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ORIGINAL ARTICLE

Assessing the Impact of Covid-19 in Mozambique in 2020

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Abstract

Taking advantage of the 2019/2020 Mozambican household budget survey, in the field both before and during the first phases of the Covid-19 pandemic, we assess the impact of Covid-19 on welfare in 2020, aiming to disentangle this impact from the effect of other shocks. Comparing a number of welfare metrics, and applying propensity score matching and inverse probability weighted regression adjustment approaches, we find that consumption levels are significantly lower and poverty rates substantially higher during the first phases of Covid-19 than in the pre-Covid-19 period. Moreover, the impact was greater in urban areas and accordingly in the more urbanised southern region. Non-food expenditures suffered relatively more than food expenditures, likely a coping strategy, while the impact on consumption levels was greater for people working in the secondary and tertiary sectors than for workers in the primary sector, mainly agriculture. Stunting among under-5 children also suffered. Only a limited number of countries have actual, collected in-person, survey data that span across the initial phases of the Covid-19 pandemic. Thus, the present analysis adds value to our understanding of the welfare consequences of Covid-19 in a low-income context, where automatic social safety nets were not in place during the early phases of the pandemic. More specifically, it helps in assessing the results of previous welfare impact simulations, compared to real data. Even though our main findings are broadly in line with existing estimates based on simulations or phone surveys, important differences between the predictions and the actual results emerge. We conclude that it is critically important for Mozambique and its development partners to develop stronger and more targeted policies and tools to respond to temporary shocks.

Keywords Welfare · Poverty · Impact of Covid-19 · Mozambique

JEL Classification I15 · I31 · I32 · O55

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Résumé
En tirant parti de l'enquête sur le budget des ménages mozambicains de 2019/20, sur le terrain avant et pendant les premières phases de la pandémie de Covid-19, nous évaluons l'impact de la Covid-19 sur le bien-être en 2020, en cherchant à distinguer cet impact de l'effet d'autres chocs. En comparant un certain nombre de mesures de bien-être, et en appliquant des approches d'appariement de scores de propension et d'ajustement de régression pondérée par la probabilité inverse, nous constatons que les niveaux de consommation sont nettement inférieurs et les taux de pauvreté nettement plus élevés pendant les premières phases de la Covid-19 qu'avant la Covid-19. De plus, l'impact a été plus grand dans les zones urbaines et donc dans la région sud la plus urbanisée. Les dépenses non alimentaires ont relativement souffert plus que les dépenses alimentaires, ceci probablement dû à une stratégie d'adaptation, tandis que l'impact sur les niveaux de consommation était plus grand pour les personnes travaillant dans les secteurs secondaire et tertiaire que pour les travailleurs du secteur primaire, principalement l'agriculture. Le retard de croissance chez les enfants de moins de 5 ans a également souffert. Seul un nombre limité de pays disposent de données d'enquête réelles, collectées en personne, qui couvrent les phases initiales de la pandémie de Covid-19. Ainsi, la présente analyse ajoute de la valeur à notre compréhension des conséquences sur le bien-être de la Covid-19 dans un contexte à faible revenu, où les reseaux de sécurité sociale n'étaient pas automatiquement en place pendant les premières phases de la pandémie. Plus précisément, notre analyse aide à évaluer les résultats des précédentes simulations d'impact sur le bien-être, par rapport aux données réelles. Même si nos principales conclusions sont globalement en accord avec les estimations existantes basées sur des simulations ou des enquêtes téléphoniques, des différences importantes entre les prédictions et les résultats réels émergent. Nous concluons qu'il est essentiel pour le Mozambique et ses partenaires de développement de développer des politiques et des outils plus forts et plus ciblés pour répondre aux chocs temporaires.

Resumen
Aprovechando la encuesta de presupuesto familiar de Mozambique 2019/20, realizada en el campo tanto antes como durante las primeras fases de la pandemia de Covid-19, evaluamos el impacto de Covid-19 sobre el bienestar en 2020, con el objetivo de desentrañar este impacto del efecto de otros shocks. Comparando una serie de métricas de bienestar, y aplicando el emparejamiento de puntajes de propensión y los enfoques de ajuste de regresión ponderados por probabilidad inversa, encontramos que los niveles de consumo son significativamente más bajos y las tasas de pobreza sustancialmente más altas durante las primeras fases de Covid-19 que en el período pre-Covid-19. Además, el impacto fue mayor en las áreas urbanas y, en consecuencia, en la región sur más urbanizada. Los gastos no alimentarios sufrieron relativamente más que los gastos en alimentos, probablemente como una estrategia de afrontamiento, mientras que el impacto en los niveles de consumo fue mayor para las personas que trabajan en los sectores secundario y terciario que para los trabajadores en el sector primario, principalmente la agricultura. El retraso en el crecimiento de los niños menores de 5 años también se vio afectado. Solo un número limitado de países tienen

datos de encuestas reales, recopilados en persona, que abarcan las fases iniciales de la pandemia de Covid-19. Por lo tanto, el presente análisis agrega valor a nuestra comprensión de las consecuencias del bienestar de Covid-19 en un contexto de bajos ingresos, donde las redes de seguridad social automáticas no estaban en lugar durante las primeras fases de la pandemia. Más específicamente, ayuda a evaluar los resultados de las simulaciones anteriores de impacto sobre el bienestar, en comparación con datos reales. Aunque nuestros hallazgos principales están en línea con las estimaciones existentes basadas en simulaciones o encuestas telefónicas, surgen diferencias importantes entre las predicciones y los resultados reales. Concluimos que es de vital importancia para Mozambique y sus socios de desarrollo desarrollar políticas y herramientas más fuertes y más dirigidas para responder a shocks temporales.

Introduction

The Covid-19 pandemic hit the world economy starting in 2020, and for the first time in decades the global poverty rate rose, partly reversing the decline achieved over the previous two decades. The deterioration of livelihoods in several low-income countries included sharp declines in income due to job and revenue losses, widespread food insecurity, and other negative effects.[1] Various estimates exist of the many million people pushed into extreme poverty—slightly less than a hundred million, according to some of the latest estimates by the World Bank (Mahler et al. 2020, 2021, 2022a, b). On top, Covid-19 affected inequality in multiple ways, and it has taken a huge toll on global economic growth, with the outlook being especially bleak for emerging and developing economies (World Bank 2020; Mahler et al. 2020). Notwithstanding a relatively low number of registered Covid-19 cases, the Mozambican economy suffered as well, with the biggest economic impact resulting from restrictions of movements and slowdown of economic activity (World Bank 2021; Squarcina and Egger 2022).[2]

Taking advantage of the 2019/2020 household budget survey, we estimate the impact of the Covid-19 shock and related containment measures on household consumption and poverty in 2020, disentangling it from the effect of other shocks. Only a limited number of countries have actual, in-person, survey data that span across the initial phases of the Covid-19 pandemic. In Mozambique, the fieldwork for the 2019/2020 household budget survey started in November 2019 and finished in November 2020 (INE 2021a; University of Copenhagen and UNU-WIDER 2023). This means data was collected during both the period November 2019–February 2020 (pre-Covid) and the period March–November 2020 (during Covid), a period in which restrictions of movements and other containment measures were put in place. Actually, restrictions in the latter period were stricter than in subsequent months.

[1] See Lakner et al. (2019), Laborde et al. (2020, 2021), Mahler et al. (2020, 2021, 2022a, b), World Bank (2020), Pereira and Oliveira (2020), Sumner et al. (2020), Bargain and Aminjonov (2021), Valensisi (2020), Buheji et al. (2020), Alkire et al. (2021).

[2] We mostly refer, in what follows, to the impact of Covid-19 containment measures (or stringency).

This makes the present analysis particularly valuable and relevant: indeed, it assesses and adds value to the global understanding of the welfare consequences of Covid-19 and related containment measures in a low-income context, where (automatic) social safety nets were not in place during the early phases of the pandemic. Moreover, it helps in assessing earlier welfare impact simulations, which are available for Mozambique, compared to real data. Even though our main findings are broadly in line with existing estimates or speculations, based on simulations or phone surveys, important differences between the predictions and the actual results emerge.

Methodologically, we apply a propensity score matching approach and compare a number of welfare metrics before and during the first phases of the pandemic. They include consumption levels, poverty rates and child malnutrition. Moreover, we compare outcomes for different sub-populations (urban/rural areas; northern, central and southern region; people working in the primary/secondary/tertiary sector of the economy; and people with different levels of education). We also test results by applying the inverse probability weighted regression adjustment (IPWRA), checking for different treatment levels (i.e., different degrees of exposure to Covid-19 health risk and containment measures), seasonal adjustments, and different time-specific treatments.

The study proceeds as follows. "Literature and Context" section presents relevant literature and context, while "Data" section introduces our data. "Methodology" section discusses the methodologies applied, and in"Results" section, we turn to our results. "Conclusions" section concludes and provides policy recommendations.

Literature and Context

We proceed to summarize literature on the welfare impacts of specific shocks, focusing on the poverty impacts of Covid-19 in contexts similar to Mozambique. Moreover, we present background on the economic context of this country case, outlining trends in consumption levels, poverty, Covid-19 cases and containment measures, and selected macroeconomic variables.

Literature on Poverty Impacts of Specific Shocks and of Covid-19

A general finding in the literature about shocks and poverty is that not all households are able to smoothen consumption, especially if they face liquidity constraints or cannot rely on support networks. This implies that income shocks will likely generate welfare losses for these households (Dercon and Hoddinott 2003). Consequently, the poor are especially vulnerable to the impact of disasters (Karim and Noy 2016, for a meta-analysis). Moreover, Hallegatte et al. (2020), in their review of the literature, highlights the existence of a vicious circle between shocks and poverty: indeed, poverty is a major driver of people's vulnerability to disasters, and, at the same time, disasters regularly increase poverty in a significant way.[3] In the same study, the author also shows that poorer people tend to find it more difficult to recover from shocks, with consumption generally less affected than income, given the ability of poorer households to smooth their food consumption by reducing the consumption of non-food items. At a more macro scale, shocks also affect growth, which indirectly impacts poverty, often in conjunction with increased inequality, when disproportionally affecting the poor, sometimes leading to situations of conflict (Hallegatte et al. 2020).

Poverty responds to many types of shocks, not only natural disasters or climate shocks. Such examples include agricultural shocks, global market and price shocks, large-scale conflicts, among others (see examples in Skoufias et al. 2011; Laborde et al. 2019; Álvarez et al. 2021; Coxhead et al. 2012; whereas analyses on the impacts of the recent Ukraine conflict are in McGuirk and Burke 2022; Arezki 2022; Rijkers et al. 2022). The literature has also discussed how short-term declines in income may lead to long-run detrimental effects. Dercon (2004) describes the poverty traps that can emerge due to distress sale of assets, while Alderman et al. (2006), Hoddinott & Kinsey (2001), among others, analyse how shocks can lead to poorer health and consequent labour market outcomes due to food insecurity. Finally, Bandara et al. (2015), Beegle et al. (2003) and Edmonds (2006), discuss possible impacts in terms of worse labour market outcomes for children not returning to school.

Covid-19 represented a major health and global economic shock, simultaneously affecting livelihoods in high- and low-income countries, and for which long-term impacts are still unknown. For lower income countries, though, the impact appears to have been devastating even in the short term. The Covid-19 pandemic reversed years of decline in poverty, simultaneously deteriorating welfare in several low-income countries, with sharp declines in income due to job and revenue losses, widespread food insecurity, and other negative effects.[4] Various estimates exist of the many millions people pushed into extreme poverty. Laborde et al. (2020) conclude that in the absence of mitigating policy interventions, an additional 140–150 million have fallen under the international 1.9 USD/day poverty line. Sumner et al. (2020) estimate that the global poverty headcount computed using the same line increased by more than 80 million in their optimistic and by more than 420 million in their pessimistic scenario. Lakner et al. (2022) conclude that Covid-19 pushed 60 million people into extreme poverty in 2020, while Valensisi (2020) estimate an increase of 68 million living below the 1.9 USD/day poverty line in 2020. Moyer et al. (2022), looking at longer-term trends, argue that global extreme poverty increased by 73.9 million in 2020, and will further grow to 63.6 million in 2030 and 57.1 million in 2050, with the greatest increases occurring in South Asia and Sub-Saharan Africa. Finally, some of the latest estimates by the World Bank contained

[3] See also Baez et al. (2019) for an analysis of the effects of multiple weather shocks on household welfare in Mozambique, which concluded that poverty increased by 12 and 17.5 percentage points in two of the three events analysed.

[4] See Lakner et al. (2019), Laborde et al. (2020, 2021), Mahler et al. (2020, 2021, 2022a, b), World Bank (2020), Pereira and Oliveira (2020), Sumner et al. (2020), Bargain and Aminjonov (2021), Valensisi (2020), Buheji et al. (2020), Alkire et al. (2021); among others.

in Mahler et al. (2020, 2021, 2022a, b) conclude that the increase in poverty could amount to slightly less than a hundred million people.

Even among lower income countries, though, the impacts on poverty have not been the same everywhere: Kharas and Dooley (2021) highlight how these have been particularly severe in a handful of countries. Especially India, where the economic contraction, combined with the vulnerability of many households (who had just escaped poverty and lived only slightly above the poverty line) led to an increase in poverty of about 46 million people in 2020. Similarly, in Nigeria the number of poor potentially passed from 84 to 92 million people in 2020, with further increases projected for 2021. Another country severely impacted by Covid-19 was Pakistan, where poverty was expected to rise from 8.7 to 10.3 million people in 2020, without signals of reduction for 2021, and Covid-19 may have accelerated the concentration of poverty in Africa (Kharas and Dooley 2021).

On top, Covid-19 also appears to have affected inequality in multiple ways. Some studies conclude that within-country inequality has risen, as low-income households, low-skilled workers and people with a lower level of education suffered harshly. Others argue that inequality may have decreased since poorer people in rural areas were relatively less impacted or because of the rescue/social assistance packages put in place (analyses include Clark et al. 2021; Lastunen et al. 2021; Lustig et al. 2021; Palomino et al. 2020). Other studies focus on between-country inequality, for which the increase due to Covid-19 is estimated to be much bigger, reverting to levels observed around 2010 (World Bank 2020; Mahler et al. 2020). Mahler et al. (2022b) estimate that Covid-19 increased the global Gini index by 0.7 point, on top of increasing extreme poverty by 90 million people at global level. The study motivates the increase in inequality with the fact that poorer countries faced relatively larger economic shocks, while they also argue that within-country inequality may have decreased in many countries.[5] At the same time, and looking at longer-term impacts in terms of inequality, Narayan et al. (2022) argue that the overall impacts of Covid-19 could be larger over the medium-to-long term. This is especially so if recovery in many lower-income countries continues to be slow and uneven, and if the negative learning consequences related to school closures during the pandemic result in long-lasting effects on inequality of opportunity and social mobility.

At country level, on top of the estimates already discussed for selected countries, there is evidence of severe impacts on welfare for Bangladesh. Rahman et al. (2022) conclude that informal workers, women, and the urban poor lost disproportionately in this case. For Ghana, Bukari et al. (2022) show that more than half of the sampled households did not get enough income, enough food to eat, clean water, or access to medicines or medical treatments due to Covid-19, with about 70% of households declaring to have suffered food insecurity. Severe welfare impacts have also been registered for South Africa (Jafta et al. 2022; Jain et al. 2020; Chitiga et al. 2022), and for Indonesia, where social protection programmes did mitigate the increase in

[5] For what concerns low-income countries, the study argues that the decrease in inequality may have been due to the pandemic not having hit rural areas—which is where the majority of the poor live—as bad as urban ones.

poverty (Suryahadi et al. 2021). Further, more recent analyses for India, for which Ram and Yadav (2021) estimate that around 150–199 million additional people could have fallen in poverty in 2021–2022, with individuals involved in casual labour and the self-employed among the most impacted groups. Dang et al. (2021) develop an interesting perspective based on a further analysis on India, applicable to other developing countries as well. While their study recognises the vulnerability of informal sector wage workers in urban areas, of women of scheduled castes and religious minorities, it also argues that the risk of long-term poverty impacts could be particularly high in rural areas. From a health-related point of view that is because new Covid-19 cases have likely been undercounted and people were less willing to test in rural areas, and because health-care infrastructures are in general less developed. However, in general, the study focuses on long-term economic consequences of the crisis and deeper and increasingly visible consequences for the rural poor (Dang et al. 2021). Salvucci and Tarp (2021) arrive at similar conclusions with respect to the greater long-term vulnerability of rural households for Mozambique.

Notwithstanding a relatively low number of registered Covid-19 cases and related deaths, the Mozambican economy suffered as well, with the biggest economic impact resulting from restrictions of movements and slowdown of economic activity (World Bank 2021; Squarcina and Egger 2022). Betho et al. (2021) assessed the macroeconomic impact of Covid-19 and related government restrictions applying a social accounting matrix multiplier analysis. They estimated a decline in growth of 3.6% and in employment of 1.9% due to Covid-19 in 2020 alone. According to the study, the hardest-hit sectors were mining, trade, and hospitality, affected by the decline in foreign demand, while lower domestic demand affected construction, manufacturing, and trade and hospitality. Hence, the decline in global and domestic demand, together with travel and movement restrictions not only kept tourists away, they also impeded most economic activities (Betho et al. 2021).

At the household level, using micro-simulation techniques, Mussagy and Mosca (2020) estimated an increase in poverty due to Covid-19 of about 9 to 18 percentage points compared to 2014/2015, with a slightly more severe impact in urban areas, in line with the projections of the latest *Poverty and Shared Prosperity* report (World Bank 2020). The study also estimated an increase in the Gini index. Similarly, the *Mozambique Economic Update* of February 2021 (World Bank 2021) stressed that in 2020 the country was likely to experience its first economic contraction in almost 30 years. The study inter alia suggested an increase in the poverty rate of more than 5 percentage points, or 1.4 million people pushed below the poverty line. Moreover, using as a basis the estimates by Betho et al. (2021), Barletta et al. (2022a) applied micro-simulation techniques and estimated an increase in poverty due to Covid-19 of about 4 to 10 percentage points in 2020, corresponding to about 2 million people entering poverty in less than a year. More recently, Squarcina and Egger (2022) investigated the short-term impacts of the Covid-19 pandemic on household food consumption and children's nutrition outcomes, finding a significant reduction in food consumption and caloric intake, together with an increase in stunting. To complicate the picture even further, the Mozambican government had a severely limited fiscal space to counteract the economic downturn, especially when compared with the generous support packages in richer economies, but also when compared with other developing countries. Prior to the pandemic, growth forecasts for Mozambique for 2020 were close to 6% (United Nations 2020). Yet, at the end of 2020, the gross domestic product (GDP) had actually decreased by 1.2 per cent, reflecting both the impact of Covid-19 and several other major shocks.

Economic context

The economic situation present in Mozambique when the Covid-19 pandemic started was dire after experiencing a period (2015–2020) of massive inter-linked shocks that followed decades of progress. After a long conflict, which afflicted Mozambique after independence in 1975 and until 1992, the country actually experienced fast growth and poverty reduction in the 1990s, 2000s and first half of 2010s. Annual growth rates were on average 7.2% during the period 2000 until 2016 and GDP per capita grew by about 4 per cent annually, making Mozambique one of the fastest growing economies in the region (World Bank 2018). Over the same period, poverty rates fell by about 25 percentage points from about 70% in 1996/1997 to about 46% in 2014/2015. Nonetheless, this positive achievement was accompanied by an increase in the number of poor people, due to very high fertility rates and consequent population growth (DEEF 2016).[6] Mozambique's consumption and poverty profile is characterized by a strong rural–urban and regional/provincial divide, in which the southern region and the capital area, in particular, show much higher consumption levels and lower poverty rates, especially when compared to the rural areas of the central and northern regions. They appear to be especially deprived when different dimensions of poverty are analysed, such as access to basic services, housing conditions and possession of durable goods (DEEF 2016; Castigo and Salvucci 2017; INE 2015, 2021a). Overall, multidimensional poverty decreased markedly over time for all provinces and areas, but rural areas and the northern and central provinces lag behind in terms of multidimensional welfare compared to their southern counterparts (DEEF 2016). In addition, income inequality has also grown to worrying levels, particularly in recent years (Barletta et al. 2022b; Gradín and Tarp 2019; World Bank 2018).

After 2015, major shocks started hitting, severely hindering the economic growth and poverty reduction process. They included a debt scandal, which led some of the major donor countries to withdraw their aid to the country. This brought an abrupt devaluation of the national currency and a steep increase in the prices of imported goods (Mahdi et al. 2018, 2019; World Bank 2018, 2020; Egger et al. 2020; University of Copenhagen and UNU-WIDER 2023). At the same time, prices and demand for some of the highest value products dropped, including coal and gas, among others. Some of the most severe weather events ever experienced (particularly, the cyclones Idai and Kenneth in 2019) also hit. They caused immense damages in the central city of Beira and surrounding areas, and in the northern province of Cabo Delgado. In addition, an armed insurgency burst in 2017 in Cabo Delgado, which keeps destabilizing the region with attacks on civilians and military, with hundreds

[6] The population numbers increased by about five million people after 2014/2015, so that the current population is above 30 million people (INE 2021a, 2021b).

of thousands of internally displaced people and refugees abroad (University of Copenhagen and UNU-WIDER 2023).

Covid-19 hit in 2020 on top of these shocks and due to their combined effect, data from the 2019/2020 household budget survey suggest a significant upsurge in consumption poverty. It seems to have increased by more than 20 percentage points, reaching 68% of the population using the national poverty line,[7] and multidimensional poverty stagnated (University of Copenhagen and UNU-WIDER 2023; Barletta et al. 2022b).[8] In Table 1, panel a, we present consumption poverty results using data from all available household budget surveys at national, urban/rural and regional level. The multidimensional poverty incidence, as computed using the Alkire–Foster method, are in Table 1, panel b.[9] The strong rural–urban and regional divide noted above is clear (DEEF 2016; University of Copenhagen and UNU-WIDER 2023). At macroeconomic level, the trend in GDP per capita started decelerating in 2015 and subsequently decreased in constant terms (Fig. 1). The impact on the population was partially mitigated by the resumption of foreign aid in 2020, which reversed the descending trend started in 2013, even though the same went down again in 2021 (Fig. 1).

The Evolution of Covid-19

The 2019/2020 household budget survey was already in the field when Covid-19 erupted, and there was an effort to continue the fieldwork even during the first phases of the pandemic. We depict new Covid-19 cases and the timing of the 2019/2020 household budget survey in Fig. 2, together with the stringency index values computed by the Oxford Covid-19 Government Response Tracker (OxCGRT) project (see Hale et al. 2021).[10] Between March 2020 and October 2022, Mozambique experienced three big waves of Covid-19 cases and a few minor ones, resulting in more than 6000 cases and some 2200 cumulative deaths (WHO COVID-19 Dashboard 2023). The first cases registered in March 2020, even though they were geographically limited to the capital area and a peninsula in the northern region where gas extraction projects were underway (ONS 2021). Many more cases were registered in 2021 and 2022 (Fig. 2) including this time all provinces.

[7] The available poverty assessments for Mozambique compute 13 region-specific poverty lines, depending on the province and area of residence (DEEF 2016). These take into account the specific consumption patterns and price faced by households in different areas. Region-specific poverty lines can then be employed to create a spatial index that is subsequently used to deflate nominal consumption. Obviously, applying the same deflator to the poverty lines results in a single poverty line, which amount to the national poverty line. For 2019/2020, this value corresponds to 58.4 MZN/person/day (MZN = Mozambican Metical, the Mozambican currency), approximately equal to 2.5 international dollars in purchasing power parity (PPP) (World Bank 2023).

[8] We calculated these results using the same poverty computation methodology applied in all previous national poverty assessments for Mozambique.

[9] DEEF (2016) estimates the consumption aggregate based on the cost of basic needs methodology, and the poverty measures belonging to the Foster et al. (1984) classes were subsequently applied. For multidimensional poverty, the Alkire–Foster method was applied, taking into account six well-being indicators, with equal weighting (DEEF 2016).

[10] More details on the survey characteristics and timing are in “Data” section.

Table 1 Consumption poverty rates and multidimensional poverty incidence, national, urban/rural and regional level, 1996/1997–2019/2020 (%)

	(a) Consumption poverty rates (%)					(b) Multidimensional poverty incidence (%)				
Area	1996/1997	2002/2003	2008/2009	2014/2015	2019/2020	1996/1997	2002/2003	2008/2009	2014/2015	2019/2020
National	69.7	52.8	51.7	46.1	68.2	85.7	75.7	69.3	54.8	53.0
Urban	61.8	48.2	46.8	37.4	52.8	50.2	41.2	31.4	18.1	18.6
Rural	71.8	55.0	53.8	50.1	76.5	95.2	92.1	85.9	71.9	71.4
North	67.3	51.9	45.1	55.1	78.1	95.3	86.8	81.3	67.8	64.9
Centre	74.1	49.2	57.0	46.2	68.4	92.5	83.8	80.3	63.6	61.5
South	65.5	59.9	51.2	32.8	50.6	63.9	48.4	33.0	18.8	14.9

Source Authors' elaboration based on University of Copenhagen and UNU-WIDER (2023)

Panel A: percentage of poor people over the total population for different areas and for data from all available household budget surveys. poverty rates computed using the national poverty line, which for 2019/2020 corresponded to 58.4 mzn/person/day (mzn = Mozambican metical, the Mozambican currency), approximately equal to 2.5 international dollars in purchasing power parity (ppp) (World Bank 2023). Panel B: the multidimensional poverty incidence are computed using the alkire–foster method. a more detailed description is available in deef (2016). the results for 2019/2020 were calculated using the same poverty computation methodology applied in all previous national poverty assessments

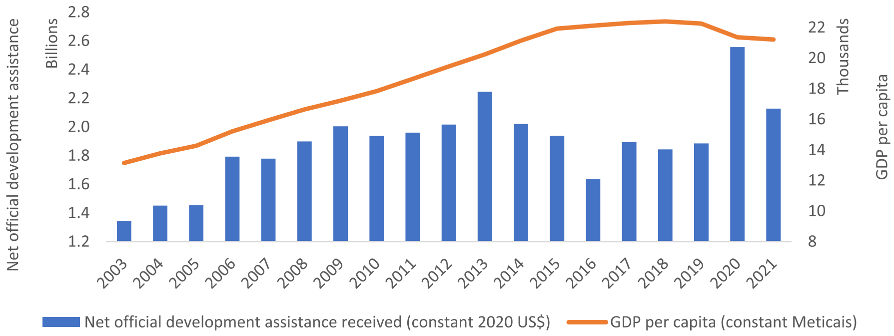

Fig. 1 GDP per capita (constant Mozambican Meticais, MZN) and net official development assistance received (constant 2020 US Dollars), 2003–2021. GDP per capita in constant 2014 local currency units, i.e. Mozambican Meticais (MZN) (thousands, right axis), and net official development assistance received in constant 2020 US Dollars (billions, left axis). *Source* World Bank (2023)

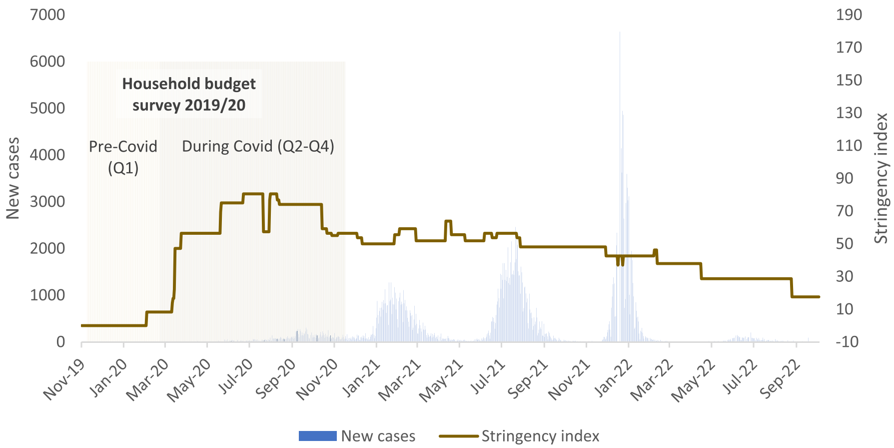

Fig. 2 Covid-19 new cases and OxCGRT stringency index, daily, November 2019–October 2022; and timing of the 2019/2020 household budget survey, divided into its pre-Covid-19 and during-Covid-19 phases. New Covid-19 cases measured on the left axis; stringency index measured on the right axis. Covid-19 new cases data are from the WHO COVID-19 Dashboard (2023). The stringency index values are from the Oxford Covid-19 Government Response Tracker (OxCGRT) project (Hale et al. 2021). The timing of the 2019/2020 Mozambican household budget survey comes from INE (2021a); the fieldwork started in November 2019 and was completed in November 2020, with the first survey quarter, Q1, (depicted in light yellow) going from November 2019 to February 2020. *Source* Authors' elaborations based on WHO COVID-19 Dashboard (2023), Hale et al. (2021), and INE (2021a)

With respect to the Government response to the pandemic, Mozambique was initially able to protect itself against the spread of the virus with early border closure, including the declaration of a state of emergency, curfews, targeted sanitary measures, travel restrictions, import and export restrictions, an economic recovery plan, a support plan for businesses, and a support plan for exporters.[11] The stringency index in Fig. 2 confirms the above-described trend, with stricter containment measures being in place between March–April and October–November 2020. Moreover, Betho et al. (2022) conclude that among the implemented measures, it seems that measures such as the reduction in utility tariffs and mobile money transaction costs as well as the strengthening of the social protection system helped to reduce the impact of the pandemic and related restrictions.

Data

The data used in this study come from the latest household budget survey conducted in Mozambique in 2019/2020 (*Inquéritos aos Agregados Familiares sobre Orçamento Familiar 2019/2020*). The National Statistics Institute (*Instituto Nacional de Estatística*, INE) collected the survey over a period of 12 months, from November 2019 to November 2020. INE has designed and implemented all Mozambican household budget surveys since 1996/1997 while the Ministry of Economics and Finance with technical assistance from various partners including IFPRI, UNU-WIDER and University of Copenhagen, depending on the survey year, performed the poverty analyses.[12] The 2019/2020 survey has a similar design compared to previous surveys conducted in the country; and it collected detailed information on consumption expenditure for 13,343 households, interviewed once over the 12 months of the survey. It is representative at national, urban–rural, regional and provincial level. However, the design implies that the subsample of households interviewed in each quarter is nationally representative. That is, each of the four survey quarters, even though only containing information for a subset of households, provide results that are representative at national level, because in each survey quarter a nationally representative subset of households, from all the provinces and areas of residence of the country, was surveyed.[13]

[11] Examples are a value-added tax (VAT) exemption for sugar, cooking oil, and soap; and a fund for micro, small, and medium enterprises (MSMEs). Exemption for customs duties and miscellaneous taxes on the import of medicines and reagents, as well as all prevention materials and ventilators, are other examples. To these come measures to waive and postpone payments of corporate taxes for firms, and negotiations about minimum wage adjustments were suspended. Utility tariffs reduced; a projected fund to assist vulnerable people in urban areas and border towns; existing beneficiaries of social assistance programmes received an additional amount and additional households were registered to receive social assistance (see Barletta et al. (2022a) and Betho et al. (2022) for additional details).

[12] Further information is available in DNPO (1998, 2004), DNEAP (2010), DEEF (2016), University of Copenhagen and UNU-WIDER (2023), INE (2004, 2010, 2015, 2021a, b).

[13] In particular, INE interviewed 3338 households in the first quarter, 1404 in the second, 3810 in the third, and 4751 in the fourth quarter of the survey. Hence, INE interviewed fewer households in the second survey quarter than originally planned, but fieldwork did not stop, and INE reinstated data collection in the months following the beginning of the pandemic. However, as mentioned, the survey design implemented by INE ensures that each quarter is nationally representative; that is, for example, the subsample of 3338 households interviewed in quarter one is representative of the population at national level.

With respect to the timing of the survey, we have noted that Mozambique is one of only a handful of countries in which a household survey was in the field during the first phases of the Covid-19 pandemic and fieldwork, with interviews conducted in person, did not stop due to the pandemic. Therefore, we have household data before and after the outbreak of the pandemic, the latter corresponding to the second to fourth survey quarters. This is a period, during which restrictions of movements were already in place and slowdown of economic activity fully underway. Actually, from Fig. 2 it is clear that the period May–October 2020 was the time during the pandemic in which the highest stringency level was in place, reinforcing the hypothesis that the effects we measure in the present analysis are in large measure due to the economic decline caused by the Covid-19-related restrictions rather than the direct health effect. In Fig. 2, we also showed the Covid-19 evolution in terms of new cases together with the timing of the survey. This is important because these figures confirm that the first survey quarter was unaffected by the pandemic, whereas the opposite is so for the remaining quarters. In addition, the survey only covered the very first phases of the pandemic, when new cases were relatively few and geographically concentrated.

Methodology

Turning to the methods used in this study, we rely on propensity score matching and inverse probability weighted regression adjustment (IPWRA) to assess the impact of Covid-19 on consumption, poverty and child malnutrition.

Propensity Score Matching and Application to Covid-19 in Mozambique

The 13,343 households selected were interviewed only once during the 12 months of the 2019/2020 household budget survey; however, from the discussion on the representativeness at various levels in "Data" section, it follows that households interviewed in each of the survey quarter should be rather similar with respect to their characteristics. We use this feature of the survey design to compare selected welfare aggregates and correlates (total, food and non-food consumption levels, consumption and multidimensional poverty rates, child stunting) in the first quarter—before the pandemic hit—with welfare aggregates and correlates in the last three quarters—during the initial phases of the pandemic characterised by strict containment measures. Given the negative effect of Covid-19 and related measures on welfare, we expect consumption levels to be lower (and poverty rates and child malnutrition to be higher) in the survey months following the first quarter. Therefore, as an initial step, we compare total, food and non-food consumption levels, consumption and multidimensional poverty rates and child stunting at national level between the first quarter, Q1 (November 2019–February 2020, pre-Covid-19) and the remaining quarters, Q2–Q4 (March–November 2020, during Covid-19).

However, it is of course more meaningful to compare only individuals with strictly similar characteristics, i.e., by matching individuals with similar observable characteristics. To compare consumption levels, poverty rates, and child stunting between households interviewed in different quarters, we therefore compute the average treatment effect on the treated (ATT) employing the propensity score matching technique (Rosenbaun and Rubin 1983). In this case, the 'treatment' reflects the outbreak of the Covid-19 pandemic. We designate the treatment or 'exposed' group as the group of households surveyed in the second, third and fourth quarter (9977 observations). The control group is the group of households interviewed in the first survey quarter (3338 observations).

To compute the ATT, we assume that observables capture all relevant differences between households in the first survey quarter and in the last three quarters, and seek to select a control group from the non-exposed pool of observations for which the distribution of the observables is as similar as possible to the distribution of the observables in the treated group. Various matching methods exist; here, we implement a standard one-to-one and nearest neighbour propensity score matching with replacement, which is among the most common matching methods. The main idea is to match individuals in the treated and control group with similar characteristics, discarding those individuals in the control group that do not represent valid matches for any treated individual (see Stuart 2010, among others).

In the one-to-one matching, we match each treated individual to only one individual in the control group, based on their similarity with respect to their observable characteristics. Clearly, "similarity" may be defined in several ways and a number of distance or similarity measures have been developed and used over time in this framework, including the commonly adopted Mahalanobis distance and the propensity score. In the present analysis, we use the latter, defined as the probability we assign an individual to the treatment, conditional on the observed baseline characteristics. Therefore, we perform the selection of matches to minimise the distance between the propensity score of the treated and control individuals. We did not use the Mahalanobis distance, since it appears to be working better when only few covariates are in the analysis (Rubin 1979; Zhao 2004; Gu and Rosenbaum 1993; Stuart 2010).

Nearest neighbour propensity score matching generalises the one-to-one matching, allowing us to have multiple matches for each treated individual. On the one hand, this has the advantage of not excluding potentially good matches from the control group, but, on the other hand, it may also result in poor matches if we select several not-very-good matches from the control group as matches for the treated individuals.[14] Given the structure of our sample, which comprises 9977 treated individuals (those interviewed in survey quarters two to four) and 3338 control individuals (those interviewed in quarter one), we can rely on a relatively large sample of both treated and control individuals, and both the one-to-one and nearest neighbour propensity score matching yield similar results. Furthermore, we decided to match with replacement, given that we have relatively fewer control individuals compared to treated individuals (Dehejia and Wahba 1999; Stuart 2010). In this way, control individuals that are similar to more than one treated individual (that is, control

[14] A more thorough discussion is in Stuart (2010).

individuals that have close propensity score values compared to more than one treated individual), can be used multiple times as matches.

Moreover, we test and expand our set of results applying the IPWRA. This involves estimating a treatment model first; then, to compute averages of predicted outcomes for each treatment level, weighted regression coefficients are used. The estimated inverse probabilities of treatment represent the weights and the averages of predicted outcomes for each treatment level are then relied on to estimate treatment effects. In this case, we also estimate and show the ATT. IPWRA has desirable properties, including that it permits to consistently estimate the treatment effect as far as only one of the two models (either the outcome or treatment) is correctly specified; a property known as “doubly robust property” (Robins and Rotnitzky 1995; Wooldridge 2007).[15] Finally, IPWRA is applicable even in case of multilevel treatments.

This permits we can refine the simple binary treatment discussed above (i.e. households surveyed pre-Covid-19 versus households surveyed during Covid-19), taking into account that the pandemic did not affect households equally. Furthermore, it accounts for the fact that—according to available information and literature—"exposure" to Covid-19 restrictions and containment measures vary substantially. This is so with respect to location, occupation, health risks associated with Covid-19 at provincial level, level of stringency in Covid-19 containment measures, housing quality and possession of durable goods, among others (Betho et al. 2021; Barletta et al. 2022a; MISAU 2023; INE (2020) INE and World Bank 2021; Anaç et al. 2022; Jones et al. 2020). We therefore create an index of likely exposure to Covid-19 restrictions and containment measures, which incorporates the findings that emerged from the literature with respect to developing countries and Mozambique, in particular. In doing so, we consider whether the individuals lived in urban areas during the survey, lived in the southern region, could be considered poor, had access to basic services such as electricity, possessed transportation means or information devices, and worked in the secondary or tertiary sector. Another consideration was whether the province in which they lived presented a cumulative number of Covid-19 cases at the end of the survey higher than 500, and whether the survey took place during a period in which the stringency index was above or below 60. The index is constructed to have five different levels of likely exposure to Covid-19 restrictions and containment measures, with value zero meaning no exposure (applied to individuals interviewed before March 2020), one representing minimal likely exposure and four indicating maximum likely exposure. The use of such an index, though simple and with limitations, is aimed at analysing the treatment intensity in the proposed framework. We investigate this employing the IPWRA approach.

[15] For further technical details, see Wooldridge (2007) and Wooldridge (2010). In particular, Wooldridge (2010) argues that the combination of the propensity score method with the regression adjustments could attain some robustness to misspecification in the parametric models, and it also advances that causal effects can be better identified using the IPWRA (Wooldridge 2010). Some recent applications of this approach for developing countries are found, among others, in Dagunga et al. (2020), Paudel et al. (2023), Mwangi et al. (2021), whereas for Mozambique see Ibraimo and Egger (2023).

The observable characteristics selected as controls in both the propensity score matching and IPWRA estimations are gender of the household head, age, age squared, education of household head, household size and household size squared, dummies on access to durable goods, safe water and sanitation, roof quality, access to electricity, and dummies for provinces and urban/rural areas. The selection aims at excluding variables which the treatment might affect (Rosenbaum 1984; Frangakis and Rubin 2002), and thus only considers those that are either time-invariant or that take a relatively longer time span compared to the survey period to vary. Descriptive statistics outcome and control variables are in Table 2.

The use of matching seems to be justified in our case: first, no relevant issues emerge with respect to the common support when assessed using the propensity score; secondly, it appears that a relatively good covariate balance is achieved, both when using one-to-one and nearest neighbour propensity score matching. However, the best results were achieved in the ten-neighbour case, shown in Table 3, with all the standardised differences in sample means between the control and treated groups being within the range [− 0.015; 0.015]. Thus, we selected this specification as our preferred estimate, even though results for one-to-one and nearest neighbour propensity score matching with fewer neighbours (matches) are also presented for robustness checking purposes. Table 3 shows that matching reduces the standardised differences in sample means between the control and treated groups with respect to the vast majority of observable characteristics. In addition, the variance ratio gets closer to one in most cases.

Exposure to Covid-19, Seasonality and Relation with Welfare Aggregates

We now pass to analyse the relation between Covid-19 and selected welfare aggregates and correlates (mainly consumption, poverty and child malnutrition), comparing simple means for our variables of interest measured before and after the start of the pandemic. In doing so, we also attempt to justify why we believe that Covid-19 is an important factor affecting welfare changes before and after March 2020, noting that the observed changes are not just due to "normal" or standard seasonal variations. An analysis of seasonality in the Mozambican context follows.

We start by making a direct comparison between the selected welfare aggregates at national level between the first and the last three quarters in the survey, and checking whether the differences are statistically significant.[16] Results are in Table 4. It appears that real consumption levels and real non-food consumption levels are lower during Covid-19, and that they are so by a relatively large amount. However, differences are not statistically significant. The same goes for most other welfare aggregates or correlates such as poverty rate and stunting. The only welfare aggregate that is statistically different in the two periods is real food consumption (Table 4),[17] an observation also made by Squarcina and Egger (2022).

[16] We dropped a few outliers for real total, food and non-food consumption in the following matching analysis. These consisted of less than 20 observations, mostly concentrated in the province of Tete.

[17] We assess statistical significance by means of a Wald test, taking into account the survey design and survey weights.

In any case and as discussed, better assessment of the effect of the pandemic on welfare emerges when comparing individuals with similar characteristics, i.e., by matching only individuals with similar observable characteristics. This is also so because, especially during the first phases of the pandemic, the impact of Covid-19 was highly localised and geographically limited to the capital area and a few other clusters in the country. On top, economic restrictions were disproportionally tight in urban as compared to rural areas. Hence, to compare consumption levels, poverty rates, child malnutrition, etc., between households interviewed in different quarters, we compute the ATT employing propensity score matching (one-to-one and nearest neighbour matching) and combine matching with inverse probability weighted regression adjustment.

Nevertheless, before proceeding with our analysis and applying these techniques, it is important to assess to what extent it is reasonable to state that a critically important factor affecting welfare changes before and after March 2020 has indeed been the surge of Covid-19 and not the typical seasonal variations occurring in the country. This is done by comparing welfare dynamics and seasonal variations in consumption in two previous surveys, the Mozambican household budget surveys 2008/2009 and 2014/2015, and contrasting them with the 2019/2020 data. Two other available household budget surveys (1996/1997 and 2002/2003) were not considered, both because they are relatively old, and mainly because the 2008/2009 and 2014/2015 surveys have a highly comparable subdivision into survey quarters with respect to the 2019/2020 one.[18]

We compare in Table 5 and Fig. 3, panel a, real total, food and non-food consumption and consumption poverty rates, respectively for the periods November–February and March–November, for the years 2008/2009, 2014/2015 and 2019/2020. It emerges that the months November (or December) to February were worse in terms of both consumption and poverty at national level than the months March–November, for both the 2008/2009 and 2014/2015 surveys. This is not the case for 2019/2020.

Even though the differences are not statistically significant for most welfare aggregates, trends seem nevertheless to consistently point to the same result. That is lower consumption values and higher poverty rates during the rainy season (going, roughly, from November to February) and higher consumption and lower poverty during the dry season (from March to October) for the 2008/2009 and 2014/2015 surveys and the opposite occurring in 2019/2020 (Table 5 and Fig. 3, panel a). The only welfare aggregate, which presents statistically different values between the two periods, is again real food consumption.

Quarterly variations in real consumption are also analysed for the same surveys. In Fig. 3, panel b, we show the average real consumption values for each survey quarter as percentages of their respective yearly averages. In this case, as well, real

[18] The subdivision in the 2008/09 survey is as follows: Q1 = September–November 2008; Q2 = December 2008–February 2009; Q3 = March–May 2009; Q4 = June–August 2009. The subdivision in the 2014/2015 survey is Q1 = mid-August-mid-November 2014; Q2 = mid-November 2014-mid-February 2015; Q4 = mid-May-mid-August 2015. For various reasons, data collection in Q3 for the 2014/15 survey did not take place (DEEF 2016).

Table 2 Descriptive statistics for the welfare indicators and control variables used in the analysis

	Obs	Mean	Std. Dev	Min	Max
Welfare indicators					
Real consumption (MZN/person/day)	13,301	65.5	101.1	0.0	2873.4
Real food consumption (MZN/person/day)	13,290	24.9	21.8	0.0	480.5
Real non-food consumption (MZN/person/day)	13,290	40.6	91.5	0.1	2873.4
Consumption poverty rate (poor = 100)	13,303	68.2	46.6	0	100
Multidimensional poverty incidence (poor = 100)	13,302	48.1	50.0	0	100
Stunting (no = 0; yes = 100)	9,147	37.7	48.5	0	100
Control variables					
Household head's gender (man = 0; woman = 1)	13,302	0.240	0.427	0	1
Household head's age	13,302	43.112	14.619	12	108
Household head's education—No education	13,302	0.492	0.500	0	1
Household head's education—Primary, 1st cycle (5 years)	13,302	0.177	0.382	0	1
Household head's education—Primary, 2nd cycle (7 years)	13,302	0.176	0.381	0	1
Household head's education—Secondary, 1st cycle (10 years)	13,302	0.058	0.234	0	1
Household head's education—Secondary, 2nd cycle (12 years)	13,302	0.059	0.236	0	1
Household head's education—Tertiary	13,302	0.038	0.192	0	1
Household size	13,303	6.050	2.839	1	35
Access to durable goods (no = 0; yes = 1)	13,302	0.420	0.494	0	1
Safe water (no = 0; yes = 1)	13,302	0.502	0.500	0	1
Quality sanitation (no = 0; yes = 1)	13,302	0.324	0.468	0	1
Roof quality (no = 0; yes = 1)	13,302	0.480	0.500	0	1
Access to electricity (no = 0; yes = 1)	13,302	0.321	0.467	0	1
Rural	13,303	0.651	0.477	0	1

Source Authors' calculations based on the 2019/2020 Mozambican household budget survey

Provincial dummies omitted

consumption values for the period November–February lie below the national yearly average in both 2008/2009 and 2014/2015, while they are well above the national yearly average in 2019/2020.

Given no remarkable climate shocks or events took place from November 2019 to November 2020, that could possibly change the standard seasonal patterns for Mozambique, we attribute this change in the typical Mozambican rainy-dry seasonal pattern to the surge of the Covid-19 pandemic. If this claim is correct, we should then also be able to see greater differences in consumption and other welfare correlates in those areas in which more Covid-19 cases were registered and/or where movement restrictions were more strongly enforced: that is, urban areas and the southern region, which is more urbanized. Moreover, if the surge of Covid-19 is responsible for the drop in welfare, we would expect that people working in the secondary and tertiary sectors of the economy suffered, compared to people working

Table 3 Standardised differences and variance ratio for raw and matched control variables used in the analysis

	Standardised differences		Variance ratio	
	Raw	Matched	Raw	Matched
Household head's gender (man = 0; woman = 1)	0.008	0.005	1.007	1.004
Household head's education—Primary, 1st cycle (5 years)	– 0.048	0.002	0.918	1.003
Household head's education—Primary, 2nd cycle (7 years)	0.016	0.001	1.025	1.001
Household head's education—Secondary, 1st cycle (10 years)	0.013	0.008	1.041	1.027
Household head's education—Secondary, 2nd cycle (12 years)	0.041	0.006	1.138	1.020
Household head's education—Tertiary	0.047	– 0.013	1.196	0.955
Household head's age	0.028	0.006	0.950	1.013
Household head's age squared	0.016	0.008	0.926	1.007
Household head's occupation (1 = agriculture; 0 = other)	– 0.015	0.008	0.991	1.019
Household size	– 0.012	0.009	1.058	1.136
Household size squared	– 0.004	– 0.006	0.999	0.999
Access to durable goods (no = 0; yes = 1)	– 0.020	0.000	1.009	1.000
Safe water (no = 0; yes = 1)	0.011	– 0.011	1.003	0.997
Quality sanitation (no = 0; yes = 1)	0.020	– 0.007	0.992	1.003
Roof quality (no = 0; yes = 1)	0.067	0.000	1.019	1.000
Access to electricity (no = 0; yes = 1)	0.008	0.005	1.007	1.004

Source Authors' calculations based on the 2019/2020 Mozambican household budget survey

Statistics for provincial dummies omitted. Results relative to a 10:1 nearest neighbour propensity score matching estimation

Table 4 Selected welfare aggregates' average values before and after the start of Covid-19 (March 2020), national level

	Q1 (pre-Covid-19)	Q2–Q4 (during Covid-19)
Real consumption (MZN/person/day)	70.3	64.0
Real food consumption (MZN/person/day)	27.0	24.3**
Real non-food consumption (MZN/person/day)	43.3	39.7
Consumption poverty rate (%)	66.0	68.9
Multidimensional poverty incidence (%)	48.6	47.9
Stunting (%)	35.5	38.5*

Source Authors' calculations based on the 2019/2020 Mozambican household budget survey

Q1 = November 2019–February 2020, pre-Covid-19; Q2–Q4 = March–November 2020, during Covid-19; MZN = Mozambican Metical, the Mozambican currency (1 USD = 63.8 MZN, as of February 2023)

$^*p < 0.1$; $^{**}p < 0.05$

in the primary sector, mainly agriculture. We investigate this in detail in "Results" section.

However, in the subsequent section we also attempt to incorporate formally the typical seasonal patterns into the analysis. Indeed, not considering any seasonal

Table 5 Selected welfare aggregates' average values in the periods November–February and March–November, national level, 2008/2009, 2014/2015 and 2019/2020

Welfare aggregate	Survey year	Nov–Feb	Mar–Nov
Real total consumption (MZN/person/day)	2008/2009	23.21	24.03
	2014/2015	44.91	48.17***
	2019/2020	70.26	64.01
Real food consumption (MZN/person/day)	2008/2009	12.75	13.7*
	2014/2015	20.37	22.97***
	2019/2020	27.02	24.28**
Real non-food consumption (MZN/person/day)	2008/2009	10.46	10.33
	2014/2015	24.54	25.19
	2019/2020	43.28	39.74
Poverty rate (%)	2008/2009	54.1	50.9
	2014/2015	50.7	43.8***
	2019/2020	66.0	68.9

Source Authors' calculations based on the 2008/2009, 2014/2015 and 2019/2020 Mozambican household budget surveys

For the 2008/2009 survey, the category "Nov–Feb" refers to the months December–February. MZN = Mozambican Metical, the Mozambican currency. We assessed the statistical significance of the difference by means of a Wald test, taking into account the survey design and survey weights

*p < 0.1; **p < 0.05; ***p < 0.01

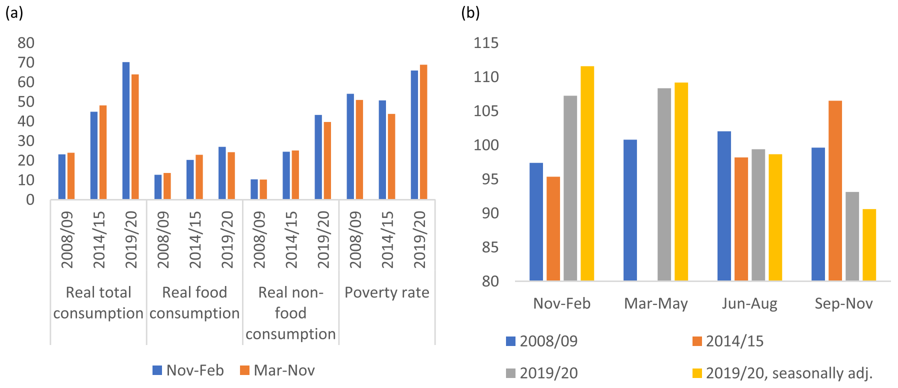

Fig. 3 **a** Selected welfare aggregates' average values in the periods November–February and March–November, national level, 2008/2009, 2014/2015 and 2019/2020; and **b** real total consumption average values by survey quarter as percentages of the yearly average values, national level, 2008/2009, 2014/2015 and 2019/2020. For the 2008/2009 survey, the category "Nov–Feb" refers to the months December–February. Real total, food and non-food consumption are expressed in MZN/person/day (MZN = Mozambican Metical, the Mozambican currency), whereas the poverty rate is expressed in percentage (same axis in panel **a**). Panel **b**: the last column to the right in each survey quarter represents the seasonally adjusted real total consumption average values expressed as percentages of the yearly average values, obtained using the seasonal variations in consumption registered in 2008/2009 and 2014/2015 as seasonal deflators. *Source* Authors' calculations based on the 2008/2009, 2014/2015 and 2019/2020 household budget surveys

adjustment would clearly end up attributing all unadjusted variation in consumption to Covid-19. Therefore, given the typical seasonality in welfare observed for Mozambique in past survey rounds and discussed above, we expect that introducing a seasonal adjustment to consumption values would return relatively bigger welfare losses. That is, we expect that the results obtained from the simple split into pre-Covid-19 and during-Covid-19 months, without considering any seasonal adjustment derived from previous survey rounds, to represent lower bounds in terms of welfare losses.

Therefore, in the results section we present results in terms of Covid-19 impact on welfare using both the observed values for consumption and poverty and their seasonally adjusted counterparts. We did the seasonal adjustment in the following way.[19] We took the quarterly values for real consumption obtained from the household budget surveys 2008/2009 and 2014/2015, respectively, expressed as percentages of the yearly average real consumption values (as shown in Fig. 3, panel b) (these represent valid seasonal deflators). Then we used the seasonal deflators obtained from the 2008/2009 and 2014/2015 surveys to adjust consumption in 2019/2020 and first applied the 2008/2009 and the 2014/2015 seasonal deflators separately, and then combined them by computing an average of the two.

We also display the 2019/2020 seasonally adjusted real consumption values in Fig. 3, panel b, for each survey quarter. As expected, the seasonal adjustment ends up increasing real consumption values for the period November–February, while increasing them more modestly for the months March–May, and decreasing the same values for the months June–August and, more markedly, September–November.

A further step in our analysis is to analyse the treatment intensity of Covid-19. Above, we discussed a rather simple binary treatment: that is, households surveyed pre-Covid-19 used as controls and households surveyed during Covid-19 considered as treated or exposed. However, we already argued how exposure to Covid-19 restrictions and containment measures varied substantially, according to a variety of characteristics. Hence, based on available information and literature, we constructed an index of likely exposure to Covid-19 restrictions and containment measures along the lines discussed in "Propensity Score Matching and Application to Covid-19 in Mozambique" section.

We weighted each of the characteristics equally in the construction of the index and gave each household a score equal to the sum of the characteristics that it possesses. We subsequently re-grouped this score, ranging from one to nine, into five levels of likely exposure to Covid-19 restrictions and containment measures. Treatment intensity, employing the proposed index, was investigated by means of the IPWRA approach, since this procedure is designed to also compute ATTs in case of multilevel treatments. Results obtained using the propensity score matching and the IPWRA, considering both seasonally adjusted and unadjusted welfare indicators, and considering the different levels of likely exposure to Covid-19 as reflected in the index are in "Results" section.

[19] We discuss here the adjustment for real consumption, but the same procedure is followed for other welfare measures.

Results

In this section, we present the results on the impact of the Covid-19 shock and related containment measures on selected welfare aggregates, with particular attention to real total consumption and to the poverty rate. First, we outline the estimates obtained using the one-to-one and nearest neighbour propensity score matching, and the IPWRA. We first present consumption results in levels (MZN/person/day) and in relative terms (i.e. using the logarithm of real total, food and non-food consumption as dependent variables). However, we subsequently prefer the relative form, after which we perform a series of robustness checks using seasonally unadjusted and adjusted welfare indicators, multilevel treatments and different specifications for the binary treatment.

In Table 6, columns 1 to 4, we present a series of estimates for the ATT obtained applying one-to-one and nearest neighbour propensity score matching to all our welfare aggregates and correlates. The nearest neighbour matching relies on using 3, 5 and 10 neighbours, respectively, without very marked differences in the results. In column 5 of the same table, we show the ATT obtained using the IPWRA; in this case, as well, the magnitude and statistical significance of the estimated coefficients are highly comparable.

The estimated ATT for real consumption ranges from − 22.0 meticais per person per day (MZN/person/day) in the IPWRA estimation to − 26.5 MZN/person/day in the three neighbour case, with our preferred estimation (10 neighbours case) being − 24.7 MZN/person/day. All results are statistically significant at 1% level. Therefore, matching on individuals with similar observable characteristics does indeed make a difference in the welfare comparisons before and after the surge of Covid-19. Real consumption appears to be lower after March 2020 by as much as 24.7 MZN/person/day (with the average consumption over the whole year being about 65.5 MZN/person/day). Food and non-food consumption are about 8 and 17 MZN/person/day lower, respectively. In relative terms, the ATT estimated using the nearest neighbour matching with 10 matches and the IPWRA show a 12–13% drop in real total consumption after March 2020, about 14% drop in food consumption, and around a 10% drop in non-food consumption. Consumption poverty also appears to have risen after March 2020 by about 6 percentage points, and child stunting is higher in the first phases of the pandemic, by about 3 percentage points.[20]

All these results are even more notable considering that the worsening in welfare occurred in what were “good” months in the past two surveys for 2008/2009 and 2014/2015. Interestingly, the multidimensional poverty incidence, as computed using the Alkire–Foster method, seems to be unaffected by the shock, reinforcing the argument that the welfare impacts depend on a short-term occurrence, which has not affected long-term welfare indicators, such as access to services, housing

[20] Squarcina and Egger (2022) point out that stunting, as opposed to wasting and being underweight, usually captures long-term malnutrition; nonetheless, the study also notices that many children in Mozambique are at a high risk of being or becoming stunted. This is so due to the high prevalence of stunting already before the Covid-19 crisis, and that this form of malnutrition may be more responsive to transient shocks as well in the Mozambican context.

Table 6 Average treatment effect on the treated (ATT) for selected welfare aggregates, before and after the start of Covid-19 (March 2020), one-to-one and nearest neighbour propensity score matching, and inverse probability weighted regression adjustment (IPWRA), national level

Welfare aggregate	ATT				
	(1)	(2)	(3)	(4)	(5)
	One-to-one	Nearest neighbour (3)	Nearest neighbour (5)	Nearest neighbour (10)	IPWRA
Real consumption (MZN/person/day)	− 22.4***	− 25.2***	− 26.5***	− 24.7***	− 22.0***
Real food consumption (MZN/person/day)	− 8.5***	− 8.1***	− 7.9***	− 7.7***	− 7.1***
Real non-food consumption (MZN/person/day)	− 18.3***	− 18.0***	− 16.8***	− 17.4***	− 15.7***
Real consumption (%)				− 12.8***	− 11.5***
Real food consumption (%)				− 14.3***	− 13.9***
Real non-food consumption (%)				− 10.7***	− 9.5***
Consumption poverty rate (%)	4.9***	6.2***	5.9***	6.0***	5.5***
Multidimensional poverty incidence (%)	− 0.1	0.3	0.3	0.2	0.3
Child stunting	5.0***	3.3***	3.4***	3.2***	2.8***

Source Authors' calculations based on the 2019/2020 Mozambican household budget survey

One-to-one = One-to-one propensity score matching. For nearest neighbour matchings, the number of matches is in parentheses. IPWRA = inverse probability weighted regression adjustment. We dropped a few outliers for real total, food and non-food consumption (less than 20 observations, mostly concentrated in the province of Tete). MZN = Mozambican Metical, the Mozambican currency (1 USD = 63.8 MZN, as of February 2023; the average real consumption is about 66 MZN/person/day). The ATT for real total, food and non-food consumption is first presented in levels and then in relative terms (%)

***$p < 0.01$

conditions or ownership of durable goods. The relatively bigger reduction in non-food consumption suggests that this may have been a reasonable response to a sudden shock, as also noted in Hallegatte et al. (2020) with respect to natural shocks.

We now introduce the seasonal adjustments presented in previous sections into the analysis. As discussed, ignoring the typical seasonal seasonality in consumption observed, ends up attributing all unadjusted variation in consumption to Covid-19. Thus, given the above discussion and findings, we expect that introducing a seasonal deflator to our consumption values would lead to estimating relatively bigger welfare losses. In Table 7, we present the ATT for real total, food and non-food consumption, in relative terms, and for the poverty rate, estimated applying the seasonal deflator obtained from the 2008/2009 and the 2014/2015 survey, separately, and from a combination of the two.

In all cases, the estimated effect is bigger when seasonal adjustments are applied. When the seasonal deflator obtained from the 2008/2009 and the 2014/2015 surveys is used, the reduction in real total consumption after the start of Covid-19 is − 17.5%. It is slightly higher for food consumption (− 18.8%) and equal to − 15.4% for non-food consumption (Table 7). The increase in the poverty rate is also larger when seasonal adjustments are applied: it passes from 6 to 7–9 percentage points, depending on the seasonal deflator used. These results confirm the expectation that the ATTs estimated without considering any seasonal adjustment are indeed lower bound estimates in terms of welfare losses.

As discussed, a further step in our analysis is to analyse the treatment intensity of Covid-19. That is, instead of applying the simple binary treatment with households surveyed pre-Covid-19 used as controls and households surveyed during Covid-19 considered as treated or exposed, we now implement the multilevel treatment introduced in the methodology section, based on likely exposure to Covid-19 restrictions and containment measures.

The findings in Table 8 confirm that if the likelihood of exposure increases, the impact on real total consumption is expected to increase as well. However, it also emerges that in the case of minimal exposure (value 1 of the Covid-19 exposure index), real consumption appears to be higher (+6.4%) after March 2020 (case 1 vs 0, first column). That may entail that for individuals only minimally affected by the surge of Covid-19 and related containment measures, the months November 2019–February 2020, corresponding to the rainy season, effectively represented a period of lower consumption, as also occurred in past surveys. The estimates in the second column of Table 8, containing the impacts on seasonally adjusted real total consumption further underpin this intuition. When consumption is adjusted taking into account the "typical" seasonal variations as obtained from the 2008/2009 and 2014/2015 surveys, then the positive impact on consumption for households only mildly affected by Covid-19 disappears. Conversely, the negative impacts for those more exposed to Covid-19 (values 2 to 4 of the Covid-19 index) amplify: − 20.5% for the case “2 vs 0”, − 29.6% for the case “3 vs 0”, and up to − 36.4% for those with maximum likely exposure to Covid-19 (case “4 vs 0″). The same occurs for food and non-food consumption (not shown), and we observe a similar dynamics for the consumption poverty rate. In the case of minimal exposure (value 1 of the Covid-19 index), the poverty rate appears to be lower after March 2020 (case 1 vs

0, third column). Moreover, when the same is adjusted taking into account the seasonal adjustments, then the impact on poverty for households only mildly affected by Covid-19 gets smaller, while the impact for households more severely affected by Covid-19 increases (Table 8, fourth column).

Focusing on the two main welfare indicators, total consumption and poverty, we now pass to the computation of the ATT with respect to the impact of Covid-19 for different sub-populations. We present the results for both seasonally unadjusted and adjusted total consumption and poverty in Table 9. It shows that urban areas were particularly affected, with a reduction in total consumption values of about minus 20.6% and a surge in the poverty rate of about 9.9 percentage points. Moreover, disentangling the results at regional and urban/rural level it is clear that the impact was greater in the urban areas of the southern region, with a drop in daily consumption of about − 26.5% and a dramatic increase in poverty of about 13 percentage points (Table 9, first and third column, respectively). This region includes the capital, Maputo where most Covid-19 cases were registered, and where government enforced movement restrictions more strongly in the early phases of the pandemic.

With respect to economic sector, Covid-19 had an impact on all sectors. However, the pandemic affected individuals working in the secondary and tertiary sectors of the economy relatively more (− 27.7 and − 20.4%, respectively, compared to about − 0.6% (not statistically significant) for the primary sector. The corresponding increases in poverty were about 13.9 and 8.7 percentage points in the secondary and tertiary sector versus an increase of about 1.7 percentage points (not statistically significant) in the primary sector) (Table 9, first and third column, respectively). Once again, these results confirm our initial assessment that the Covid-19 pandemic had a harsh impact on welfare. This is so mainly for those indicators that react to short-term shocks, such as consumption and the consumption poverty rate, and mainly in those areas in which more Covid-19 cases were registered and/or where movement restrictions were more strongly enforced: that is, urban areas and, in particular, the urban areas of the southern region. Moreover, we find a more marked drop in welfare for those people working in sectors more affected by the Covid-19-related restrictions, such as the secondary and tertiary sectors of the economy. As expected, rural areas and people working in agriculture appear less impacted.

We also compute in Table 9 the impact of Covid-19 for households headed by individuals with different levels of education. This analysis adds to the previous findings because it confirms that the effect on consumption for people with no education (mostly concentrated in rural areas and subsistence agriculture) was smaller than for households headed by individuals with higher levels of education (− 5.1 versus − 28.6% for households headed by individuals with upper secondary or tertiary education). However, regarding the poverty rate the household categories that seem more hardly hit were those in the middle. They include families headed by individuals with some education, mainly upper primary education, perhaps working as street vendors in urban areas, in informal settings, or with secondary education and working in the tourism and accommodation sector, or in the construction and trade sector.

Results are also robust to changes in the specification of the treatment variable. In the bottom panel of Table 9, we take the same welfare indicators and compute

Table 7 Average treatment effect on the treated (ATT) for seasonally unadjusted and adjusted real total, food and non-food consumption, before and after the start of Covid-19 (March 2020), nearest neighbour propensity score matching (10 matches), national level

Seasonal adjustment	ATT		Nearest neighbour (10)	
	Real consumption (%)	Real food consumption (%)	Real non-food consumption (%)	Consumption poverty rate (%)
None	– 12.8***	– 14.3***	– 10.7***	6.0***
Based on the 2008/2009 survey	– 15.7***	– 17.1***	– 13.6***	7.4***
Based on the 2014/2015 survey	– 19.1***	– 20.5***	– 17.1***	9.2***
Based on the 2008/2009 and 2014/2015 surveys	– 17.5***	– 18.8***	– 15.4***	8.3***

Source Authors' calculations based on the 2019/2020 Mozambican household budget survey

Nearest neighbour matchings, 10 matches. We dropped a few outliers for real total, food and non-food consumption (less than 20 observations, mostly concentrated in the province of Tete). MZN = Mozambican Metical, the Mozambican currency. The ATT is reported in relative terms, as percentage of real total, food and non-food consumption, respectively. The ATT for real total, food and non-food consumption, in relative terms, is presented applying: no seasonal deflator; the seasonal deflator obtained from the 2008/2009 survey; the seasonal deflator obtained from the 2014/2015 survey; the seasonal deflator obtained as an average of the 2008/2009 and 2014/2015 seasonal deflators

***$p < 0.01$

Table 8 Average treatment effect on the treated (ATT) for real total consumption and consumption poverty rate, before and after the start of Covid-19 (March 2020), applying an index of likely exposure to Covid-19 restrictions and containment measures, estimated using IPWRA, national level

Covid-19 index	ATT		IPWRA	
	Real consumption (%)	Real consumption, seasonally adjusted (%)	Consumption poverty rate (%)	Consumption poverty rate, seasonally adjusted (%)
(1 vs 0)	6.4***	0.9	– 9.2***	– 6.5***
(2 vs 0)	– 15.9***	– 20.5***	15.3***	17.0***
(3 vs 0)	– 25.6***	– 29.6***	27.2***	28.7***
(4 vs 0)	– 32.5***	– 36.4***	37.9***	39.3***

Source Authors' calculations based on the 2019/2020 Mozambican household budget survey

IPWRA = inverse probability weighted regression adjustment. We dropped a few outliers for real total consumption (less than 20 observations, mostly concentrated in the province of Tete). MZN = Mozambican Metical, the Mozambican currency. The ATT for real consumption is reported in relative terms (%). We apply an index of likely exposure to Covid-19 restrictions and containment measures, constructed so to have five different levels of exposure, with value 0 meaning no exposure (applied to individuals interviewed before March 2020), 1 representing minimal likely exposure and 4 indicating maximum likely exposure. The seasonal deflator applied is based on an average of the 2008/2009 and 2014/2015 seasonal deflators, obtained from the quarterly seasonal variations in consumption recorded in the 2008/2009 and 2014/2015 surveys, respectively

***$p < 0.01$

Table 9 Average treatment effect on the treated (ATT) for selected welfare aggregates, before and after the start of Covid-19 (March 2020), nearest neighbour propensity score matching (10 matches), national, urban/rural, regional and regional-urban/rural level, by economic sector, by education level of the household head, and excluding the second survey quarter (Q2) or both the second and third survey quarters (Q2–Q3)

	ATT		Nearest neighbour (10)	
	Real consumption (%)	Real consumption, seasonally adjusted (%)	Consumption poverty rate (%)	Consumption poverty rate, seasonally adjusted (%)
Area				
National	− 12.8***	− 17.5***	6.0***	8.3***
Urban	− 20.6***	− 24.8***	9.9***	11.9***
Rural	− 1.0	− 6.3***	1.7	4.6***
North	− 5.7**	− 10.6***	2.4	4.3***
Centre	− 5.6**	− 10.6***	3.4**	6.1***
South	− 21.2***	− 25.4***	10.2***	12.9***
North rural	4.7	− 0.9	− 1.2	1.2
North urban	− 20.5***	− 24.5***	8.2***	9.3***
Centre rural	− 1.4	− 6.7**	3.5*	5.7***
Centre urban	− 11.3***	− 15.9***	5.1**	7.6***
South rural	− 10.4***	− 15.2***	4.0	7.3***
South urban	− 26.5***	− 30.5***	13.2***	15.2***
Economic sector				
Primary	− 0.6	− 5.9***	1.7	4.3***
Secondary	− 27.7***	− 31.5***	13.9***	16.0***
Tertiary	− 20.4***	− 24.6***	8.7***	10.5***
Education level				
No education	− 5.1**	− 10.1***	3.1**	5.7***
Primary, 1st cycle (5 years)	− 11.6***	− 16.3***	6.2***	9.5***
Primary, 2nd cycle (7 years)	− 13.7***	− 18.2***	8.4***	11.0***
Secondary, 1st cycle (10 years)	− 20.5***	− 24.7***	9.0***	11.1***

Table 9 (continued)

	ATT		Nearest neighbour (10)	
	Real consumption (%)	Real consumption, seasonally adjusted (%)	Consumption poverty rate (%)	Consumption poverty rate, seasonally adjusted (%)
Secondary, 2nd cycle (12 years)	− 28.6***	− 32.4***	11.6***	12.7***
Tertiary	− 28.6***	− 32.4***	6.6***	6.9***
Survey quarters considered				
Q1 vs Q2–Q4	− 12.8***	− 17.5***	6.0***	8.3***
Q1 vs Q3–Q4 (no Q2)	− 13.0***	− 17.9***	5.9***	8.5***
Q1 vs Q4 (no Q2–Q3)	− 15.1***	− 20.6***	8.2***	11.2***

Source Authors' calculations based on the 2019/2020 Mozambican household budget survey

ATT computed using nearest neighbour propensity score matching, 10 matches. We dropped a few outliers for real total, food and non-food consumption (less than 20 observations, mostly concentrated in the province of Tete). MZN = Mozambican Metical, the Mozambican currency. The ATT for real consumption is reported in relative terms (%). The seasonal deflator applied is based on an average of the 2008/2009 and 2014/2015 seasonal deflators, obtained from the quarterly seasonal variations in consumption recorded in the 2008/2009 and 2014/2015 surveys, respectively

*$p < 0.1$; **$p < 0.05$; ***$p < 0.01$

the ATT comparing Q1 with Q3–Q4, and Q1 with Q4, respectively. We motivate the exclusion of the second survey quarter (or the second and third survey quarters) by the fact that in these quarters there were relatively few Covid-19 cases. Containment measures were already in place, so people may have adapted to difficult-to-enforce restrictive measures, ending up feeling the impact of the beginning of the pandemic less than in later months. Another reason is the fact that in the first months of the pandemic people could rely on savings or on the sale of some of their assets, so that the effect on consumption/poverty was less evident. It turns out that the comparison between Q1 and Q3–Q4 results are similar, with respect to consumption and poverty, to those obtained when comparing Q1 and Q2–Q4. In contrast, when Q1 is compared to Q4 only, the impact on total consumption appears to be greater (− 15%), and the impact on poverty is greater than the baseline scenario (+ 8.2 percentage points) (Table 9, bottom panel).

This robustness check also provides an insight into the timing of the impact of the Covid-19 pandemic on the population. It appears that the impact was relatively small in the immediate aftermath of the onset of the pandemic, becoming bigger towards the end of 2020. This is likely associated with the effect of the upcoming rainy season, which reflects in lower consumption and higher poverty, and with the increase in the number of registered Covid-19 cases in all the provinces of the country, as discussed in the context and data sections.

As in previous tables, when the ATTs are computed adopting the seasonally adjusted indicators for consumption and poverty (Table 9, second and fourth column), they present a more pessimistic scenario, with larger drops in consumption and bigger surges in poverty. This reconfirms that the impacts estimated without considering any seasonal adjustment are lower bound estimates in terms of welfare losses.

Summarising our results, it emerges that the Covid-19 shock and, in particular, its related containment measures, had a substantial impact on welfare in Mozambique. At national level, after March 2020 consumption decreased by about 12–13% and the poverty rate increased by about 6 percentage points; also, when seasonal variations are taken into account, the estimated impact on consumption increases—in absolute terms—to 16–19% and the one on poverty to 7–9 percentage points. Moreover, the impact is even larger accounting for the likelihood of exposure to Covid-19, with most exposed individuals experiencing a decrease in consumption of about 33–36%. Regarding the geographical dimension, urban households were affected significantly more than rural ones, with an estimated impact on consumption of about 21–25% and on poverty of about 10–12 percentage points, well above the national average. A comparable impact is estimated for individuals living in the more urbanised southern region; this is much larger than the one experienced by individuals in the northern and central regions, for which the drop in consumption is estimated in the range 6–11% and the one on poverty around 2–6 percentage points, depending on the specification. People working in the secondary and tertiary sectors were particularly hard hit, with reduction in consumption between 20 and 32%, and increases in poverty between 9 and 16 percentage points, whereas individuals primarily involved in the primary sector were hardly affected. With respect to the timing, it appears that the reduction in consumption experienced immediately after

March 2020 was not as relevant as the one experienced in subsequent months, when it increased—in absolute terms—from about 12–13% to 15–21% at national level.

On the one hand, these results are in line with some of the available estimates obtained either from simulation exercises or from phone surveys: World Bank (2021) highlighted that Covid-19 mainly affected vulnerable urban households, and that small businesses were particularly affected, with worsening living conditions to be expected especially for the urban poor working in the informal sector. INE and World Bank (2021), reporting results from a high frequency survey conducted by INE, argues that about 41% of the urban households interviewed reported a reduction in their income. Moreover, World Bank (2021) presents as a reasonable assumption a short to medium-term reduction of 10% in consumption per capita by all households, only slightly lower than the reduction we estimated using actual household data. This contraction was estimated to drive an increase in the poverty rate by 5 percentage points, which is also not far from our estimated impact on poverty. Barletta et al. (2022a) also estimate an average reduction in consumption due to Covid-19 slightly above 10%, with a simulated poverty rate increase between 4 and 10 percentage points, with an average increase of 6.8 percentage points. Again, this is not far from our drop in consumption and increase in poverty. However, Barletta et al. (2022a) estimated a comparable effect for urban and rural households, with the latter experiencing larger increases in poverty and comparable reductions in consumption. This was not confirmed in our analysis, which conversely highlighted the notably bigger impact on welfare felt by urban households. Our results also differ from those of Mussagy and Mosca (2020), which estimate an increase in the poverty rate of about 9–18 percentage points, depending on the scenario; these estimates, especially the more pessimistic ones, are higher than those computed in the present analysis. With respect to food consumption and malnutrition, our results are broadly in line with those by Squarcina and Egger (2022); using a different methodology, we also find a significant reduction in food consumption and an increase in stunting.

On the other hand, our analysis adds value to the existing literature and estimates because it contains a significantly larger amount of information on the welfare impacts of Covid-19 on different subpopulations. Our assessments provide actual magnitudes for the consumption and poverty effects that are robust to changes in the underlying specification. Furthermore, we employed refinements, such as seasonal adjustments and treatment intensity specifications, which corroborate the finding that Covid-19 did indeed represent a major welfare shock, which did disproportionally affect specific household categories and areas.

In this respect, our estimates also provide a reference to understand if the measures put in place by the Government of Mozambique and/or development partners to help vulnerable households were well targeted or of a sufficient magnitude given the estimated welfare losses. For example, World Bank (2021) reports that the National Social Action Institute (INAS), with World Bank financial support, aided 570,000 beneficiaries in one of the existing social assistance programmes with an additional one-off payment of 50 USD, equal to three months of regular subsidies. Moreover, an additional 290,000 vulnerable households in urban and peri-urban areas, including many informal workers, were in another of the existing social assistance programmes, with beneficiaries receiving a bimonthly cash transfer of 50 USD for six months.

Now, our analysis documents that the average impact on consumption for urban people was about − 37.6 MZN/person/day. Simplifying, we could say that a transfer equivalent to half the estimated impact (that is, 18.8 MZN/person/day) would have been sufficient to offset the welfare loss, targeting such a transfer at the poorest 20% of the urban population. The hypothetical cost of social transfers that would have minimized the impacts for this vulnerable groups (about 1.5 million people), would have been equal to about 27.4 million MZN/day, or about 430 thousand USD/day (roughly 13.1 million USD/month).

World Bank (2021) reports that for the above-mentioned reinforcements of the existing social assistance programmes, the World Bank provided 21.7 million USD. In the scenario just described, this value would thus have been sufficient to cover about 1.6 months of social transfers.[21] Limiting the number of beneficiaries to the poorest 10% of the urban population and reducing the value of the transfer to a third of the estimated reduction in consumption (about 12.5 MZN/person/day) would have provided some relief in terms of social assistance for about 6 months.

Conclusions

The Covid-19 pandemic affected both developed and developing economies, and recent estimates show that it caused an increase in the global poverty rate for the first time in decades, reversing many years of fight against poverty.[22] The same happened in Mozambique even though it only recorded a relatively low number of Covid-19 cases (WHO COVID-19 Dashboard 2023). The restrictions of movements and other containment measures, and slowdown of economic activity affected several economic sectors, including mining, trade, and hospitality, and primarily urban labour (World Bank 2021; Betho et al. 2021). In the Mozambican case, it is important that when the pandemic started the country was already facing several other critical shocks. They severely limited the fiscal space available to counteract the economic downturn to which Covid-19 contributed. Consequently, GDP decreased in 2020 and only modestly increased in 2021 (INE 2023).

However, a rigorous assessment of the impact of the pandemic on household welfare has been lacking. In this study, we attempted to fill this gap, for the year 2020. We took advantage of the 2019/2020 household budget survey, which represents a unique data source. This is so given it is one of the few household surveys in the world that was in the field both before the eruption of the pandemic (November 2019–February 2020) and during the first phases of Covid-19 (March–November 2020). Moreover, even during the latter period, the Mozambican National Statistics

[21] In case of perfect targeting and in absence of costs associated with delivering the transfers and/or targeting the beneficiaries.

[22] See Lakner et al. (2019), Laborde et al. (2020, 2021), Mahler et al. (2020, 2021, 2022a, b), World Bank (2020), Pereira and Oliveira (2020), Sumner et al. (2020), Bargain and Aminjonov (2021), Valensisi (2020), Buheji et al. (2020), Alkire et al. (2021).

Institute managed to continue the survey fieldwork and collected in-person data. The present analysis thus adds value to our understanding of the welfare consequences of Covid-19 in a low-income context, where automatic social safety nets were not in place during the early phase of the pandemic. It helps in assessing the results of the welfare impact simulations produced beforehand compared to real data.

We applied propensity score matching and inverse probability weighted regression adjustment approaches to compare selected welfare indicators before and during the first phases of the pandemic. The welfare indicators mainly included total, food and non-food consumption, and consumption poverty rates, considerations about multidimensional poverty rates, and we looked at child malnutrition. We compared consumption and poverty before and during Covid-19 at national level and for different sub-populations: urban/rural areas, northern, central and southern region, regional-urban/rural level, people working in the primary/secondary/tertiary sector of the economy, and people with different levels of education.

We estimated that real total household consumption decreased, in levels, by about 25 meticais (per person per day, about 0.40 USD/person/day) during the period March–November 2020, and that food and non-food consumption reduced by about 7 and 15 meticais, respectively, in the same period. These represent notable reductions, given that the national averages for the above indicators are equal to about 66, 25 and 41 meticais, respectively for total, food and non-food consumption. The consumption poverty rate also appears to have risen after March 2020 by more than 5 percentage points, and stunting among under-5 children was about 3 percentage points higher in the early phases of the pandemic. In relative terms, we estimated a decrease in consumption of about 12–13% at national level; however, all welfare impact estimates substantially increase when we account for seasonal variations and/or when we consider the likelihood of exposure to Covid-19, with most exposed individuals experiencing a decrease in total consumption of about 33–36%.

From comparisons with two previous household budget surveys, these results are even more remarkable, considering that this deterioration in welfare occurred in months typically seen as "good" or favourable months due to seasonal variation. Indeed, deflating consumption and poverty values for seasonal variations brings about even bigger welfare loss estimates. Results are also robust to changes in the specification of the treatment variable, i.e. to the exclusion of the months March–May 2020, and to the exclusion of the months March–August 2020. This robustness check also provided insights into the timing of the impact of the Covid-19 pandemic on the population. It emerged that the impact may have been relatively small in the beginning of the pandemic, becoming bigger towards the end of 2020. This is associated with the effect of the upcoming rainy season that started around the end of October-beginning of November 2020, which is usually associated with lower consumption and higher poverty, and with the increase in the number of registered Covid-19 cases.

Our results also suggest that, in terms of real total consumption and poverty, urban areas were more deeply affected than rural areas, with a reduction in total consumption of about 21–25% and a surge in the poverty rate of about 10–12 percentage points. The most impacted areas were the urban areas of the southern region, with a drop in consumption of about 27–31% and an increase in the poverty rate of about 13–15 percentage points. This is exactly the region in which most Covid-19 cases were registered, and where government enforced movement restrictions and other containment measures more strongly, in the early phases of the pandemic.

Regarding economic sectors, we found that the pandemic affected individuals working in the secondary and tertiary sectors of the economy more heavily compared to those working in the primary sector, likely because of the relatively large impact on the secondary and tertiary sectors of the Covid-19-related restrictions and the economic slowdown. With respect to the education level, we found that the household categories more hardly hit by the pandemic were those headed by individuals with some education, either upper primary or secondary education. These categories include individuals working as street vendors or working in other informal settings in urban areas, or individuals working in the tourism and accommodation sector, or in the construction and trade sector. Households headed by individuals with no education are mostly concentrated in less-affected agriculture, and similarly for people with tertiary education, concentrated in public administration or formal business sectors.

We discussed how our findings are broadly in line with some of the existing welfare impact estimates produced for Mozambique at national or sub-national level, by means of simulation exercises or phone-surveys. Nonetheless, we also noticed that important differences emerged between the predictions and the results obtained from actual household survey data, especially for what concerns the ability to provide exact magnitudes of the shocks and to provide robust estimates for different groups and geographic areas.

We conclude that it is critically important for Mozambique and its development partners to develop stronger and more targeted policies and tools to respond to temporary shocks, given the vulnerability of its economy and the extremely high likelihood of falling into poverty for vulnerable and non-poor people. In this respect, we discussed how targeted social transfers could have minimised the welfare impact on the poorest segments of the population that were most exposed to the Covid-19 containment measures, such as the poorest 10 or 20% of the urban population, also providing some associated cost to such a measure. At the same time, we are aware that the costs associated with targeting and delivering the transfers can be substantial in the Mozambican context, which is characterised by an extremely high percentage of poor people and severe logistical and transportation challenges. In this situation, promoting financial inclusion, especially by means of expanding phone-based money transfers and saving, could likely be of help.

As a final point, we would like to stress again that the 2019/20 household survey only covered the very first phases of the pandemic, when new cases were relatively few and geographically concentrated. This is to reinforce the point made by both Dang et al. (2021) and Salvucci and Tarp (2021) that notwithstanding the larger drops in consumption felt in urban areas during 2020, it is entirely possible that the risk of long-term poverty impacts could turn out to be particularly high in rural areas. Indeed, Mozambique has not overcome, yet, the economic crisis which has started before Covid-19 and that continued after the pandemic, so that the long-term economic consequences of the crisis could have deeper and increasingly visible consequences in rural areas and for the (many) rural poor, prevalently living in the northern and central regions of the country.

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Data availability The data that support the findings of this study are available upon request from the National Statistics Institute of Mozambique (INE) or from the Ministry of Economics and Finance of Mozambique (MEF). Restrictions apply to the availability of these data, which were used under agreement with MEF for this study.

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