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Maastricht Economic and social Research institute on Innovation and Technology (UNU-MERIT)
email: **info@merit.unu.edu** | website: **http://www.merit.unu.edu**

Boschstraat 24, 6211 AX Maastricht, The Netherlands
Tel: (31) (43) 388 44 00

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Spatial Inequality during the COVID-19 pandemic in Africa, using Night-time lights data

Bruno Martorano[a], Elena Perra[b], Marco Tiberti[c]

[a] *UNU-MERIT and University of Maastricht,*
[b] *Department of Economics and Statistics, University of Turin,*
[c] *World Bank,*

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Abstract

In this paper, we study the evolution of spatial inequality during the recent COVID-19 pandemic in Africa and assess if there is any association between the outbreak of the health crisis, the strictness of policy restrictions and the changes observed in spatial inequality. Using remotely sensed night time lights data, we find that spatial inequality decreased after the COVID-19 outbreak. Yet, there are huge differences within and between countries. Spatial inequality decreased in Southern and Northern African countries while it increased in Central African countries. Spatial inequality mainly decreased in countries implementing more stringent measures but also in those areas that were richer before the outbreak of the COVID-19 pandemic.

Keywords: Spatial Inequality, Real-time satellite data, COVID-19, Causal-ARIMA, Africa
JEL: C22, D63, I18, O55

*Martorano (email: bruno.martorano@maastrichtuniversity.nl); Perra(email: elena.perra@unito.it; corresponding author); Tiberti (email: mtiberti@worldbank.org) *Acknowledgments:* We are very grateful to Fiammetta Menchetti for her suggestions and support in implementing the Causal-ARIMA methodology. We thank Kenneth Harttgen, Nicolas Büttner, Stephan Dietrich and Valerio Giuffrida for very useful comments and suggestions. We also thank for their helpful comments participants to the Nordic Conference in Development Economics (2023) and to the UNU-MERIT Internal Conference (2022). All remaining errors are our own.

1. Introduction

The COVID-19 pandemic has deeply impacted societies worldwide provoking important distributional consequences. In Africa, where inequality is a longstanding and pressing issue, the full extent of the pandemic's impact is still not completely comprehended because data are sorely lacking. This paper aims to address this knowledge gap by utilizing satellite data to measure spatial inequality in Africa, providing real-time insights into how containment measures have affected inequality.

After the first case of COVID-19 was officially registered on 14th February 2020 in Egypt (Africa Union, 2020b), many other cases were reported in other countries. At the end of April 2020, there were about 3 million laboratory-confirmed cases of COVID-19 and more than 200 thousand deaths (Nachega *et al.*, 2020). At the beginning of February 2020, the African Union constituted the Africa Task Force for Coronavirus with the objective of implementing a continental strategy devised to face the spread of the virus, by adopting lockdown protocols which had already been activated in other regions of the world (Africa Union, 2020a). The scope and types of government responses to the pandemic differed among countries. However, a common trend can be observed across Africa, where the stringency index, which measures the severity of government policies, experienced a sudden increase in March 2020. The aftermaths of these restriction measures and their impact in terms of health systems, social, political, and economic implications in the African context is extremely complex to understand. Their implementation produced both benefits and harms which were not equally shared across country's population and geographical areas. The International Labour Office (2021) reports how the pandemic and lockdown measures have exacerbated pre-existing work deficits worldwide, contributing to a significant increase in unemployment levels, which reached 205 million people in 2022, a substantial increase compared to the 187 million in 2019. Recent estimates also predict that for each percentage point reduction in the size of the global economy, the number of people living in poverty worldwide would increase by 2% - up to 14 million people. In Africa the enforcement of drastic containment measures triggered already fragile economies, disrupting economic activities and increasing financial insecurity (Africa Center for Strategic Studies, 2020; Haider *et al.*, 2020). Reductions in per capita income due to the pandemic also increased extreme poverty with a significant share of the population who have already fallen into extreme poverty or are expected fall in the near future (Africa Development Bank, 2021; Anyanwu and Salami, 2021; Teachout and Zipfel, 2020). Existing evidence also shows that the health crisis increased food insecurity because it reduced access to, and availability and affordability of food resources (Amare *et al.*, 2021; Durizzo *et al.*, 2021; Makoni and Tichaawa, 2021; Trotter *et al.*, 2020; Zidouemba *et al.*, 2020; Andam *et al.*, 2020; Teachout and Zipfel, 2020). There is also a certain consensus that the pandemic in Africa hit disproportionately certain vulnerable population segments, such as women, young individuals, and poorer households (Contreras-Gonzalez *et al.*, 2022; Bargain and Aminjonov, 2021). Also, the effects of the COVID-19 pandemic were not the same across different areas in Africa. While there is still limited research on the topic, recent contributions seem to indicate that the pandemic amplified urban inequalities, and poor urban communities were affected more than suburbs (Turok and Visagie, 2021). Food prices increased in regionally integrated markets but not in segmented markets and food security of households in urban areas was more deeply affected than that of households in rural areas (Dietrich *et al.*, 2022; Adjognon *et al.*, 2020). These results thus seem to highlight an interesting paradox: while inequality has increased within areas where the poor suffer most, it is possible that spatial inequality is decreasing because previous differences between poor and less poor areas are narrowing.

The goal of this paper is therefore to address this puzzle by investigating the evolution of spatial inequality during the recent COVID-19 pandemic for the whole African continent and by analyzing if there is any association between the outbreak of the health crisis, the strictness of policy restrictions and changes observed in spatial inequality. Measuring inequality is not straightforward due to several issues such as lack of reliable information on traditional economic and welfare measures (Chen and Nordhaus, 2011). This holds particularly true in the case of low income countries in which inequality represents a serious trigger in exacerbating economic, social and cultural tensions. Therefore, it is not surprising that little evidence was available about the relation between the spread of the COVID-19 pandemic and the measurement undertaken to tackle the pandemic and their spatial distributional effects. In order to overcome this issue, we rely on satellite data. During time of crisis, satellite observations offer two main advantages: immediate availability and cross-country comparability. In particular, we proceed by constructing the Spatial Gini indicator at the lowest administrative level available for the whole African continent by combining monthly night-time lights data for the period 2015-2021, with the gridded population data at the same level of spatial resolution. We then estimate the cost of the COVID-19 pandemic in terms of Spatial Gini by employing a novel empirical approach called Causal-ARIMA (C-ARIMA) (Menchetti *et al.*, 2023). This methodology allows us to detect whether the Spatial Gini index time series has registered a significant change in correspondence of March 2020 - the period in which most of the countries have enforced some sort of containment measures.

Our results show that on average, however, the Spatial Gini decreased in conjunction with the spread of COVID-19 and the implementation of containment policies. Yet, there are huge differences within and between countries. Spatial inequality decreased in Southern and Northern African countries while Central African countries seem to have registered a positive and significant increase in the spatial inequality index. We also investigate the role of the pandemic-related policies as a factor shaping spatial inequality. Policy restrictions to reduce the spread of the virus, such as lockdowns and stay-at-home orders, seem to have provoked significant damages to local economies due to the closure of many business activities, the rapid increase of unemployment and the fall in consumption. The impact of these measures on local economy might be explained by their stringency and duration, as well as on the degree of integration of local economy into the larger regional, national or global economy. Our results show that spatial inequality mainly decreased in countries implementing more stringent measures and in those areas who were richer and with higher value added in agriculture and industry. Our findings thus underpin an alarming situation showing that the overall inequality decrease observed in African countries after the outbreak of the COVID-19 pandemic was mainly driven by a worsening of economic activities in those areas that were wealthier prior to the COVID-19 shock.

We believe that this work contributes to the existing literature in three main directions. First, our paper relates to a new and growing literature on the social and economic consequences of pandemics (Deb *et al.*, 2022; Atkeson, 2020; Barro *et al.*, 2020; Martin *et al.*, 2020; Blair *et al.*, 2017; Voigtländer and Voth, 2013; Almond, 2006). In particular, it sheds light on the distributional consequences of the COVID-19 pandemic; while much attention has been paid to the impact of the pandemic on rich countries, for which real-time data are more easily accessible, (Angelov and Waldenström, 2023; Galletta and Giommoni, 2022; Clark *et al.*, 2021; Almeida *et al.*, 2021; Stantcheva, 2021; Furceri *et al.*, 2020; O'Donoghue *et al.*, 2020), this paper focuses on developing countries, providing new evidence on the impact of the interaction between the health crisis, policy stringency and inequality in the time of COVID-19. Differently from other papers, we contribute to the evidence on the spatially heterogenous impact of the COVID-19 crisis on African economies, investigating its direction and identifying the factors that have contributed the most to such different dynamics. Second, we contribute to a new and growing literature using non-traditional survey data and employing near-time remotely sensed satellite information to measure economic and social outcomes (Ayush *et al.*, 2021; Yeh *et al.*, 2020; Jean *et al.*, 2016; Blumenstock *et al.*, 2015). Night lights have been increasingly used in the academic literature as a proxy for economic activities (Gibson *et al.*, 2020; Levin *et al.*, 2020; Elvidge *et al.*, 1997; Croft, 1978)[1]. But it is only recently that NTLs have been employed to detect poverty and spatial inequality (Montalvo *et al.*, 2021; Ivan *et al.*, 2019; Smith and Wills, 2018; Jean *et al.*, 2016; Mveyange, 2015; Ezcurra and Rodríguez-Pose, 2014; Ghosh *et al.*, 2013; Elvidge *et al.*, 2012; Elvidge *et al.*, 2009; Sutton and Costanza, 2002)[2]. Our work takes inspiration from Mirza *et al.* (2021) who developed a remotely sensed Spatial Gini indicator. However, our Spatial Gini index is measured at a monthly, rather than yearly, frequency, and thus allows to track short-lived shocks in inequality within years. Importantly, we also validate our measure for higher spatial resolution. Last, we believe this work can provide an important policy contribution. The availability and comparability of timely data across countries pose challenges for cross-country analysis. This is especially relevant for developing countries, where reliable and accurate data on economic inequality are often scarce. In light of the urgency posed by the COVID-19 crisis, our alternative approach using the Spatial Gini indicator emerges as a valuable and innovative solution. By studying the effects of the shock and its local-level consequences, this approach provides critical insights that can inform policymakers in designing more effective and timely interventions.

The paper is structured as follows: Section 2 provides a detailed description of the data employed in the analysis and the construction of the Spatial Gini indicator; Section 3 provides

[1]While their first appearance in an economic journal dates back to the early 2000s, with the work of Sutton and Costanza (2002), it was just with the work of Henderson *et al.* (2012) and Henderson *et al.* (2011) that economists increasingly started to understand the opportunity that satellite observations could offer for a multitude of studies and applications.

[2]Recent studies also demonstrate that NTLs data are very helpful to estimate patterns of economic change at subnational level even in developing countries Pérez-Sindín *et al.* (2021).

a panoramic of African government responses after the outbreak of the pandemic; Section 4 illustrates the distributional consequences of the COVID-19 pandemic; Section 5 concludes.

2. Data Description

In this paper, we follow the approach of Mirza *et al.* (2021) to construct a light-based Spatial Gini estimator. The unit of analysis employed in this work is the lowest homogeneous administrative level available for each African country. For these subnational observational entities, we construct our Spatial Gini indicator, by employing multiple sources of information such as monthly night lights and population data. This section provides a description of the data and the methodology employed to construct the Spatial Gini index.

2.1. Spatial Gini Index

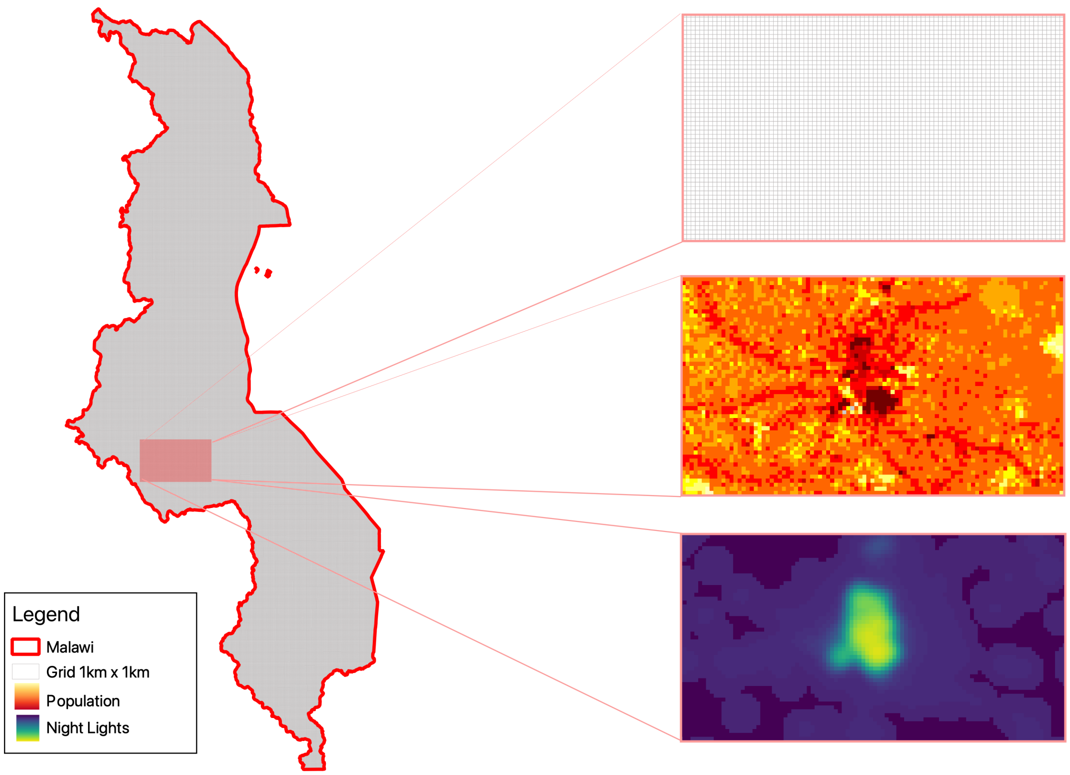
This paper uses monthly night lights (together with population data) to build a measure of spatial inequality. Satellite data have proved to be optimal to investigate population dynamics, pollution, but also to map geographical areas and monitor disasters and conflicts (Donaldson and Storeygard, 2016; Li *et al.*, 2016; Elvidge *et al.*, 2012; Sutton *et al.*, 2012; Doll *et al.*, 2006; Ebener *et al.*, 2005). These information are also considered a valid alternative of information to proxy economic and welfare conditions in fragile and poor contexts, characterized by rudimentary administrative systems, no reliable economic accounting agencies, and in areas where the data collection process was logistically hampered by conflicts and pandemics. Compared to traditional estimates, satellite data have a number of advantages: i) they can measure phenomena in real time; ii) they have a higher temporal and spatial resolution, iii) they are inexpensive and immediately available iv) they provide a higher comparability at population subscales; v) they do not suffer from measurement error related biases (Mirza *et al.*, 2021; Singhal *et al.*, 2020; Ivan *et al.*, 2019).

We construct the Spatial Gini indicator at lowest homogeneous administrative level available for the whole African continent by aggregating monthly night lights data with gridded population information at the same level of spatial resolution. Monthly night lights data are obtained from VIIRS Nighttime Day/Night Band Composites Version (Google Earth Engine, 2021) and they refer to the period between January 2015 to December 2021. These data are already filtered to exclude observation that are impacted by stray light, lunar illumination, and cloud cover. The observational units are pixels of size 15 arc-seconds, corresponding to approximately 500 meters at the equator. Population information are from the Gridded Population of World Version 4 (GPWv4), Revision 11 (Google Earth Engine, 2018), which models the distribution of global human population for the years 2000, 2005, 2010, 2015 and 2020 at a 30 arc-seconds resolution, approximately 1 Km at the Equator. Population counts are calculated following population distributions according to proportional allocation from census data, administrative units and population registers.

2.1.1. Construction of the Spatial Gini

Following the methodological approach provided by Mirza *et al.* (2021), we construct the Spatial Gini indicator through three main steps. First, we create a grid of square cells with resolution 0.00833 decimal degrees (1Km2 at the equator) for the whole African continent, by calculating the mean radiance value for each grid cell from the raw VIIRS rasters in Google Earth Engine (GEE). We then proceed by aggregating NTLs and population raster data at the same spatial resolution (see Figure 1 for Malawi as illustrative example). After that, we assign each grid cell to the corresponding administrative unit by performing an exact spatial join of the grid cell layer to the administrative units' shapefile using the R statistical software.

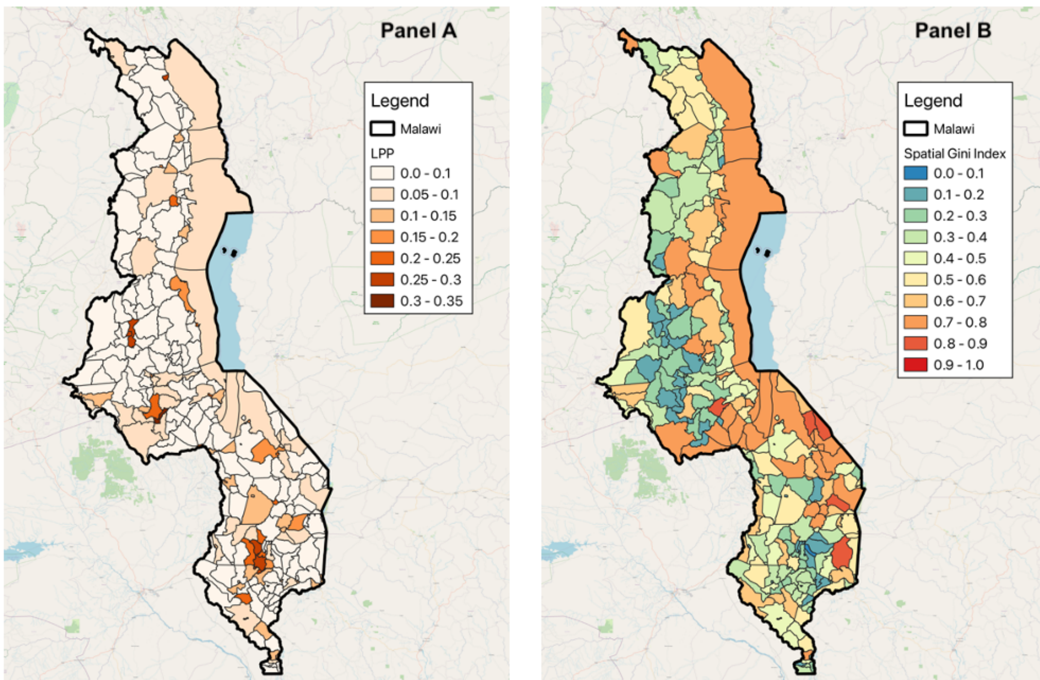
Figure 1: Construction of the 1km x 1km Grid and Aggregation of NTLs and Population data



Notes: This map illustrates the procedure used in the construction of the Spatial Gini, using Malawi as an example. First, we construct grid cells of 1Km x 1Km, in the top right panel. Then, we extract population and night-time lights rasters, respectively, onto the grid cells. Source: Authors' elaboration.

Second, we calculate the average light per person (hereafter LPP) for each grid cell as the ratio between night lights and population count (Figure 2, Panel A). Following Mirza *et al.* (2021), we exclude from the analysis those cells that are characterized by zero population, namely areas such as deserts and forests. We instead, keep cells with zero NTLs, in order to detect very poor or remote rural areas or informal settlements in the case of cities. To calculate the LPP, we thus consider only those grid cells which have NTLs greater or equal than zero and population count greater than one[3]. Third, for each administrative unit and for the whole African continent, we aggregate the average grid cell LPP, and then we compute the inequality using the Gini index formula for each administrative unit (Figure 2, Panel B). The calculation of the NTL-based Spatial Gini is akin to the traditional income Gini: each grid cell is equivalent to an economic unit in the traditional Gini formula, and their LPP value is akin to welfare variable. The Spatial Gini is then calculated via the deviation of the cumulative distribution of LPP per grid cell from the 45° line.

Figure 2: Distribution of Light per Person (Panel A) and Spatial Gini Index in Malawi (Panel B)



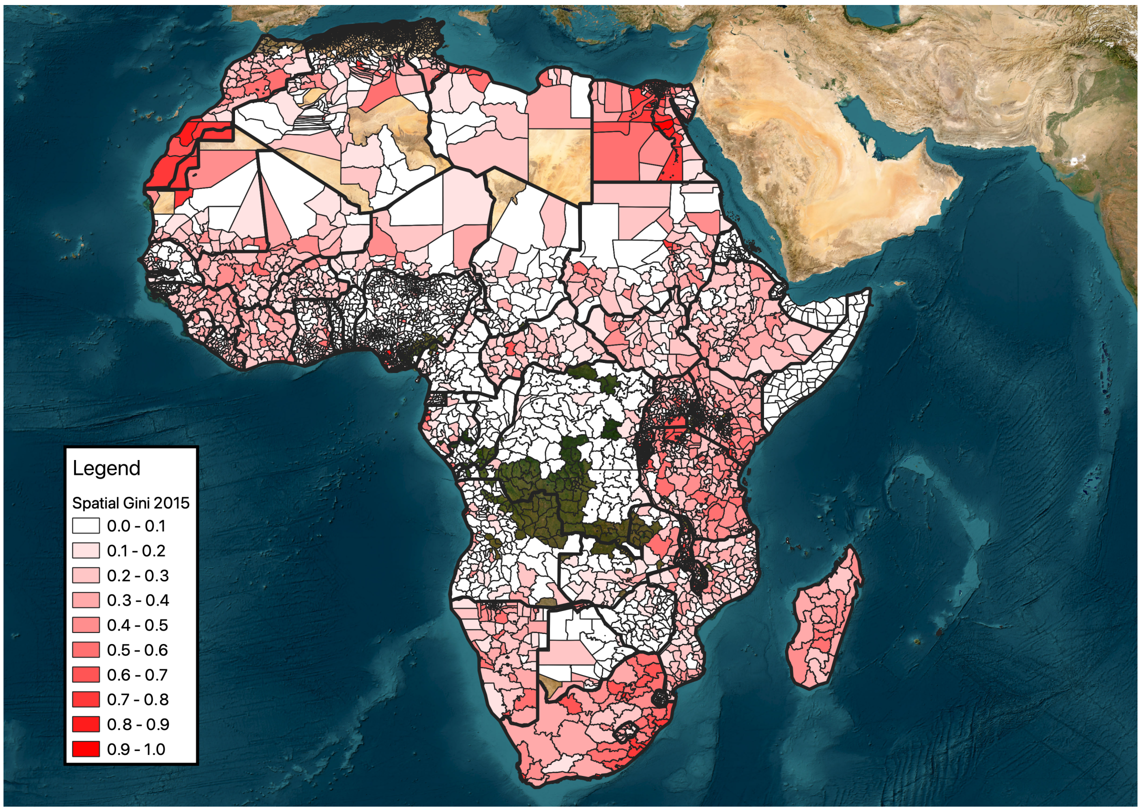
Notes: Panel A shows the geographical distribution of the Light Per Person (LPP) for each grid cell, namely the ratio between night lights and population count; Panel B shows the Spatial Gini indicator, derived from the LPP for the case of Malawi. Source: Authors' elaboration.

The construction of the Spatial Gini indicator, however, lies on two main assumptions. The first one is that night lights can be considered as indirect proxy of local economic activity, therefore as income increases for example, the emitted light per person should increase as well Henderson *et al.* (2012) . The second relies on the concept of geographical segregation of Bischof (2021), referring to the fact that economic units are quite homogenous within each

[3] We explore alternative definitions of Spatial Gini by excluding cells with NTLs that are lower or equal to the sample mean, as well as values that are lower or equal to one. Among these definitions, our preferred approach is to retain cells with zero NTLs. This choice allows us to capture remote, rural, and informal areas, providing a comprehensive view of the spatial distribution of NTLs.

geographical unit and heterogeneously distributed across geographical areas. Figure 3 reports the Spatial Gini in January 2015, namely the first period of our analysis. The locations colored with a darker shade of dark red are those that were originally characterized by a more pronounced spatial Inequality in 2015. This map sheds light on the spatial heterogeneity of this index.[4]

Figure 3: Spatial Gini Index



Notes: This figure shows the Spatial Gini index for the whole Africa in 2015. Source: Authors' elaboration.

2.1.2. Reliability Tests

In order to check the reliability of our Spatial Gini indicator in capturing inequality across areas and over time in Africa, we carry out two exercises. In the first one, following the insights of Mirza *et al.* (2021), we propose a simple OLS estimate with country and year fixed effects to verify the association between traditional national Gini estimates and our light-based Gini indicator, calculated at national-year level. The second exercise allows us to investigate the relation between canonical consumption Gini estimates and our indicator calculated at different geographical levels of aggregation. We take advantage of two nationally representa-

[4]For more detailed about inequality and its trend over the period of analysis, see Appendix A.

tive panel household surveys implemented in Ethiopia by the Ethiopian Statistical Service in collaboration with the World Bank prior and just after spread of the COVID-19 pandemic. The 2018/19 Ethiopian Socioeconomic Survey (ESS4), implemented between September 2018 and August 2019 (the consumption module was implemented in June-August 2019), and the 2021/22 ESS5, implemented between September 2021 and June 2022 (the consumption module was implemented between April and June 2022).

Traditional National Gini Estimates and Spatial Gini. We employ the World Income Inequality Database (WIID) (UNU-WIDER, 2022) to extract information on traditional measures of inequality. Unfortunately, there are few information for African countries over the period of our analysis (2015-2021), reinforcing the need for alternative indices to measure inequality in the African region. All the countries included in this exercise have maximum two observations available (Figure B.1 and Table B.1 in Appendix B report which countries are included)[5]. Then, we calculate the Spatial Gini index at the country-year level. Table 1 reports a significant and positive correlation between traditional inequality estimates and our remotely sensed inequality proxy measure. These results are in line with the ones reported by Mirza *et al.* (2021), in which they show how their measure of inequality and traditional estimates are significantly correlated. Therefore, we are confident of the ability of our remotely sensed Gini to be able to detect correctly heterogenous inequality patterns across African countries.

Table 1: Gini and Spatial Gini at the national level

	(1)	(2)	3)
Spatial Gini	0.768*	2.36*	5.27***
	(0.390)	(1.38)	(1.64)
Population		✓	✓
GDP			✓
Adjusted R^2	0.88	0.77	0.84
Observations	44	44	44
Country FE	✓	✓	✓
Year FE		✓	✓
N countries	35	35	35

Notes: The Table shows the correlation between traditional inequality estimates and the Spatial Gini indicator calculated annually at the national level. The covariates included in the regression are log-transformed. Source: Authors' elaboration.

[5]The only country for which we have more than two values of traditional Gini estimates is Mali.

Traditional and Spatial Gini Estimates at sub-national level. We construct the Gini index based on the per-capita total consumption information from the 2018/19 ESS4 and the 2021/22 ESS5 data. We then aggregate these values of consumption Gini at different administrative levels and we assess their correlation with our Spatial Gini constructed at the same level of resolution. Figure 4 reports in Panel A, B and C the resulting correlation at the woreda (district), zone, and regional level, respectively for 2018 and 2021. The correlation appears to be positive in all instances. When calculated at the woreda level, the Spatial Gini index is skewed towards zero with respect to the consumption Gini index; this could be due to the smaller geographical scale including districts with low night-time luminosity, inflating the left tail of the Spatial Gini distribution[6]. The positive and significant association between our indicator and the consumption Gini is confirmed also in a basic pooled OLS regression, reported in Table 2. However, an important drawback of relating our Spatial Gini indicator to the traditional, consumption based, yearly Gini is that by smoothing the Spatial Gini over 12 months, most of the information is lost. Indeed, the most prominent advantage of our proposed measure is that it allows to detect changes in inequality at a high frequency and at a granular scale; therefore, we regard the Spatial Gini as a tool to be used in parallel with the traditional Gini.

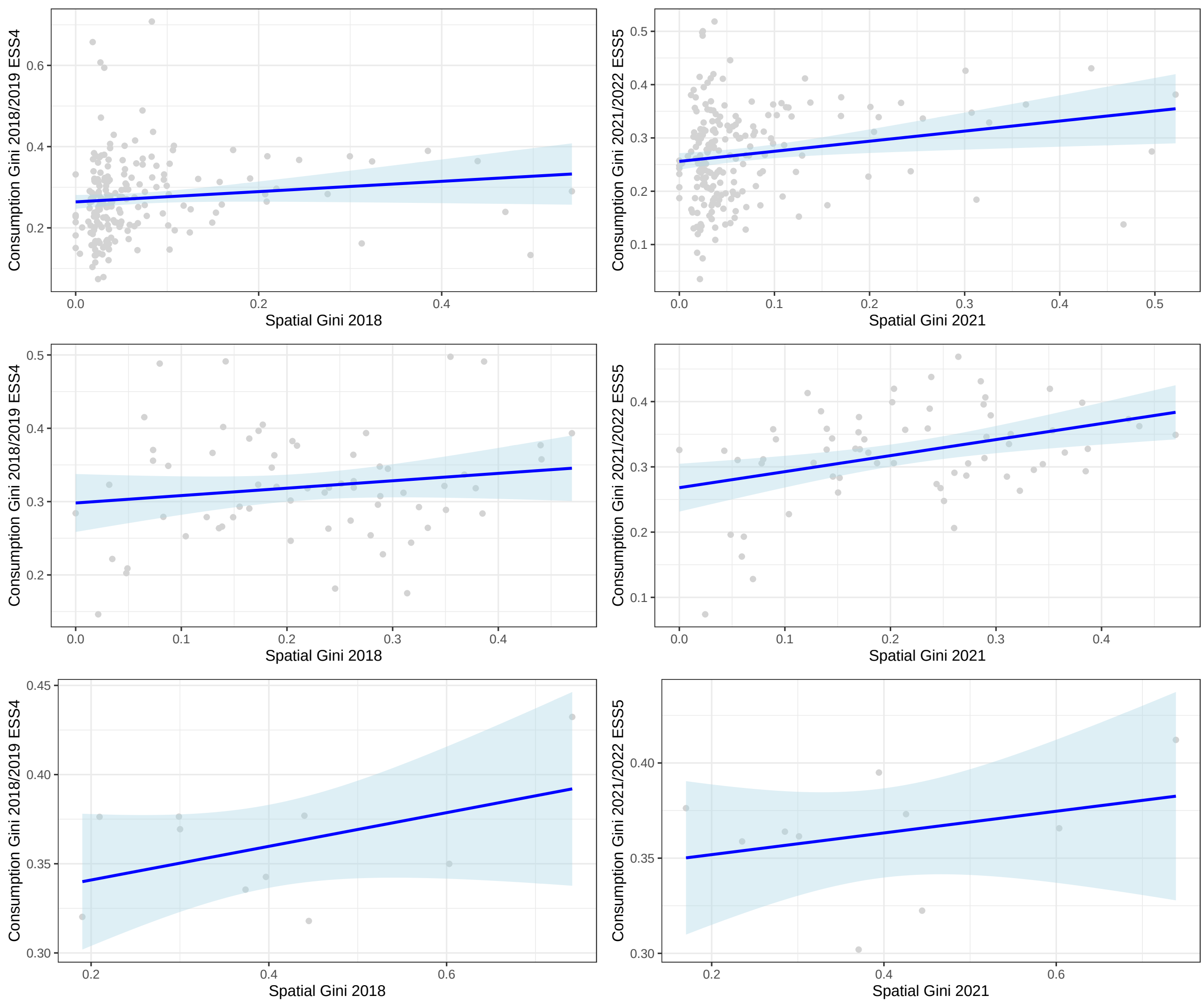
Table 2: Pooled OLS: Ethiopia 2018/19 ESS4 and 2021/22 ESS5

	District	Zones	Regions
Spatial Gini	0.14***	0.172***	0.076*
	(0.047)	(0.055)	(0.041)
Adjusted R^2	0.020	0.064	0.105
Observations	390	130	20

Notes: The table reports the coefficients of the pooled OLS regression between Gini estimates derived from household survey and the Spatial Gini indicator calculated annually at different level of aggregation. Source: Authors' elaboration.

[6]By exploring different definitions of Spatial Gini at this level of aggregation, we conducted tests to evaluate their impact on the correlation between the difference in Consumption Gini from 2018 to 2021 and the corresponding difference in Spatial Gini over the same period. When restricting the analysis to cells with NTLs values greater than or equal to the sample mean or greater than or equal to one, the correlation is 0.36 or 0.298, respectively. However, our preferred definition is the one in which we keep all values of NTLs greater or equal to zero. In that case the correlation is significantly lower and stands at 0.08.

Figure 4: Correlation between Consumption Gini and Spatial Gini at different Administrative level for Ethiopia 2018/19 ESS4 - 2021/22 ESS5

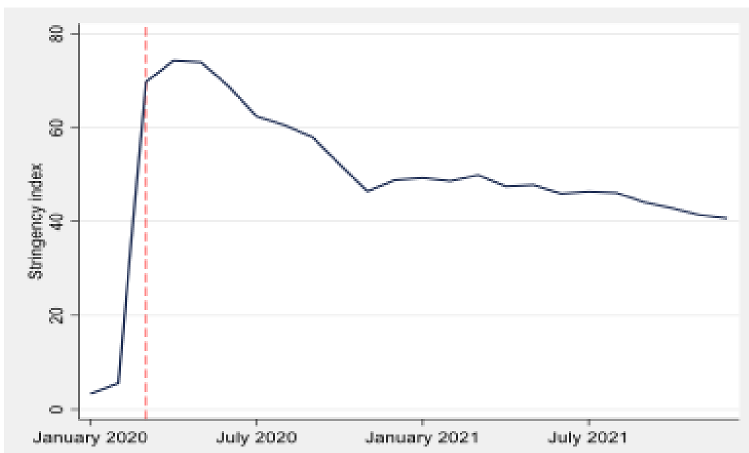


Notes: Panel A shows the correlation between Consumption Gini and Spatial Gini at woreda level. In 2018/19 ESS4 the correlation is 0.11, while in 2021/22 ESS5 is 0.19. Panel B reports the correlation of the two indicators calculated at zone level. In 2018/19 ESS4 is 0.16, while in 2021/22 ESS5 is 0.37. Finally in Panel C we report the correlation calculated a the regional level. In 2018/19 ESS4 is 0.47, while in 2021/22 ESS5 is 0.31. Source: Authors' elaboration based on information from ESS4 and ESS5.

2.2. Government responses to the COVID-19 Pandemic

Information about government responses to COVID-19 pandemic are from Oxford COVID-19 government response Tracker (University of Oxford, 2023). The stringency index is a measure of the strictness of pandemic-related policies. It is calculated by using a composite response metric which considers workplace/school closures, cancellations of events, restrictions on public gatherings and on internal/external movements. It ranges between 0 and 100, where a higher score corresponds to a stricter response adopted by the government. Figure 5 shows that in Africa the stringency index reaches its peak in March 2020, suggesting that this is the period in which most of the countries have imposed some sort of containment strategy. The stringency index kept on increasing in April, but started to decrease since then. In particular, many governments started easing restrictions in the second half of 2020, as the number of total COVID-19 cases began to decrease.

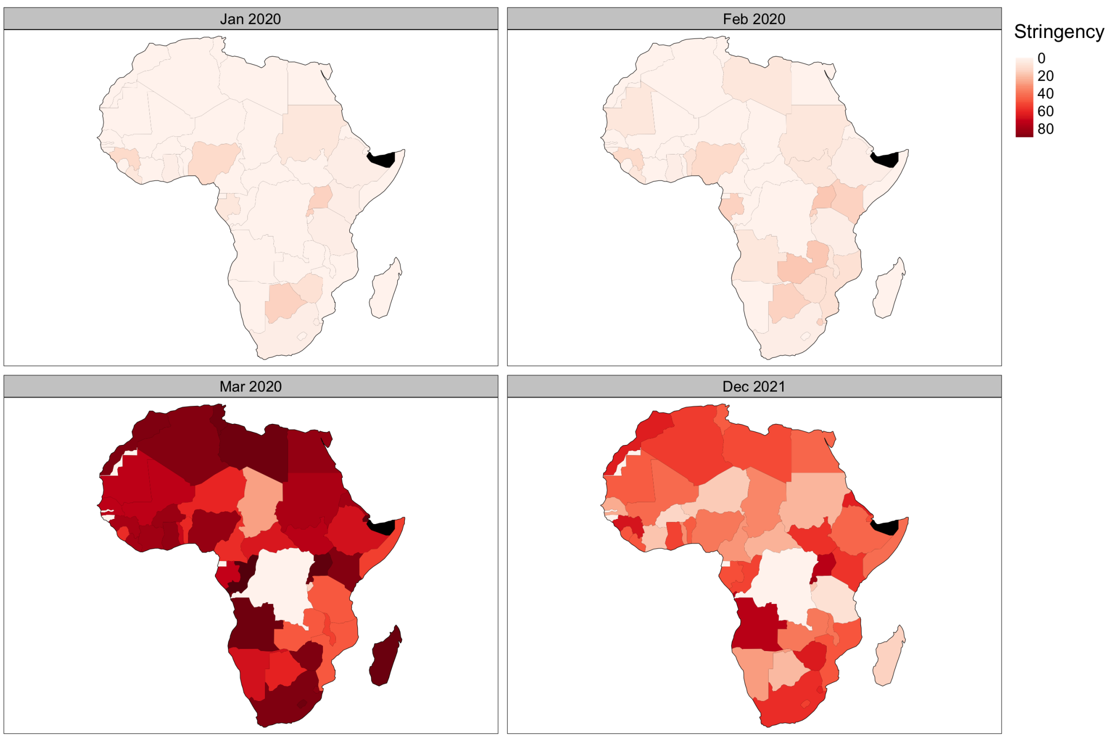
Figure 5: Stringency index changes during the period of analysis



Notes: The y-axis illustrates the stringency index, ranging from 0 to 100; the x-axis denotes time restricted to the periods immediately before and after the Covid-19 outbreak (January 2020 - December 2021). Source: Authors' elaboration based on information extracted from the Oxford COVID-19 government response Tracker.

In March 2020, numerous Sub-Saharan countries implemented relatively similar containment measures in an effort to curb the spread of COVID-19 (Figure 6). Some countries had already reported their first cases, while others had not yet recorded any. Nonetheless, media reports and official government statements indicated significant variations among countries. As shown in Figure 5 and 6, however, it is reasonable to say that March 2020 marks the period when each country experienced a change in their containment measures, albeit with varying levels of intensity.

Figure 6: Stringency Index across African countries



Notes: The map located in the upper left corner displays the level of stringency index at a national level in January 2020, whereas the one in the upper right corner portrays the same indicator in February 2020; The bottom left and bottom right maps report the stringency index in March 2020 and December 2021, respectively. Stricter measures are depicted with darker shades of red. Source: Authors' elaboration based on information extracted from the Oxford COVID-19 government response Tracker.

3. What are the distributional consequences of the COVID-19 pandemic?

We undertake a three-step approach to assess the impact of the COVID-19 pandemic and containment measures on inequality dynamics in Africa: i) first, we test for the presence of a structural break in the Spatial Gini index series; ii) second, we estimate the distributional consequences of the COVID-19 pandemic; iii) third, we run a heterogenous analysis in order to detect which are the factors that may explain the unequal impact of the pandemic across the African territory.

3.1. Structural Break

First, we proceed by testing the imposition of containment measures, proxied by a stringency indicator, on actual structural changes in Spatial Gini dynamics. The main goal is to investigate whether there are structural breaks in the Spatial Gini data and whether one of these breaks occurred in correspondence of March 2020 or right after that period i.e. the outbreak of the COVID-19 pandemic. For this purpose, we collapse our Spatial Gini indicator for the whole African continent. Our results confirm the existence of a break in March 2020 (chi2(2) = 8.5607; Prob > chi2 = 0.0138). As a second step, we test the existence of structural breaks in our panel time series employing a static linear regression model to analyze the relationship between lockdown measures and the Spatial Gini index (Ditzen *et al.*, 2021). By relying on the test proposed by Bai and Perron (2003), we use a sequential F-test for multiple breaks at unknown breakpoints with critical values, in order to detect the existence of multiple breaks and the true points in time. The sequential F-test for multiple breaks of Bai and Perron (2003) identifies, for the analysis at the administrative level, four different structural breaks (see Table 3). According to the results, there is a break in June 2020 – just few months after the outbreak of the COVID-19 pandemic and subsequent government reactions. The other breaks are estimated at February 2016, October 2017 and March 2019.

Table 3: Test for Structural Breaks

	Bai & Perron Critical Values			
	Test Statistic	1% Critical Value	5% Critical Value	10% Critical Value
$F(1\|0)$	-291.09	3.22	2.70	2.46
$F(2\|1)$	21.14	3.39	2.92	2.69
$F(3\|2)$	107.28	3.46	3.04	2.83
$F(4\|3)$	11.22	3.51	3.15	2.92
$F(5\|4)$	-0.18	3.61	3.21	2.99

Notes: Bai and Perron (2003) F sequential F-test for multiple breaks at unknown breakpoints with critical values is used to detect the true number of breaks and the true points in time. The detected breaks are in February 2016, October 2017, March 2019 and June 2020. Source: Authors' elaboration.

3.2. Estimating the Causal Effect of the Containment Measures in a time series setting

To assess the impact of COVID-19 pandemic and containment measures on inequality dynamics in the African context, we employ a novel empirical approach called Causal-ARIMA (C-ARIMA) (Menchetti *et al.*, 2023). This empirical methodology allows us to detect whether (and how) the Spatial Gini index time series has registered a significant change after the outbreak of the COVID-19 pandemic and the resulting government responses by computing the temporal average causal effect, i.e. the average monthly deviation between the observed and forecasted Spatial Gini index due to the COVID-19 shock. Formally:

$$\bar{\tau}_t(1;0) = \frac{1}{t - t^*} \sum_{s=t^*+1}^{t} \tau_t(1;0) = \frac{\Delta_t(1;0)}{t - t^*} \tag{1}$$

where $\bar{\tau}_t(1;0)$ is the temporal average causal effect; t is the time at which the effect is calculated; t^* is the time of the shock, in our context March 2020. We choose March 2020 because this is the period in which most of the countries have enforced some sort of containment measures. As shown in section 3.1, this period is also right before the observed structural break in the Spatial Gini data. In order to increase the forecast quality, we also include in our model time-invariant predictors, namely: quality of government, ethnic fractionalization, population and GDP at the baseline period (which by definition cannot be altered by the COVID-19 shock), interacted with a linear time-trend[7]; and time-variant covariates which are orthogonal with the shock (e.g. weather covariates such as minimum and maximum temperature, precipitation, wind, and drought index)[8]. Importantly, the results are robust to the exclusion of covariates.

This method relies on two main assumptions: a) the shock is exogenous and; b) all the units are affected during a similar period. Both assumptions are satisfied in our setting since the COVID-19 pandemic is an exogenous shock that took places for all the observed units during the first half of 2020. The advantage of C-ARIMA is that it does not require any control unit. The algorithm builds a counterfactual by learning the treated series' dynamics over time and forecasting it after the shock. It is thus able to predict what the series would have been like in the absence of the shock and identify the cumulative and the temporal average effect of an exogenous shock (Menchetti *et al.*, 2023). Moreover, by relying on ARIMA models, this procedure appears to be very flexible, since it is able to describe a variety of complex, non-stationary and seasonal data. Usually, in a granular, sub-national setting such as ours, a

[7]From World Bank open data (World Bank, 2021), we collect information on population and GDP data for all our countries in the sample for the period under investigation. Variables on the quality of government are derived from the QoG standard dataset 2022 (University of Gothenburg, 2021), while geo-localised data on ethnic fractionalization, consistent global roads dataset, urbanization, distance of region centroid to closest country border are derived from GREG (ETH Zurich Institute of Computational Science (ICR), 2021), GLOBIO (GLOBIO, 2021), and GHS-BUILT (Joint Research Centre (JRC), 2021), respectively.

[8]Retrieved from (Climatology Lab, 2021), which provides monthly data at a global scale with a ≈4km spatial resolution from 1958-2021.

first-order concern would be due to spatial autocorrelation across unit-level outcomes. However, by examining each time series in isolation, our C-ARIMA approach is shielded from these instances, as geographically proximate units do not contribute to inference about the unit under consideration.

The C-ARIMA methodology is also closely related to synthetic control and difference-in-differences (DiD) methods. As the synthetic control approach, the C-ARIMA methodology builds a synthetic control for a time series subject to an intervention or an exogenous shock (such as the COVID-19 pandemic) by learning its time dynamics before the shock took place. As the DiD approach, the method entails observing a treated and a counterfactual group before and after the intervention. The impact of a shock is calculated by comparing the change in the average outcome for the treated group and the control one, assuming that, without the intervention, the outcomes of both groups would have followed similar paths.

3.2.1. Results

As explained above, by relying on the C-ARIMA procedure, we can assess the significance of the COVID-19 shock and related containment measures on inequality in Africa at different levels of geographical aggregation[9]. We start testing the impact of the COVID-19 shock on the Spatial Gini time series, by collapsing our Spatial Gini indicator for the whole African continent[10]. In this way, we obtain a unique time series for the period of analysis (represented in blue) and a forecasted series for the whole period (in red). The forecasted series has been obtained by allowing the algorithm to improve the prediction of the outcome in the absence of the intervention. Visually, the algorithm calculates the differences between the areas among the two series, before and after the intervention, and it assesses whether there has been a significant change before and after March 2020 (see Figure 7)[11].

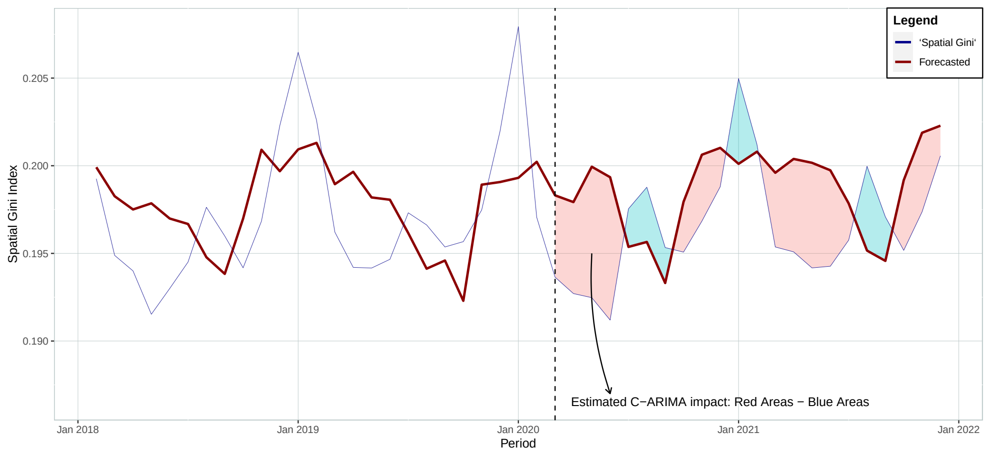
The C-ARIMA approach indicates that the detected temporal average effect in the Spatial Gini appears to be negative (-0.02) and statistically significant at the $\alpha = 0.05$ (0.02) significance level (Table 4). The cumulative effect appears to be consistent and in the same direction, reaching a value of -0.05 at the end of the sample period (see Figure C.1 in the Appendix D). At the aggregate level, the African continent thus seems to have experienced a significant negative decline in the Spatial Gini index. Although informative, this result may have been driven by some outliers, and could still mask substantial heterogeneity. In order

[9] The following countries are not included in the analysis: Cape Verde, Sao Tome & Principe, Réunion, Seychelles. We just focus on the African continent. These countries have been excluded from the analysis at present due to the practical challenges associated with including their more remote islands. Specifically, incorporating these islands would necessitate specific code adaptations and considerably lengthen the processing time.

[10] We collapse the information both at the administrative level and at the national level. In both cases the results appear coherent. Aggregating the data from national level, we obtain a negative effect of -0.004 at the same level of significance.

[11] In the Appendix it is reported another graphical representation of this analysis. In particular, Figure C.2 displays the difference between the forecasted series and the actual Spatial Gini, showing that in correspondence of March 2020 there has been a significant change.

Figure 7: C-ARIMA results for the African continent



Notes: The red line represents the forecasted series for the whole period of our analysis. The blue line represents the Spatial Gini trend. The C-ARIMA methodology compares the change in the average difference between the forecast and the actual series, before and after the shock, March 2020, and estimates its significance. Source: Authors' elaboration.

to have a more detailed understanding of the shock on inequality, we re-run the analysis at different geographical levels: i) macro-regional, ii) national, and ii) lowest administrative level for each African country.

Table 4: C-ARIMA results at the Continent Level

	Estimate	Cumulative
Estimate	-0.002	-0.048
Standard Error	0.001	0.02
p-value	0.016	0.016

Notes: The table summarises the results of the C-ARIMA analysis at the continent level. Average and the cumulative effects of the shock are reported. Source: Authors' elaboration.

Results at regional and national level. Table 5 shows that almost all the macro regions have experienced a decline in the Spatial Gini in correspondence with March 2020. In particular, inequality has decreased in Southern and Northern African countries, while for the Western and Eastern African countries it appears that just the cumulative estimate has been negative, but registered changes are not statistically significant. Only the Central African countries have registered a positive and significant increase in the spatial inequality index (see also Figure C.3 in the Appendix D).

Table 5: C-ARIMA results Macro Regions

	Central		Eastern		Northern		Southern		Western	
	Avg.	Cml.	Avg.	Cml.	Avg.	Cml.	Avg.	Cml.	Avg.	Cml.
Estimate	0.002	0.049	-0.001	-0.012	-0.006	-0.126	-0.003	-0.064	0.000	-0.006
St. Error	0.001	0.024	0.001	0.014	0.002	0.036	0.001	0.026	0.002	0.034
p-value	0.040	0.040	0.407	0.407	0.000	0.000	0.015	0.015	0.851	0.851

Notes: The table reports the results of the C-ARIMA analysis at the Macro-regional level. Source: Authors' elaboration.

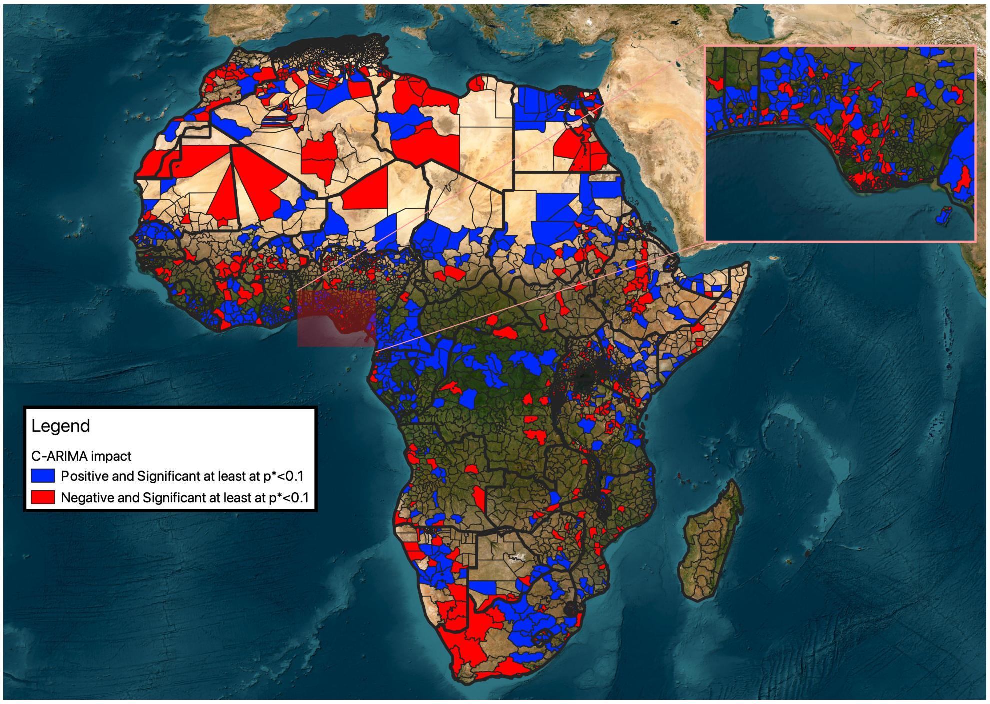
For the Northern region, it appears that all countries have been negatively impacted by the shock; indeed, almost all of them have registered a significant negative decline in the average Spatial Gini, with the exception of Algeria, Sudan and Western Sahara (see Figure C.4 in the Appendix D). For the Central macro area, most of the countries have registered a positive and significant increase in the Spatial Gini indicator; the only exceptions are Togo, the Central African Republic and the Democratic Republic of Congo, for which the direction is negative, although not significant (see Figure C.4 in the Appendix D). For the Southern, Eastern and Western regional areas, instead, the national analysis offers a more heterogeneous picture of the shock. Starting with the Southern area, it appears that the negative and significant impact of the COVID-19 pandemic and policy restrictions has been mostly driven by Mozambique, Namibia, Swaziland, Zambia and Zimbabwe (see Figure C.5 in the Appendix D). For South Africa, instead, the estimates appear to be positive and significant. For the Western and Eastern macro area, each country seems to have reacted differently to the imposition of the restrictions, although in most cases they seem to have been negatively impacted (see Figure C.6 and C.7 in the Appendix D).

Results at sub-national level. The main advantage of the Spatial Gini indicator resides in the fact that it can be calculated at different levels of aggregation: in turn, this implies that the results above can be unpacked at an even lower scale, within countries. Although the aggregated direction of the result is a generally reliable estimate of the impact of the intervention, it is interesting to analyze which sub-national unit weighs the most in determining the direction of the result at the national scale. For readability purposes, we report a geographical visualization of the result of the C-ARIMA for each subnation unit in Figure 8, which shows the direction, and the significance (α=0.10) of the estimates derived the C-ARIMA analysis[12]. Figure 8 shows that national results mask important differences at sub-national level. For example, the increase of inequality in South Africa is mainly driven by changes in the administrative units in the eastern part of the country. By contrast, the administrative units located in the western part of the country experienced a decrease of inequality. Hence, the

[12] In the Appendix D, Figure C.8 and C.9 report the values of the C-ARIMA independently of the significance level at national and sub-national level. Table C.1 shows the average and cumulative effect for each country that belongs to each macro area.

heterogeneity of the result highlights the importance of investigating the shock at a lower scale allowing policy makers to target resources to the most needed administrative units.

Figure 8: C-ARIMA for the lowest administrative level available for each African country



Notes: The map displays the estimated significant result of the C-ARIMA analysis for the lowest administrative level available for each African country. Red shading denotes negative values, i.e. areas in which a significant drop in the Spatial Gini was registered; blue shading denotes areas in which the Spatial Gini significantly increased after March 2020. Source: Authors' elaboration.

3.3. Factors Associated to Changes in Inequality

This section first explore the potential pathway through which the COVID-19 pandemic might have affected the changes in spatial inequality and then investigates which factors might have contribute to shape the impact of COVID-19 on spatial inequality.

Policy restrictions. Policy responses to COVID-19 pandemic disrupted already fragile and precarious local economic activities increasing financial insecurity. However, it is very plausible that lockdowns and restrictions had heterogenous effects hitting mostly regionally urban areas and integrated markets (Dietrich *et al.*, 2022). This section thus aims at testing the association between inequality changes and the level of stringency of the lockdown measures implemented by African countries. To capture these effects, we split our sample according to the stringency of lockdown measures. Panel A, in Table 6, clearly shows an association between changes in inequality and the strictness of pandemic-related policies. Countries that exhibited a pronounced response to the crisis in March 2020 experienced more substantial reductions in inequality. These results are further confirmed considering the stringency of pandemic-related policies during the period between March 2020 and December 2021. Indeed, Panel B ,in Table 6, shows that inequality decreased only in the group of countries implementing on average more stringent measures after the outbreak of the COVID-19 pandemic.

Table 6: C-ARIMA results by different degrees of stringency

	Panel A March 2020		Panel B Mar 2020 – Dec 2021	
	Avg.	Cml.	Avg.	Cml.
		Less Stringent		
Estimate	-0.002	-0.038	0.001	0.027
Standard Error	0.001	0.024	0.001	0.014
p-value	0.117	0.117	0.065	0.065
		More Stringent		
Estimate	-0.003	-0.056	-0.002	-0.049
Standard Error	0.001	0.017	0.001	0.022
p-value	0.001	0.001	0.023	0.023

Notes: The table reports the results of the C-ARIMA analysis, subdividing the sample by the strictness of the containment measures adopted in each country. Source: Authors' elaboration.

Pre-esisting economic structure. We finally assess the role of the pre-existing economic conditions in shaping the distributional effects of the crisis. For this purpose, we consider the GDP per capita and the economic structure before March 2020. The results in Table 7 seem to suggest that a significant reduction in Spatial inequality has been registered in those areas which reports a higher GDP per capita before the outbreak of the COVID-19 pandemic. This is a further confirmation that the results could be interpreted as a worsening of living conditions or a deterioration of economic activities in the better off areas. Moreover, Table 7 shows that the economic structure before COVID-19 influenced the changes in inequality after the outbreak of the pandemic. Inequality declined mainly in the countries in which the agricultural and manufacturing sectors played a major role before the outbreak of the COVID-19 pandemic. By contrast, the pre-existing share of services on value added does not seem to be an important predictor of the magnitude of the COVID-19 shock on spatial inequality.

Table 7: C-ARIMA results by baseline economic structure

	GDP per capita		Agriculture		Manufacturing		Service	
	Avg.	Cml.	Avg.	Cml.	Avg.	Cml.	Avg.	Cml.
			Below Median					
Estimate	-0.002	-0.037	-0.002	-0.04	-0.001	-0.015	-0.001	-0.03
Standard Error	0.001	0.024	0.001	0.025	0.001	0.012	0.001	0.022
p-value	0.128	0.128	0.11	0.11	0.225	0.225	0.179	0.179
			Above Median					
Estimate	-0.002	-0.054	-0.002	-0.047	-0.002	-0.055	0.001	0.018
Standard Error	0.001	0.018	0.001	0.022	0.001	0.025	0.001	0.012
p-value	0.003	0.003	0.031	0.031	0.026	0.026	0.14	0.14

Notes: The table reports the results of the C-ARIMA analysis, subdividing the sample depending on whether: i) GDP per capita at the baseline is above or below the median GDP per capita within our sample; ii) the share of Agriculture, Service and Manufacturing on GDP in terms of value added (% of GDP) in 2020 is above or below the median value within our sample. Source: Authors' elaboration.

4. Conclusion

This paper analyses the evolution of spatial inequality in Africa during the recent COVID pandemic and investigates the association between the outbreak of the health crisis, the strictness of policy restrictions and changes observed in spatial inequality.

The results of our analysis show that inequality decreased in the period of the COVID-19 pandemic. Nonetheless, important disparities exist both within and between regions. While Southern and Northern African countries recorded a reduction of inequality, Central African countries reported a positive and significant increase in the spatial inequality index. Furthermore, our study shows that spatial inequality mainly decreased in countries implementing more stringent policy measures designed to contain the spread of the virus. The analysis also demonstrates that spatial inequality mainly decreased in areas richer and with higher value added in agriculture and industry before the outbreak of the pandemic. This might be explained by the fact that lockdowns and stay-at-home orders have provoked significant losses to local economies due to the closure of many business activities, the rapid increase of unemployment and the fall in consumption. Hence, our interpretation is that the decrease of spatial inequality was mainly driven by a worsening of economic activities in those areas that were more developed prior to the COVID-19 pandemic.

Finally, this research offers significant guidance for policymakers in times of crisis. By pinpointing the elements that contribute to the unequal consequences of the pandemic throughout Africa, this study illustrates the potential to promptly inform policy measures designed to effectively address unexpected crises, even in low-income countries where obtaining real-time, reliable data on economic inequality is often challenging.

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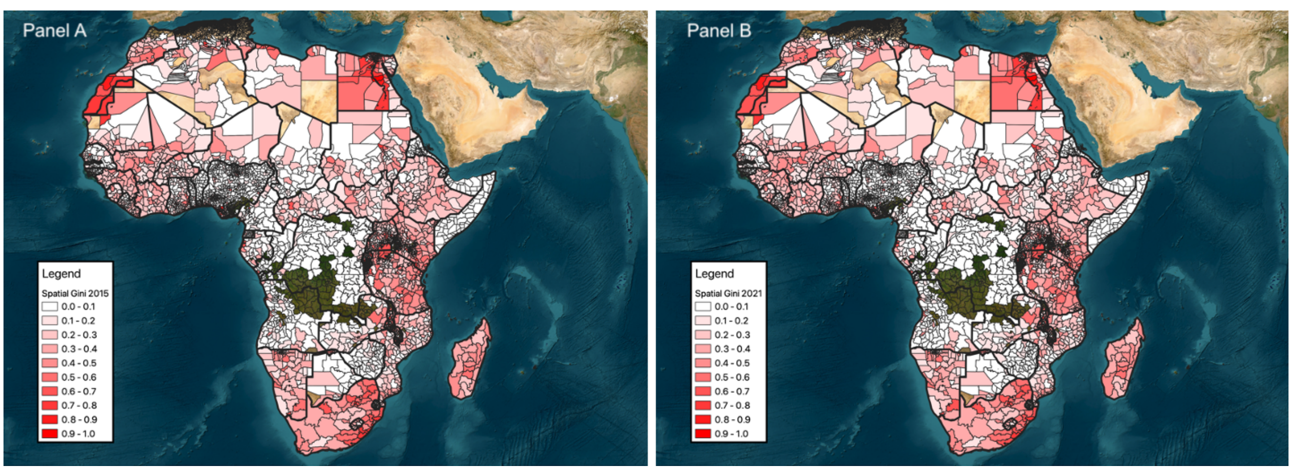
A. Appendix

Inequality and its trend over the period of analysis

Figure A.1 shows the Spatial Gini in January 2015 and December 2021. The most unequal countries in these two periods are Madagascar, Mauritius and South Africa (Table A.1 in Appendix C). However, the national result can be deconstructed into a more detailed analysis, unbundling differences between spatial units within the same country (Figure A.1). Hence, it is possible to observe interesting differences within each country. For example, eastern areas are more unequal than western areas in South Africa while areas nearby Cairo and Alexandria are the most unequal areas in Egypt. At the same time, we can observe some interesting changes occurred between January 2015 and December 2021. Some countries such as Ghana (3.2 points), Mauritius (1.5 points) and Senegal (1.5 points) have registered a rise in the spatial inequality while others such as Eswatini (2.1 points), Zimbabwe (1.5 points) and South Sudan (1.2 points) have registered a decline (Table A.1 in Appendix C). We also calculate for descriptive purpose the registered difference in the Spatial Gini indicator occurred between March 2020 - the period in which most of the countries have enforced some sort of containment measures - and December 2021. Although very descriptive and preliminary, Figure A.2 sheds light on the spatial heterogeneity of the dynamic of this indicator, which has followed different trends within and between countries.

Figure A.1: Spatial Gini Index in 2015 (Panel A) and in 2021 (Panel B)



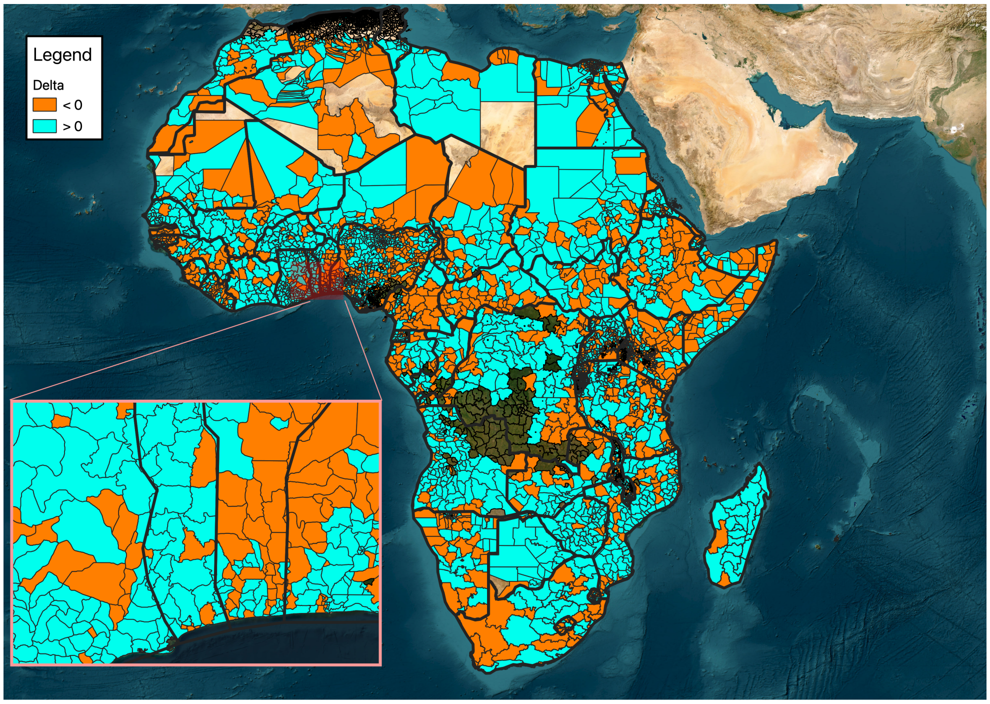
Notes: Panel A shows the geographical distribution of the Spatial Gini index in 2015; Panel B shows the distribution of the Spatial Gini index in 2021. Source: Authors' elaboration.

Table A.1: Spatial Gini in 2015 and 2021. Summary Statistics at National Level

Country	Gini 2021	Gini 2015	Variation: 2021-2015
Angola	0.098	0.093	-0.005
Burundi	0.072	0.066	-0.006
Benin	0.117	0.126	0.009
Burkina Faso	0.216	0.214	-0.002
Botswana	0.187	0.189	0.002
Central African Rep.	0.185	0.185	0.001
Cote d'Ivoire	0.306	0.31	0.004
Cameroon	0.104	0.109	0.006
Dem. Rep. Congo	0.061	0.059	-0.002
Congo	0.059	0.059	0.000
Comoros	0.124	0.126	0.002
Djibouti	0.133	0.137	0.004
Algeria	0.211	0.207	-0.004
Egypt	0.348	0.34	-0.007
Eritrea	0.045	0.042	-0.003
W. Sahara	0.753	0.747	-0.006
Ethiopia	0.216	0.214	-0.002
Gabon	0.125	0.126	0.001
Ghana	0.199	0.231	0.032
Guinea	0.28	0.278	-0.002
Guinea-Bissau	0.102	0.092	-0.01
Eq. Guinea	0.106	0.098	-0.008
Kenya	0.265	0.263	-0.002
Liberia	0.19	0.19	0.000
Libya	0.304	0.307	0.003
Lesotho	0.26	0.261	0.000
Morocco	0.305	0.302	-0.003
Madagascar	0.386	0.381	-0.005
Mali	0.294	0.292	-0.002
Mozambique	0.232	0.227	-0.005
Mauritania	0.275	0.274	-0.002
Mauritius	0.385	0.400	0.015
Malawi	0.329	0.329	0.000
Namibia	0.298	0.296	-0.002
Niger	0.159	0.16	0.002
Nigeria	0.107	0.103	-0.004
Rwanda	0.335	0.342	0.006
Sudan	0.212	0.209	-0.002
Senegal	0.141	0.156	0.015
Sierra Leone	0.232	0.231	0.000
Somalia	0.031	0.034	0.003
S. Sudan	0.223	0.210	-0.012
Swaziland	0.161	0.139	-0.021
Chad	0.081	0.083	0.002
Togo	0.127	0.13	0.003
Tunisia	0.289	0.285	-0.004
Tanzania	0.333	0.33	-0.003
Uganda	0.223	0.219	-0.004
South Africa	0.515	0.508	-0.007
Zambia	0.158	0.155	-0.003
Zimbabwe	0.074	0.059	-0.015

Notes: The table reports the Gini coefficient at the country level for 2021 and 2015, and the difference between the two values. Source: Authors' elaboration.

Figure A.2: Geographical representation of the difference in Spatial Gini between March 2020 and December 2021



Notes: The map shows the geographical distribution of the registered change in Spatial Gini between March 2020 and December 2021. In orange the registered change has been negative, and in light blue positive. Source: Authors' elaboration.

B. Appendix

Spatial Gini index and traditional Gini index

Information of traditional measure from inequality are extracted from the World Inequality Database (WIID). There are few information and available for some countries over the period of analysis (2015-2021). Figure B.1 reports which countries are included. Table B.1 reports additional information such as year of the information. All these countries have maximum two observations available for the period of analysis. The only country for which we have more than two values of traditional Gini estimates is Mali. For the case of Mali, the correlation between our Spatial Gini indicator and Income per capita Gini is 0.283 and it reaches 0.423 when using the income square definition of traditional Gini estimation.

Figure B.1: Countries included in the analysis of the statistical relationship between income inequality and yearly Spatial Gini at the national level.

Notes: This map illustrates the countries that have been included in the exercise in which shows the correlation between the traditional Gini estimates and our Spatial Gini indicator (Table 1.Source: Authors' elaboration.

Table B.1: Countries and years included in the analysis of the statistical relationship between income inequality and yearly Spatial Gini at the national level.

Country	Year	Gini	Detailed Resource Concept	Detailed Equivalence Scale
Angola	2019	51.27	Consumption	per capita
Benin	2015	47.76	Consumption	per capita
Benin	2019	37.81	Consumption	per capita
Botswana	2016	53.33	Consumption	per capita
Burkina Faso	2019	47.35	Consumption	per capita
Chad	2019	37.50	Consumption	per capita
Cote d'Ivoire	2015	41.47	Consumption	per capita
Cote d'Ivoire	2019	37.18	Consumption	per capita
Djibouti	2017	41.59	Consumption	per capita
Egypt	2015	31.72	Consumption	per capita
Egypt	2018	30.30	Consumption	per capita
Eswatini	2017	54.58	Consumption	per capita
Ethiopia	2016	33.00	Consumption	per capita
Gabon	2017	38.02	Consumption	per capita
Gambia	2016	35.92	Consumption	per capita
Ghana	2017	43.52	Consumption	per capita
Guinea	2019	29.59	Consumption	per capita
Guinea-Bissau	2019	34.77	Consumption	per capita
Kenya	2016	40.78	Consumption	per capita
Lesotho	2018	44.88	Consumption	per capita
Liberia	2016	35.27	Consumption	per capita
Malawi	2017	42.30	Consumption	per capita
Malawi	2020	37.90	Consumption	per capita
Mali	2015	36.20	Consumption	per capita
Mali	2016	35.07	Consumption	per capita
Mali	2017	35.63	Consumption	per capita
Mali	2018	35.28	Consumption	per capita
Mali	2019	36.55	Consumption	per capita
Mali	2020	40.40	Consumption	per capita
Mauritius	2017	36.76	Consumption	per capita
Mozambique	2015	47.00	Consumption	per capita
Namibia	2016	59.07	Consumption	per capita
Niger	2019	37.28	Consumption	per capita
Nigeria	2016	35.88	Consumption	per capita
Nigeria	2019	35.13	Consumption	per capita
Rwanda	2017	43.71	Consumption	per capita
Senegal	2019	38.12	Consumption	per capita
Sierra Leone	2018	35.69	Consumption	per capita
Somalia	2016	40.50	Consumption	per capita
Somalia	2017	36.82	Consumption	per capita
South Africa	2015	66.44	Consumption	per capita
South Africa	2017	67.00	Consumption	per capita
South Sudan	2017	44.14	Consumption	per capita
Tanzania	2018	40.49	Consumption	per capita
Togo	2015	43.06	Consumption	per capita
Togo	2019	42.35	Consumption	per capita
Tunisia	2016	32.82	Consumption	per capita
Uganda	2017	42.75	Consumption	per capita
Uganda	2020	42.71	Consumption	per capita
Zambia	2015	57.14	Consumption	per capita
Zimbabwe	2017	44.34	Consumption	per capita
Zimbabwe	2019	50.26	Consumption	per capita

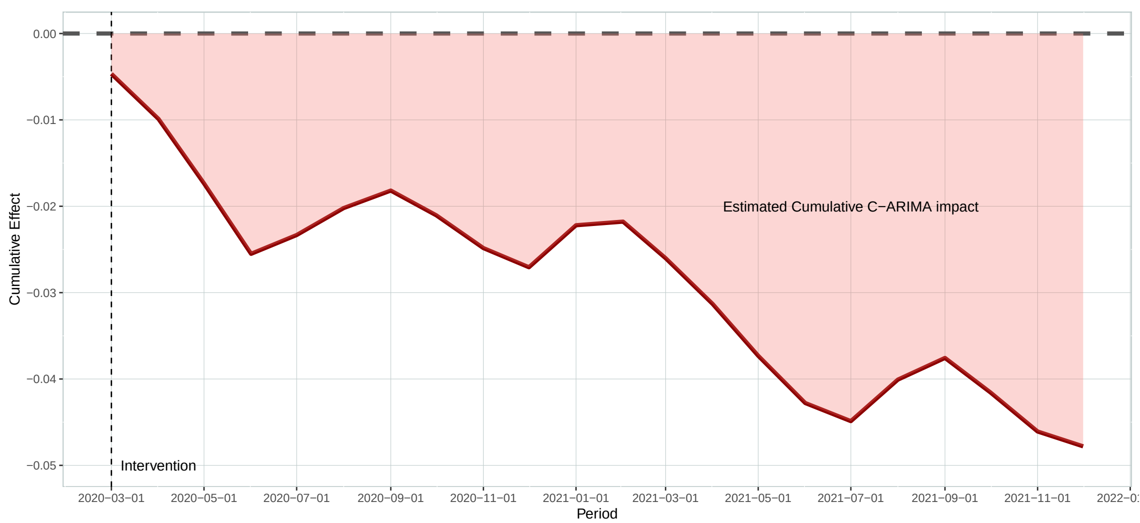
Notes: The Table reports the available data for the regression reported in Table 1. Source: Authors' elaboration.

C. Appendix

Impact of COVID-19 pandemic on Spatial inequality

Figure C.1 shows the cumulative effect of COVID-19 pandemic on Spatial inequality. In line with the results reported in Table 4, it seems that the cumulative effect of the COVID-19 pandemic reached a value of -0.05 at the end 2021 (Figure C.1).

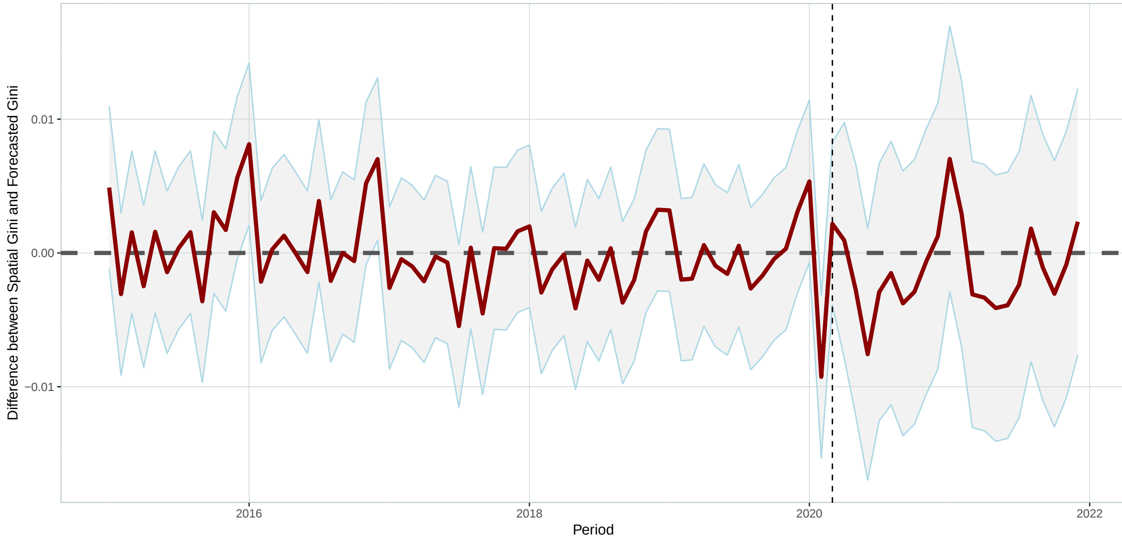
Figure C.1: C-ARIMA: Cumulative Effect at the Contintent level



Notes: The figure shows the estimated cumultative effect of the C-ARIMA analysis at the African continent level.Source: Authors' elaboration.

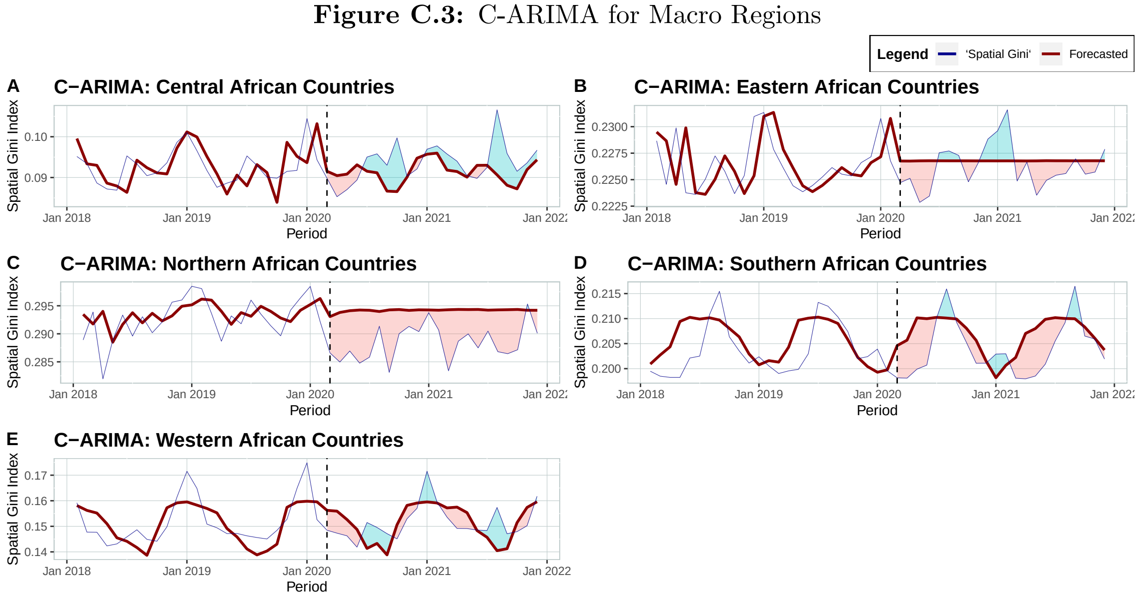
This result is confirmed also by a graphical inspection of the difference between the forecasted Gini and the actual Spatial Gini over time, which appears to suffer a significant negative drop in conjunction with the outbreak of the COVID-19 shock, i.e. in correspondence with March 2020 (Figure C.2).

Figure C.2: C-ARIMA: Difference between Spatial Gini and Forecasted Gini



Notes: The figure shows the difference between the forecasted Spatial Gini calculated by the C-ARIMA and our Spatial Gini. In correspondence of the shock, March 2020, the change is persistent and significant. Source: Authors' elaboration.

Figure C.3: C-ARIMA for Macro Regions

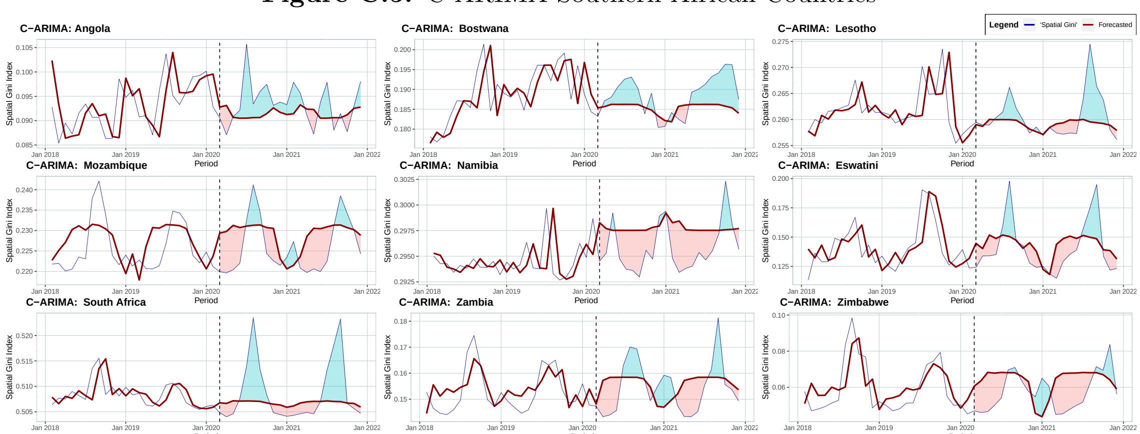


Notes: The figure shows the C-ARIMA forecasted Spatial Gini series and the actual Spatial Gini for each African Macro Region. Source: Authors' elaboration.

Figure C.4: C-ARIMA Northern African and Central African Countries

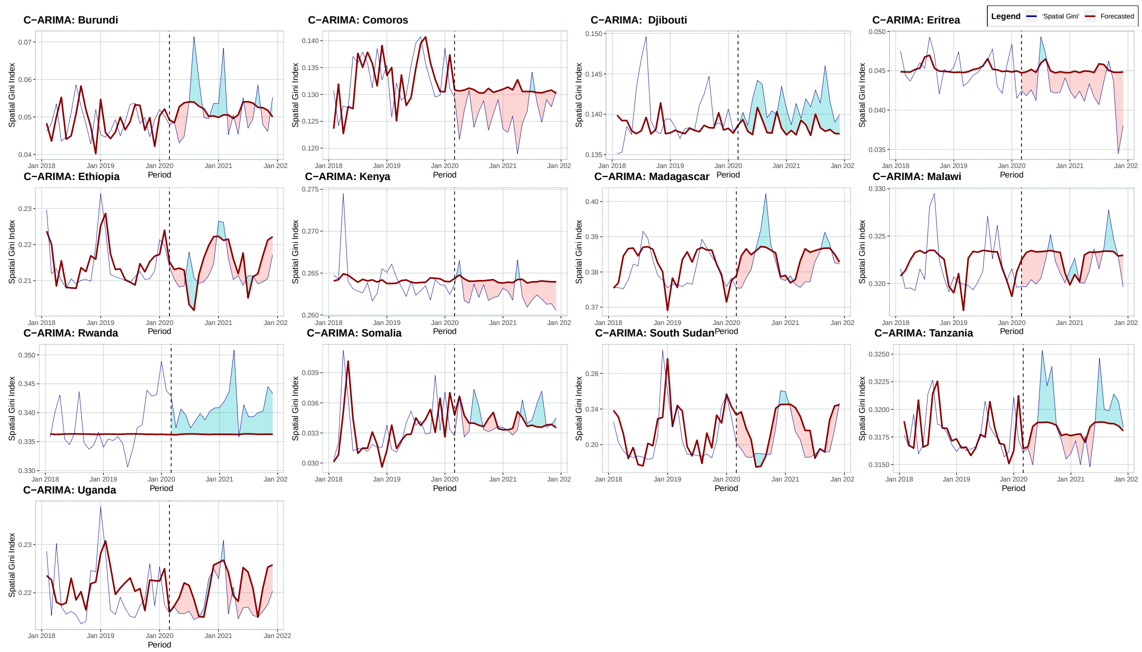
Notes: The figure shows the C-ARIMA forecasted Spatial Gini series and the Spatial Gini for each country which belongs to the Central and Northern African region. Source: Authors' elaboration.

Figure C.5: C-ARIMA Southern African Countries



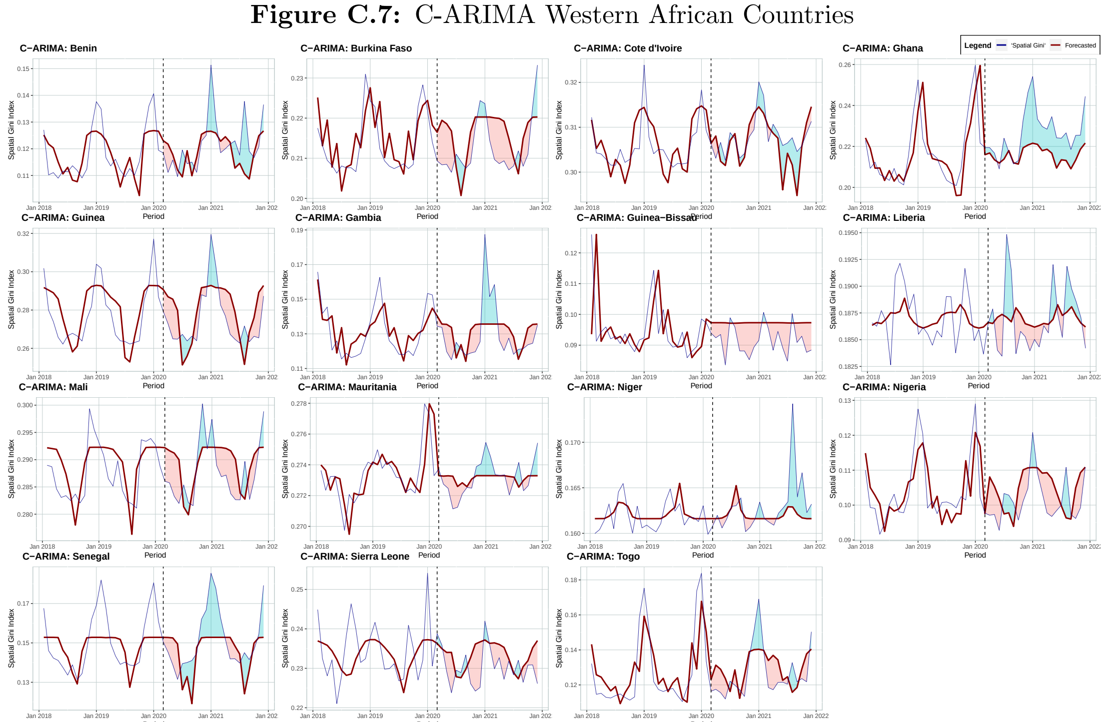
Notes: The figure shows the C-ARIMA forecasted Spatial Gini series and the Spatial Gini for each country which belongs to the Southern African region. Source: Authors' elaboration.

Figure C.6: C-ARIMA Eastern African Countries



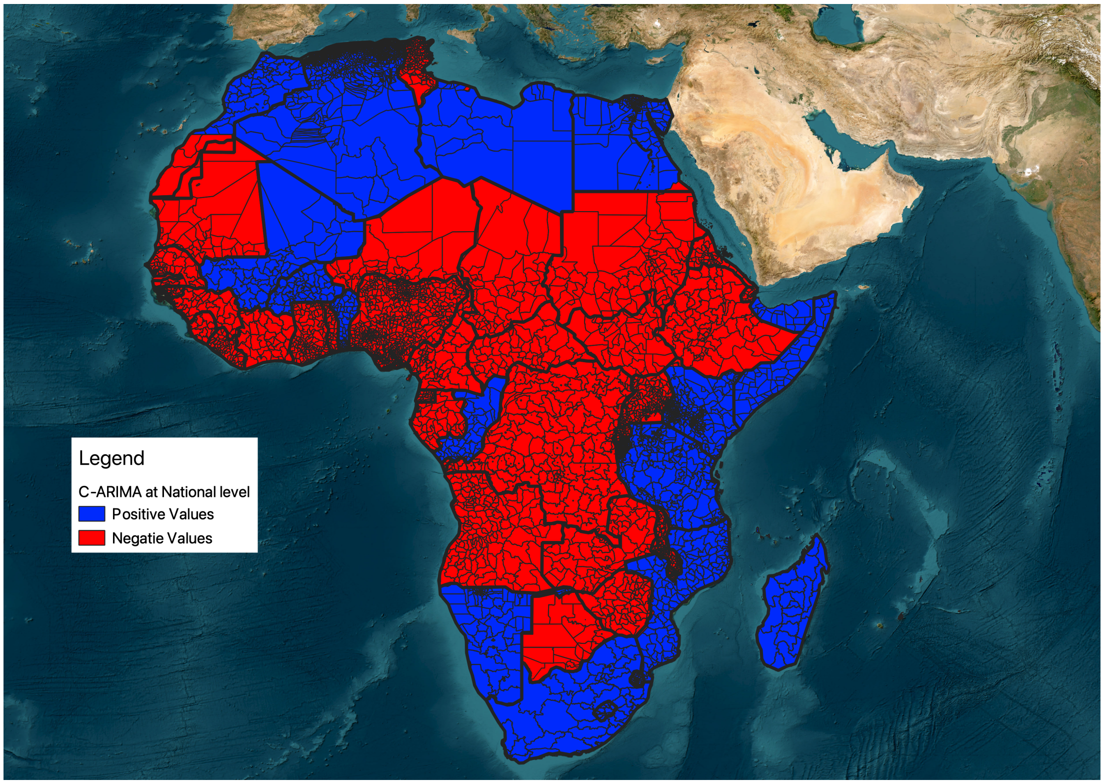
Notes: The figure shows the C-ARIMA forecasted Spatial Gini series and the Spatial Gini for each country which belongs to the Eastern African region. Source: Authors' elaboration.

Figure C.7: C-ARIMA Western African Countries



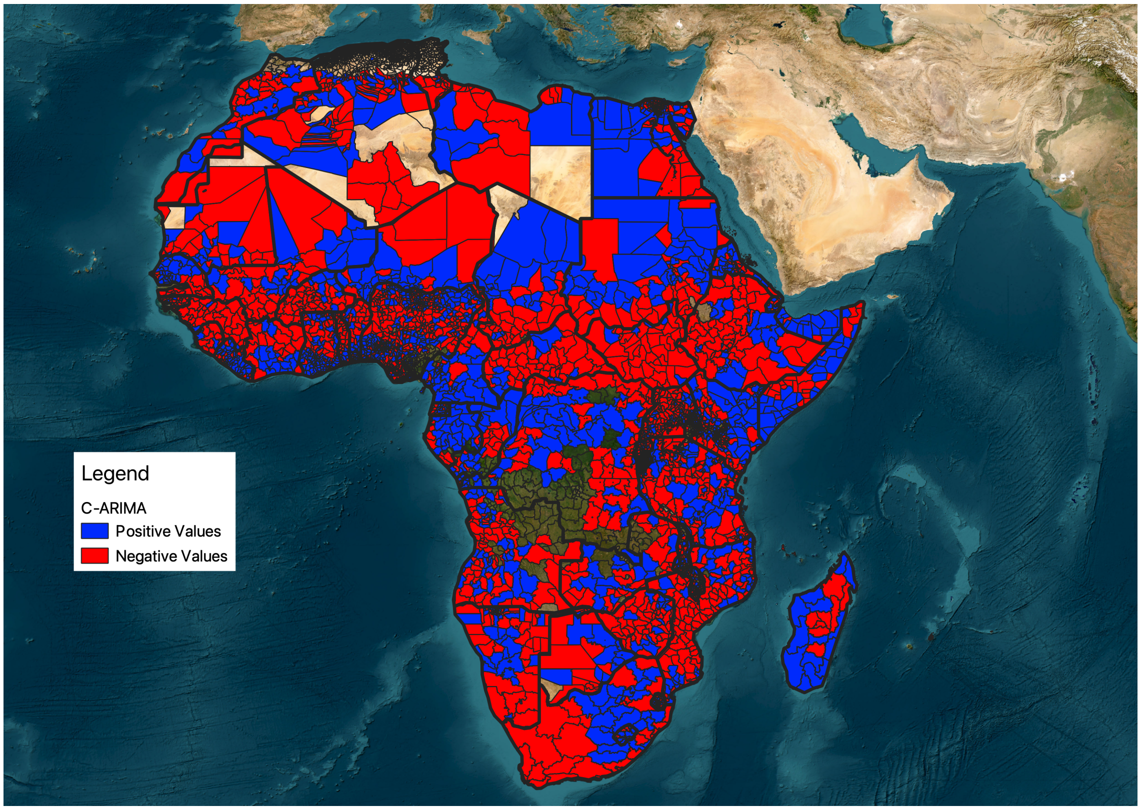
Notes: The figure shows the C-ARIMA forecasted Spatial Gini series and the Spatial Gini for each country which belongs to the Western African region. Source: Authors' elaboration.

Figure C.8: C-ARIMA for the lowest administrative level available for each African country



Notes: The map reports the C-ARIMA results at the national level, independently of their significance. Source: Authors' elaboration.

Figure C.9: C-ARIMA for the lowest administrative level available for each African country



Notes: The map reports the C-ARIMA results at the lowest administrative level available independently of their significance. Source: Authors' elaboration.

Table C.1: C-ARIMA: Average and cumulative effects at the national level

	Average Effect			Cumulative Effect		
Country	Estimate	SE	p-value	Estimate	SE	p-value
North African Countries						
Algeria (DZA)	-0.006	0.004	0.114	-0.137	0.087	0.114
Egypt (EGY)	-0.008	0.001	0.000	-0.171	0.029	0.000
Western Sahara (ESH)	-0.001	0.001	0.266	-0.030	0.027	0.266
Libya (LBY)	-0.004	0.002	0.034	-0.088	0.042	0.034
Morocco (MAR)	-0.002	0.001	0.001	-0.040	0.013	0.001
Sudan (SDN)	-0.001	0.002	0.484	-0.026	0.037	0.484
Tunisia (TUN)	-0.012	0.001	0.000	-0.258	0.012	0.000
Central African Countries						
Central African Republic (CAF)	-0.004	0.003	0.211	-0.086	0.069	0.211
Cameroon (CMR)	0.004	0.001	0.001	0.085	0.027	0.001
Democratic Rep. of the Congo (COD)	-0.001	0.002	0.601	-0.020	0.038	0.601
Congo (COG)	0.006	0.002	0.023	0.122	0.054	0.023
Gabon (GAB)	0.002	0.001	0.032	0.047	0.022	0.032
Equatorial Guinea (GNQ)	0.004	0.002	0.005	0.096	0.034	0.005
Southern African Countries						
Chad (TCD)	-0.002	0.003	0.518	-0.043	0.067	0.518
Angola (AGO)	0.002	0.002	0.214	0.041	0.033	0.214
Botswana (BWA)	0.003	0.001	0.022	0.068	0.030	0.022
Lesotho (LSO)	0.001	0.001	0.228	0.029	0.024	0.228
Mozambique (MOZ)	-0.003	0.001	0.038	-0.067	0.032	0.038
Namibia (NAM)	-0.002	0.000	0.000	-0.043	0.011	0.000
Eswatini (SWZ)	-0.003	0.004	0.528	-0.056	0.089	0.528
South Africa (ZAF)	0.002	0.001	0.027	0.042	0.019	0.027
Zambia (ZMB)	-0.001	0.003	0.730	-0.022	0.064	0.730
Zimbabwe (ZWE)	-0.006	0.006	0.354	-0.131	0.141	0.354
Eastern African Countries						
Burundi (BDI)	0.000	0.003	0.892	0.008	0.057	0.892
Comoros (COM)	-0.004	0.001	0.004	-0.092	0.031	0.004
Djibouti (DJI)	0.003	0.001	0.000	0.059	0.014	0.000
Eritrea (ERI)	-0.003	0.000	0.000	-0.057	0.010	0.000
Ethiopia (ETH)	-0.002	0.002	0.328	-0.046	0.047	0.328
Kenya (KEN)	-0.002	0.000	0.000	-0.034	0.008	0.000
Madagascar (MDG)	-0.001	0.001	0.294	-0.033	0.031	0.294
Malawi (MWI)	-0.001	0.001	0.218	-0.020	0.016	0.218
Rwanda (RWA)	0.005	0.001	0.000	0.099	0.021	0.000
Somalia (SOM)	0.000	0.000	0.683	0.004	0.010	0.683
South Sudan (SSD)	-0.013	0.010	0.194	-0.284	0.219	0.194
Tanzania (TZA)	0.001	0.001	0.339	0.013	0.013	0.339
Uganda (UGA)	-0.003	0.002	0.161	-0.065	0.046	0.161
Western African Countries						
Benin (BEN)	0.003	0.002	0.202	0.056	0.044	0.202
Burkina Faso (BFA)	-0.003	0.003	0.242	-0.071	0.061	0.242
Côte d'Ivoire (CIV)	0.001	0.001	0.209	0.029	0.023	0.209
Ghana (GHA)	0.010	0.003	0.000	0.231	0.064	0.000
Guinea (GIN)	-0.005	0.003	0.175	-0.103	0.076	0.175
Gambia (GMB)	-0.002	0.004	0.667	-0.038	0.089	0.667
Guinea-Bissau (GNB)	-0.006	0.002	0.006	-0.126	0.046	0.006
Liberia (LBR)	0.000	0.000	0.905	0.001	0.010	0.905
Mali (MLI)	-0.002	0.001	0.198	-0.037	0.028	0.198
Mauritania (MRT)	0.000	0.000	0.932	0.001	0.010	0.932
Niger (NER)	0.001	0.000	0.019	0.018	0.008	0.019
Nigeria (NGA)	-0.003	0.003	0.305	-0.062	0.060	0.305
Senegal (SEN)	0.005	0.003	0.061	0.117	0.062	0.061
Sierra Leone (SLE)	-0.003	0.002	0.067	-0.066	0.036	0.067
Togo (TGO)	-0.003	0.007	0.677	-0.063	0.152	0.677

Notes: The table reports the average and the cumulative estimate of the C-ARIMA analysis for each African Country. Source: Authors' elaboration.

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