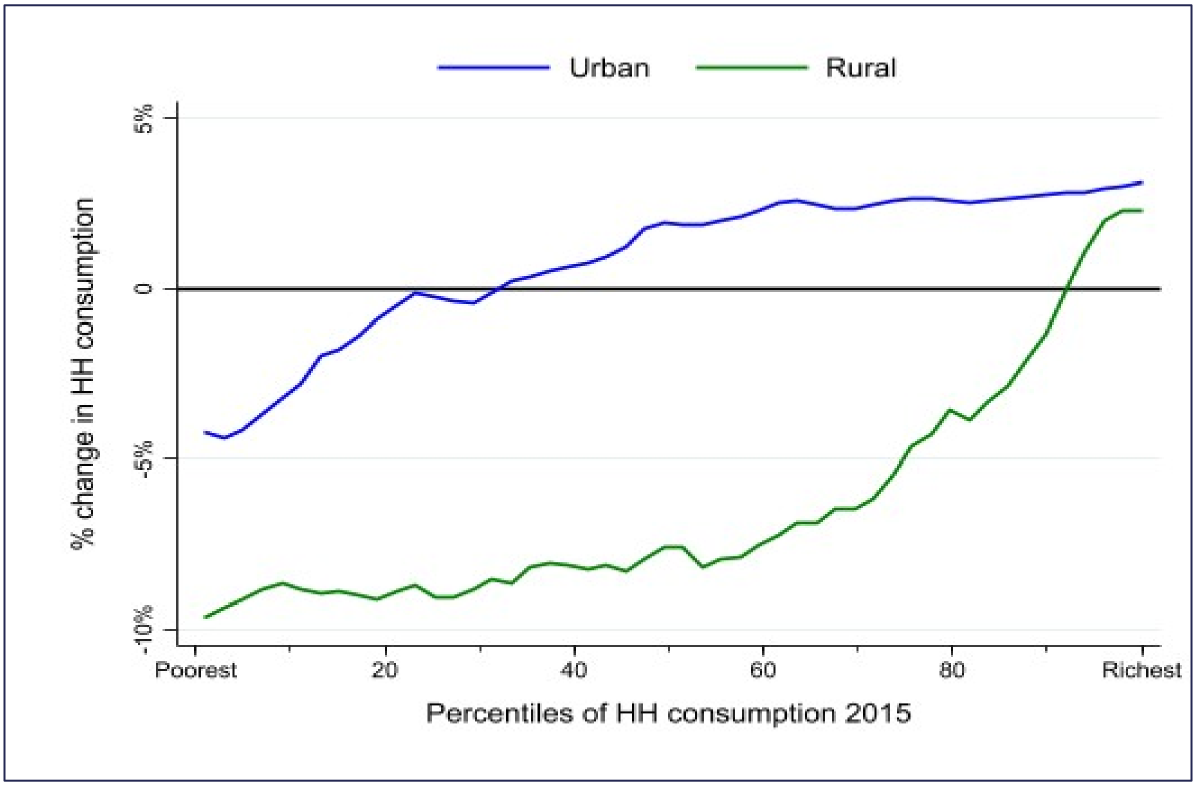
[10] Monthly amount of ZMK 90 (US$ 4.5) per regular HH and ZMK 180 (US$ 9) per HH where HH head is disabled.

[11] Monthly amount of ZMK 150 (US$ 7.5) per regular HH and ZMK 300 (US$ 15) per HH where HH head is disabled.

[12] The UN-led Emergency Cash Transfer response is also operational and comprising of provision of temporary cash transfers to existing SCT beneficiaries as well as informal sector workers in urban and semi-urban areas to meet immediate consumption needs for six months. 22 districts have been targeted based on a combination of COVID-19 infection rates, and areas most susceptible to the economic shocks of COVID-19 (e.g., tourist towns and busy border towns). This is not included in the simulations due to its substantially smaller scale, technical issues with identification of beneficiaries using a similar methodology as that used for SCT simulations, and because it is not part of the government's official COVID-19 response.

2019. Only the very top of the rural distribution experienced positive growth – correlated to rural households that have some exposure to non-farm income sources – and the worst effects were concentrated among the poorest rural households.

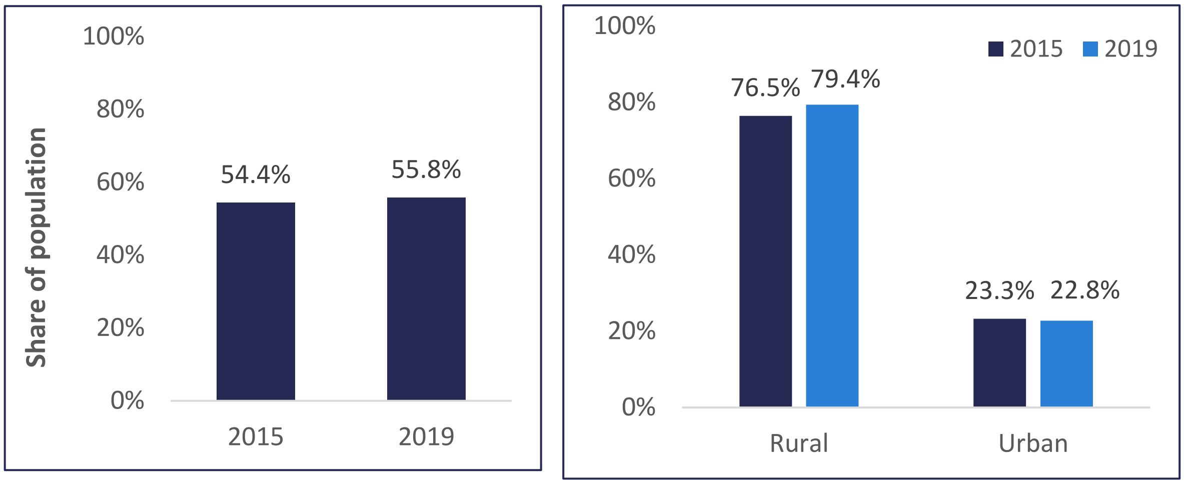
Figure 2 Average change in HH consumption between 2015 and 2019 by urban/rural location



Source: Authors' calculations from LCMS 2015, IMF sectoral data, ZamStats CPI data, and UN Population Prospects data.

Between 2015 and 2019 the national poverty rate rose from 54.4 percent to 55.8 percent, and this was driven entirely by increases in rural poverty. The numbers in Figure 3 summarize what is clear in Figure 2 above – poverty increased overall because rural poverty increased over the period. Poverty in rural Zambia was projected to have risen by almost 3 percentage points between 2015 and 2019 in rural areas, with almost 8 out of every 10 rural Zambians falling below the national poverty line. In urban areas there was a small decrease of about half a percentage point, and this was mainly driven by changes in Lusaka. The analysis reveals that there is a strong correlation between sectoral changes and urban/rural distribution because of the how sectors are concentrated with services in urban and agriculture in the rural areas. As a result of the negative real GDP growth between 2015 and 2019 especially in primary sector, a number of people just above the poverty line fell into poverty.

Figure 3 National poverty and poverty by region, 2015-2019



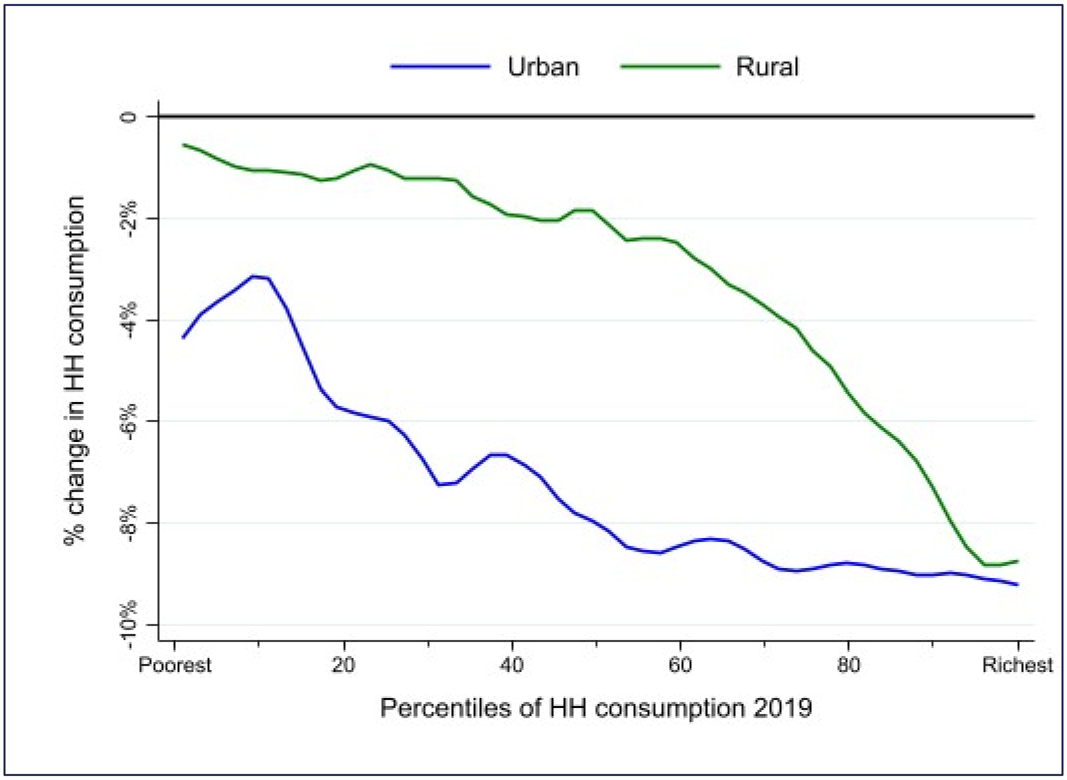
Source: Authors' calculations from LCMS 2015, IMF sectoral data, ZamStats CPI data, and UN Population Prospects data.

The pandemic: Changes in the household consumption distribution from 2019 to 2020

The economic consequences of COVID-19 have been felt most strongly by the relatively well-off urban households. While the projections from 2015 to 2019 showed that urban households did relatively better than rural households, the economic impact of COVID-19 has disproportionately impacted urban households in general, and richer urban households in particular.

Figure 4 shows the average change in household consumption between 2019 and 2020 for rural and urban households in Zambia. This is effectively the welfare impact of the COVID-19 pandemic across the two consumption distributions. The poorest 40 percent of rural households experienced falls of between 1 and 2 percent, while the best-off rural households experienced losses that were around 4 times as large. The poorest urban households also experienced significant losses of around 4 percent, with losses increasing over the distribution to about 9 percent for the richest urban households.

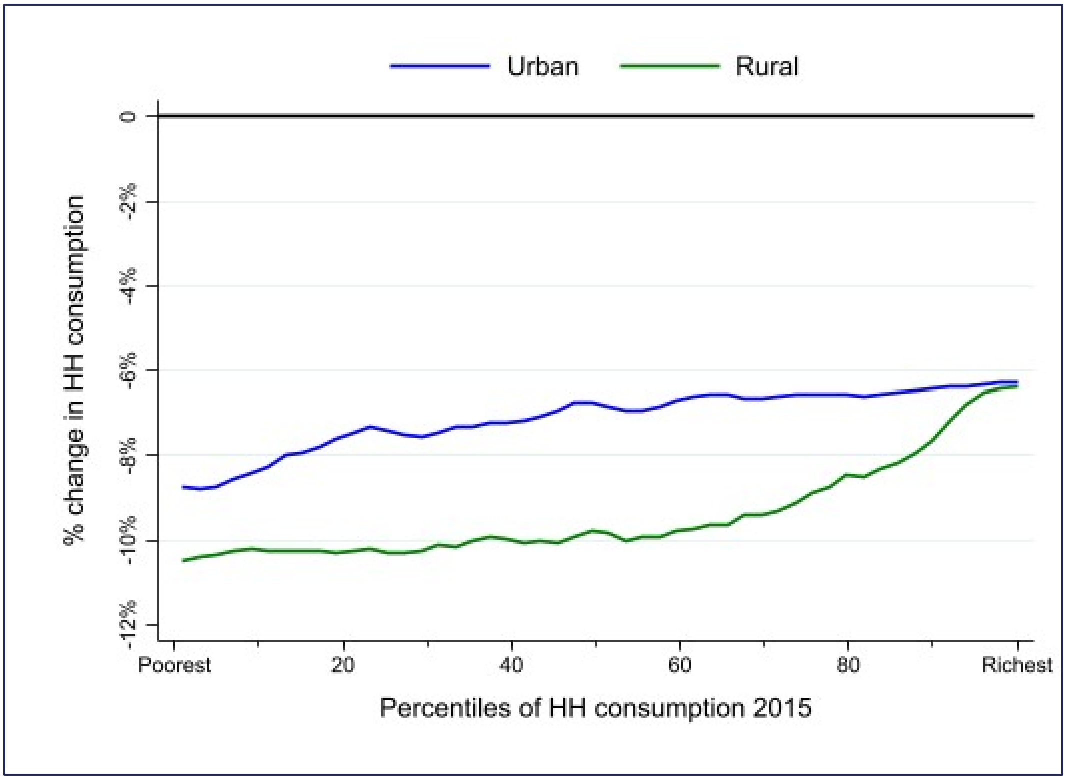
Figure 4 Average change in HH consumption between 2019 and 2020 by urban/rural location



Source: Authors' calculations from LCMS 2015, IMF sectoral data, ZamStats CPI data, and UN Population Prospects data.

The overall change between 2015 and 2020 shows that welfare levels have deteriorated significantly in both rural and urban areas in Zambia. Figure 5 combines the results presented in Figure 2 and Figure 4 to show the changes over the full 2015 to 2020 period. The projections suggest that consumption levels dropped by more than 10 percent for the poorest rural households, and by a little over 8 percent for the poorest urban households. Both urban and rural households generally experienced smaller losses as households got wealthier, but at no point was the average change positive.

Figure 5 Average change in HH consumption between 2015 and 2020 by urban/rural location

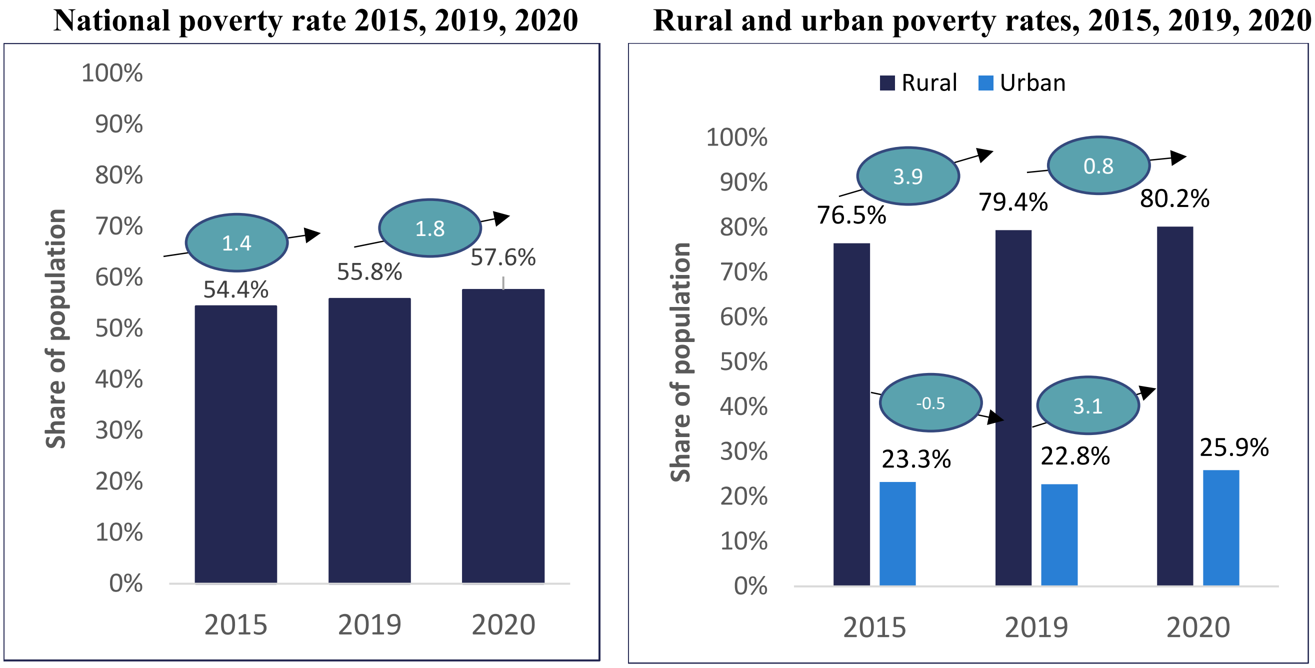


Source: Authors' calculations from LCMS 2015, IMF sectoral data, ZamStats CPI data, and UN Population Prospects data.

The result of the changes in the previous figures is that the national poverty rate is projected to have increased by 1.4 percentage points between 2015 and 2019, and by a further 1.8 percentage points between 2019 and 2020. The changing rural/urban storyline from 2015 to 2019 and then from 2019 to 2020 is clear in the second panel of Figure 6. The rural poverty rate increased by 3.9 percentage points between 2015 and 2019, mainly because of the effect of two years of severe drought on agriculture. Projections suggest that rural areas have been relatively less impacted by the economic consequences of the pandemic, though poverty still rose by 0.8 percentage point in 2020. In urban areas the story is inverted. Poverty decreased by about half a percentage point between 2015 and 2019 and is expected to have risen by more than 3 percentage points in 2020. The upshot is that the projected 2020 poverty rate is 57.6 percent, with rural and urban poverty rates of 80.2 percent and 25.9 percent, respectively.

Welfare changes over the full 2015 to 2020 period

Figure 6 National and rural/urban poverty rates 2015, 2019, 2020



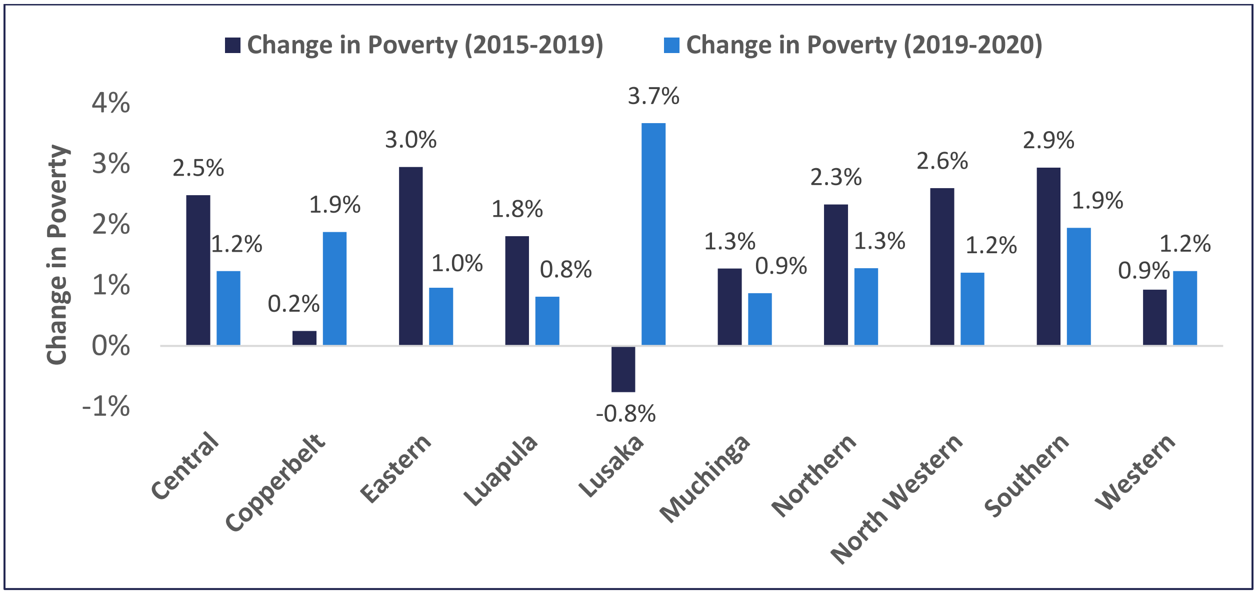
Source: Own calculations from LCMS 2015, IMF sectoral data, ZamStats CPI data, and UN Population Prospects data.

The national poverty gap in Zambia is projected to have increased significantly between 2015 and 2020 – from 26.3 percent to 29.1 percent. In rural areas the increase was particularly large, growing from 39.1 percent in 2015 to 43.1 percent in 2020. The increase in the urban poverty gap was not as large, ending at 9.6 percent in 2020. As can be expected given the patterns of growth shown in the incidence curves, it is projected that inequality as measured by the Gini index increased slightly, from 54.5 percent in 2015 to 55.1 in 2020.

Poverty is projected to have increased in all provinces except Lusaka between 2015 and 2019. As shown in Figure 7, the provinces that experienced the largest increases in poverty over the period were Eastern, Southern, North-Western and Central. Increases in the poverty rate were more muted in Muchinga (1.3 percent) and Copperbelt (0.2 percent), while the poverty rate in Lusaka is projected to have declined by almost 1 percent to 2019.

The changes in provincial poverty brought about by the pandemic are markedly different, with Lusaka's poverty rate now increasing the most. The economic impact of COVID-19 in 2020 is projected to have increased the poverty rate in Lusaka by 3.7 percent, almost double the next highest province of Copperbelt. In the provinces with the highest rural population shares the increase in poverty is projected to have been at or under 1 percent. Clearly the results presented in Figure 2 and Figure 4 are reflected at the provincial level as well, with more rural provinces experiencing steeper declines in consumption to 2019, compared to more urban provinces in 2020.

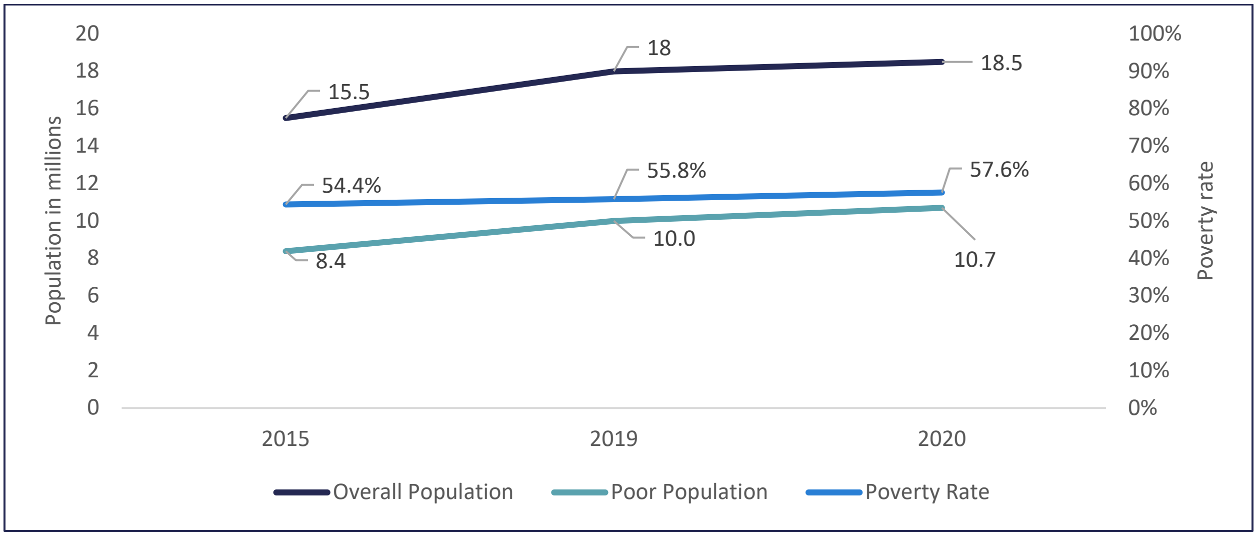
Figure 7 Changes in poverty by province, 2015 to 2019 and 2019 to 2020



Source: Authors' calculations from LCMS 2015, IMF sectoral data, ZamStats CPI data, and UN Population Prospects data.

Zambia's population grew at an average annual rate of 2.9 percent between 2015 and 2020. The increase in the poverty rate from 54.4 percent to 57.6 percent translated into a poor population that grew by over 2 million people over the period. As shown in Figure 8, the population of Zambia increased from 15.5 million people in 2015 to 18.5 million people in 2020. The overall number of poor in the country increased by about 400,000 per year between 2015 and 2019. The impact of the pandemic is expected to have increased the poor population by a further 700,000 in 2020, meaning that around 10.7 million people in Zambia's total population of 18.5 million are expected to be in poverty.

Figure 8 Total population, number of poor (millions) and national poverty rate 2015, 2019, 2020



Source: Authors' calculations from LCMS 2015, IMF sectoral data, ZamStats CPI data, and UN Population Prospects data.

The potential impact of social assistance response

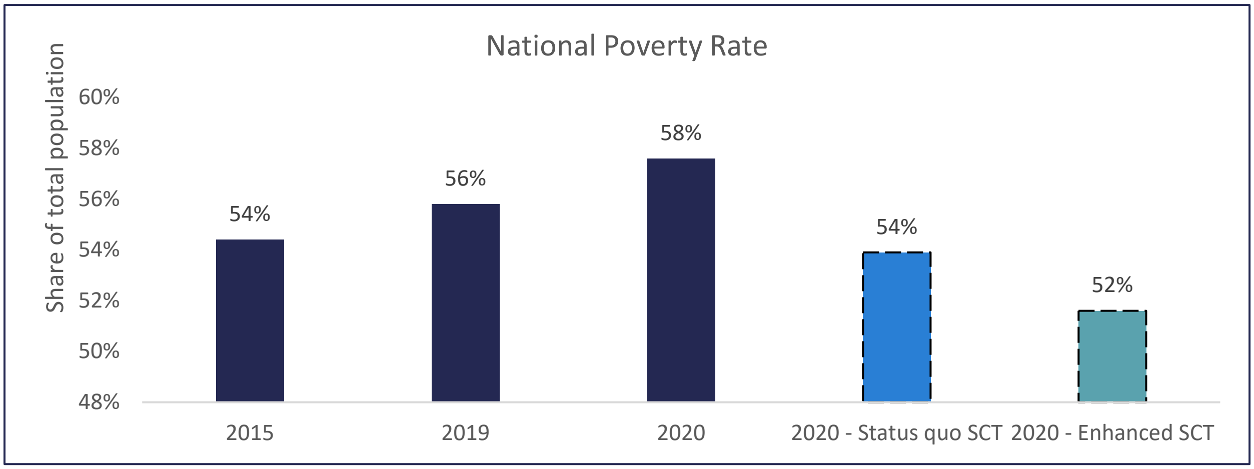
Despite the increase in poverty due to COVID-19 and the erosion of the real value of the transfer, the SCT has the potential to significantly reduce the incidence of poverty in Zambia. Extrapolating the national poverty headcount rate over time suggests poverty would have increased by 1.8 percentage points between 2019 and 2020,[13] largely due to the economic consequences of the COVID-19 crisis. However, if all those enrolled in the SCT were paid full benefits, this would bring down poverty by 3.7 percentage points. As a result, the overall poverty in 2020 would be expected to be at the 2015 level (Figure 9 below). Looking at the disaggregated picture, this translates to rural poverty of 75.8 percent compared to 76.5 percent in 2015, while urban poverty is about the same at 23.3 percent. This implies that, in 2020, 0.7 million fewer people are expected to be in poverty if the SCT pays benefits to its full caseload, compared to the case if only the current partial caseload is paid.

An enhanced SCT could potentially reduce poverty incidence below the 2015 level, largely mitigating the deleterious impacts of the pandemic (Figure 9). An enhanced SCT could reduce poverty incidence by up to six percentage points. Factoring in the COVID-induced increase in poverty in 2020, this translates to a net poverty reduction of 4.2 percentage points. Under this scenario too, the effect on rural poverty is larger than that on urban poverty—rural poverty is about

[13] Estimates assume that the no households receive Social Cash Transfers and therefore provide a counterfactual to the social assistance response simulations.

4 percentage points below the 2015 level while urban poverty is 1 percentage point below the 2015 level. Holding the real transfer value constant in 2017 terms can therefore aid the country's overall anti-poverty agenda.

Figure 9: Simulated Poverty Impact of fully funded SCT program



Source: Own calculations from LCMS 2015, IMF sectoral data, ZamStats CPI data, and UN Population Prospects data.

4. Discussion and policy implications

Zambia's economy has been increasingly fragile over the last decade with very high and stubborn poverty levels. The COVID-19 shock is expected to further aggravate the poverty and inequality situation in the country. This paper finds that there is an overall increase in poverty by about 4 percentage points, with about half of the percentage point increase happening just in 2020. Nevertheless, the country had managed to invest in a large-scale safety net, the Social Cash Transfer program since 2015, but financing to which had been limited due to the worsening debt and macroeconomic situation in the country. The country's COVID-19 response strategy, therefore, focused squarely on improving financing to the existing programs, i.e., setting up of a first line of defense. This is expected to not only help mitigate the impact of COVID-19 but go beyond in terms of the country's broader poverty reduction goals.

More generally, the COVID-19 pandemic represents a large covariate shock, just like those related to climate change or forced displacement or conflict, that has affected both urban and rural households in Zambia. Climate related vulnerabilities and shocks are not uncommon in Zambia. According to the Global Report on Food Crisis 2020, in 2019, a severe drought affected much of the country, with maize production in the Southern and Western provinces falling substantially and about 2.3 million people or 24 percent of the population in crisis or worse facing severe acute food insecurity or higher between October 2019–March 2020. This is an increase of 10 percentage points from the previous year. If anything, the rapid deleterious effect of COVID-19 generally highlights the importance of investments in improved national shock response systems with social protection as a key pillar.

In these contexts, cash transfers can improve household resilience to these shocks by smoothing consumption (Premand and Stoeffler 2020 and Ulrichs, et. al. 2019). By including 'accompanying measures' focused on economic inclusion, human capital and climate adaptation, cash transfers can also help diversify households' livelihoods, further building their resilience. Designing an appropriate response, though, requires good data. While robust and extensive data are preferred to get an understanding of the impact of shocks on households and its heterogeneity, 'quick and dirty' methods using basic existing data can be valuable and provide critical indicators to design timely and appropriate shock responses. As highlighted in Bowen, et. al. 2020, in post-shock assessment, there is a need to balance the trade-off between timely and accurate shock response. Recently, various mechanisms have been used to understand COVID-19's effects on macroeconomic stability as well as on household welfare and enterprise health. A review of some of these has been presented in Section 1. The simulations undertaken in this paper show that even imperfect and dated data can help to rationalize shock responses and make sense of their impacts on resilience of households and more broadly on the country's overarching development goals.

The simulations highlighted here, and examples of similar approaches used in other countries, however, do not in any way replace the need to set up a pre-emptive shock responsive system. Yet, by their very nature, shocks and crises come unannounced. Hence, the creative use of existing data will likely always continue to be an important facet of shock response.

While the importance of such analysis has already been stressed sufficiently, an important aspect of being able to do such analysis was the collaborations across institutions—the World Bank, the IMF and the government— to make data available rapidly. Going forward, planning for shock responsiveness should include building such collaborations and synergies, across as many potentially relevant actors as possible. These include other international organizations, research organizations, across multiple ministries within the government, the private sector, and civil society. Zambia may choose to set up a Data Exchange for Adaptive Shock Responsiveness to formalize these collaborations or simply make informal arrangements to aggregate data in the aftermath of shocks and preferably, in pre-empting them. Additionally, future research should also include retrospectively analyzing the efficacy of data in informing an appropriate and timely response. Over time, this could provide greater evidence on what types and quality of data work better to inform shock responsiveness, and in so doing, improve the methods used to undertake such analysis.

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Annex 1: Caveats and Considerations for Future Analysis

Real GDP Growth Rate and Poverty Line: Analysis is undertaken in real terms as it was not possible to obtain accurate spatial price information. In reality, however, the inflation might have hit poor households harder, especially if the food inflation was higher adversely affecting poor households. IMF uses GDP growth deflator to make growth forecasts 'real.' We use the real poverty line from 2015 (214 ZMK) to estimate poverty levels in our analysis from 2015 through 2020.

Passthrough Rate: The pass-through rate is considered 1:1 from real GDP growth to HH Consumption. Additionally, the pass-through rate is assumed to be distribution neutral within the sectors.

Urban-Rural Distribution: The analysis does not account for the amount of urbanization that has occurred in Zambia in the last 5 years as revealed by the recent Labor Force Survey 2019.

Employment Sector and Sectoral Distribution: The employment sector of the Household Head is used to extrapolate consumption even if other household members may be employed in a different sector. Since the consumption is aggregated at the household level in LCMS 2015, it would have required additional assumptions to distribute the share of consumption across other members of the household. Also, our methodology assumes that all household heads continue to work in the same employment sector in 2020. Though, it is likely that as structural transformation takes place in the country, some household heads have switched to a different employment sector between 2015 and 2020.

Change in Household Expenditure: Our simulations do not factor in additional health expenditures likely to arise from COVID-19. Furthermore, the deleterious effects of 2 years of severe drought may not be fully captured in the sector-level adjustments, for instance certain parts of the country and/or rural households might have been affected disproportionately.