Heterogeneous Effects of AGOA Trade Agreement on Economic Activity

An empirical study of Sub-Saharan African countries

Geospatial Data Science and Economic Spatial Models

Oliver Gatland, Luis Francisco Alvarez, Richard O'Shea

March 28, 2024

Barcelona School of Economics

Contents

1 Introduction

1.1 Context

Firstly introduced in the year 2000, the African Growth and Opportunity Act (*AGOA*) has been at the core of U.S. economic policy and commercial engagement with Africa. It enables eligible sub-Saharan African countries duty-free access to the U.S. market for over 1,800 products. By providing new market opportunities, *AGOA* has helped bolster economic growth, promoted economic and political reform, and improved U.S. economic relations in the region.[1]

Currently, 32 countries are eligible for *AGOA* benefits in 2024. The original pool of countries was 34, however while the agreement has been active several changes have been made, with countries leaving it for different reasons. In 2015, US Congress passed legislation modernizing and extending the program to 2025. To meet *AGOA*'s rigorous eligibility requirements, countries must make continual progress toward establishing a market-based economy, the rule of law, political pluralism, and the right to due process. Additionally, countries must eliminate barriers to U.S. trade and investment, enact policies to reduce poverty, combat corruption, and protect human rights.[2]

While the *AGOA* policy is likely to boost output on the aggregate within Sub-Saharan African countries, it is unclear how heterogeneous the gains from the policy will be. Since over 90% of Africa's imports and exports are conducted via the sea,[3] it could be the case that only settlements within close proximity to ports experience significant gains from the trade agreement. This is the main question we investigate in this project; did the *AGOA* trade agreement have heterogeneous impacts on settlements based on the proximity to the nearest port within their country.

1.2 Motivation

The core idea of the analysis is inspired by part of the analysis in Demet and Gomes, (2023) "*Ethnic Remoteness Reduces the Peace Dividend from Trade Access*"[4]. The primary objective of this study was to show that ethnically remote locations do not reap the full peace dividend from increased market access. As part of this analysis they look at within-country variation in trade access, which they measure as how far different settlements are from ports. We look to build on this, by understanding how these different distances from the port may impact economic activity after countries enter the *AGOA* agreement.

The methodology employed on this study involves the use of artificial light intensity as a proxy for economic activity in urban areas. This approach relies on the assumption that nighttime light throughout time, serves as a indicator of economic activity, something we will later test. We take this approach as there is little output data available for smaller districts or remote towns across Sub-Saharan Africa, so the night-light approach offers significant advantages in terms of the accuracy of measurements given the accessibility of data. This approach follows the precedent established by Henderson et al. (2012)[5], who successfully applied this methodology to gauge economic growth from outer space.

The main hypothesis is that settlements near ports naturally benefited more from the increase in international commerce than others which might be more inland. We would expect to observe a relative bigger growth for the city and towns closer to ports in countries which were part of this policy in the last two decades.

2 Data

2.1 Sources

The analysis primarily draws on data collected from three key sources. All three data sources will later be used in an econometric analysis as well as in the geographic plotting. The chosen countries for this analysis were those partaking in *AGOA*.[1]

First, we implemented spatial data from Natural Earth[6], a collaboration resource involving cartographers volunteering from around the world. In particular, we make use of the *Countries*, *Populated Places* and *Ports datasets* from the "Cultural Vectors" section. This data will be filtered and manipulated to create geographic visualizations and provide context in the analysis as well as key variables in the econometric exercise. The areas that we focus on for the analysis are all those cities and towns identified in the *Populated Places* dataset.[2]

Second, drawing from Environmental Systems Research Institute, we utilized the road transportation network of Africa in GIS. We will use the roads to calculate the distance from urban settlements to the closest port in their country. Furthermore, a discrimination in types of road will serve us to make our assessment more precise.[7]. One limitation of our investigation is that we assume the road networks to be constant over all time periods, i.e. at 2020 levels. This is due to a lack of readily aviailbale historical road data.

Finally, the night lights we used come from National Geophysical Data Center, more specifically the Earth Observation Group (EOG). As we mentioned previously, this data, dated from 1992 to 2013, will be our estimation of economic activity at the regional level, without incurring the use of national statistics.[8]

2.2 Nightlight extraction

The nightlight data comes in raster form which we had to convert to a variable to be used in our econometric analysis. For this process, we used the *exactextractr* package, which is used to extract pixel values from raster layers in R. For each settlement in the *Populated Places* data, we set a buffer of 10,000 meters around the point the settlement is located, and

[1] Note we were unable to include The Gambia due to the quality of road data.

[2] We had to remove some cities close to country borders as they were falling into the wrong countries. This was only a problem with a handful of cities and is likely to have minimal impact on our results.

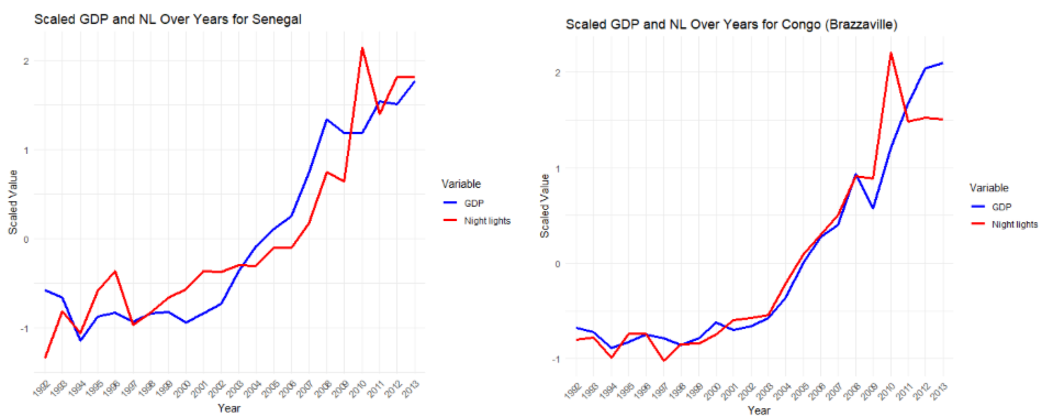

Figure 1: Nightlights v GDP

extract the total sum of nightlights within this area. This sum of nightlights is the variable of interest we will focus on in this project, and will act as our measure of economic activity for each settlement. Since this sum of nightlights has no intrinsic value we will not interpret magnitude changes from this variable.

2.3 Nightlight GDP comparison

To confirm our use of nightlights as a proxy for GDP is valid, we plot the trends of nightlights and GDP at a country level to confirm the correlation between the variables. For this exercise, we used GDP data from the World Bank[9]. Before plotting the trends, both the level of nightlights and GDP were standardised at a country level, allowing us to easily compare trends over time. We find for almost all countries in our sample, the trend of nightlights and GDP follow each other very closely over the period analysed, with Figure 1 displaying these trends for Senegal and The Republic of the Congo. This provides evidence that the GDP level and nightlight level are strongly correlated at a national level, and justifies our assumption that nightlights will be a good proxy for GDP at a settlement level across Sub-Saharan Africa. The trends for the rest of the countries can be found in the R markdown file submitted with this report.

3 Modelling

3.1 Distance to ports

As a key variable in our analysis, we needed to calculate the distance of each area in our data to the nearest port within its country borders. To ease the computational workload we only considered coastal countries and we only plot the shortest distance to ports within a given country. Otherwise, we would have to calculate the minimum distance from a given city to each port in Africa (or some arbitrary subsection) and this process is too computationally expensive. To calculate this distance, accounting for the road quality, we took the following steps. We first loaded the *Populated Places* data and filtered it by Africa (our interest) using *st_intersection* from the *sf* package and our shapefile for Africa, a necessary step as there is no continent variable in this data. We take similar steps to identify our ports of interest and label which country they belong to. We then create a loop which applies the *shortestPath* function to calculate the minimum distance for each city in a given country to every port in that country. We create an empty raster, crop[3] it to the shapefile of each country and then use *rasterize()* to create a raster using our road networks. Non-road values were set to 0.01 to make them very unlikely to cross and also to avoid issues when calculating with NA. We initially treated all road types equally. We then later assigned tiered values to the various road types, e.g Motorway=1, Primary Road=0.7 etc. This ensures that our transition matrix takes into account road quality when finding the shortest path to a given port, leading to some significant differences in the shortest path we find. In order to assign different values to each road type, we created a loop which creates an individual raster for each type before merging them together with *merge()*. This values were chosen intuitively to reflect the fact that, for example, we believe a lorry could roughly travel at 70% of its top motorway speed on a primary road. Of course, in a full analysis we would need to measure these differences more accurately. This shortest path, in meters, will be one of the variables used later in the linear regression for night lights.

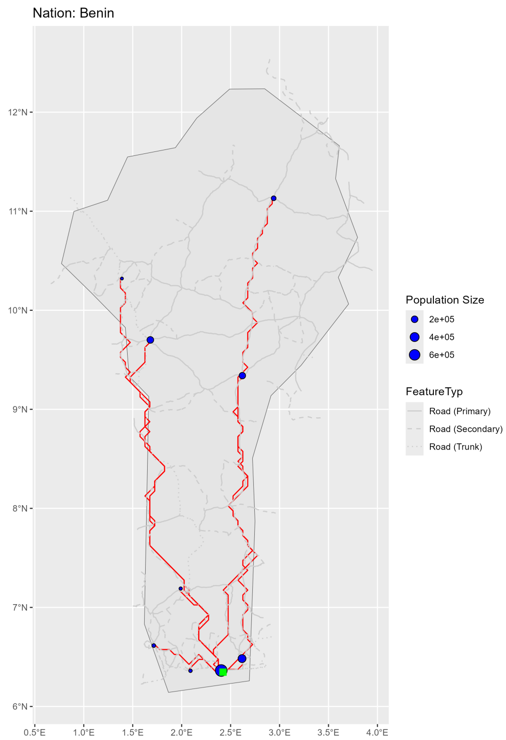

Figure 2: Benin without cost function

Let's consider the Benin scenario to showcase how the differentiated costs, by types of routes, modify the final outcome when calculating the shortest path to the port. In Figure 2, no

[3]We ran into an issue here of cities at the border being cut out off our raster. We fixed this by specifying *snap="out"* in the crop function which insured the full extend of our shapefile was maintained.

difference within roads is accounted for and the minimum route is chosen as the most direct way possible. On the other hand, in Figure 3 we incorporate the cost function we defined in our calculation; we can observe that the final output is not as straightforward as before. For instance, most paths that were being considered from the eastern side of the country are now redirected to an alternative course, clumping together at the central-south trunk road. We consider this to be a more realistic approach to the real world circumstances.

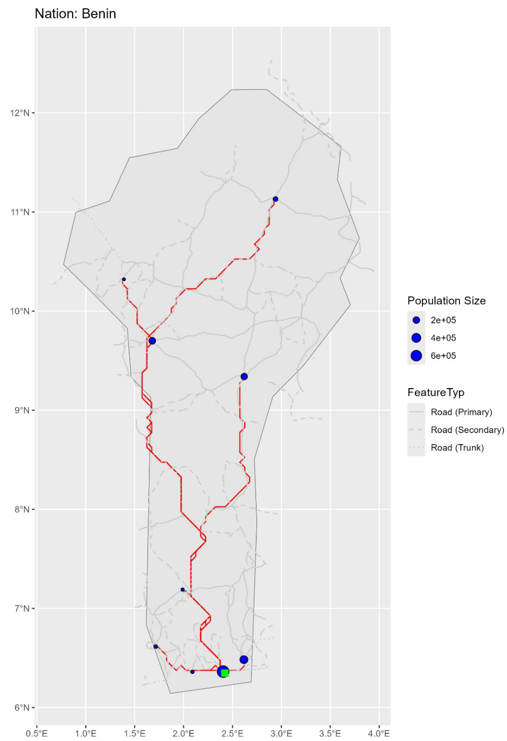

Figure 3: Benin with cost function

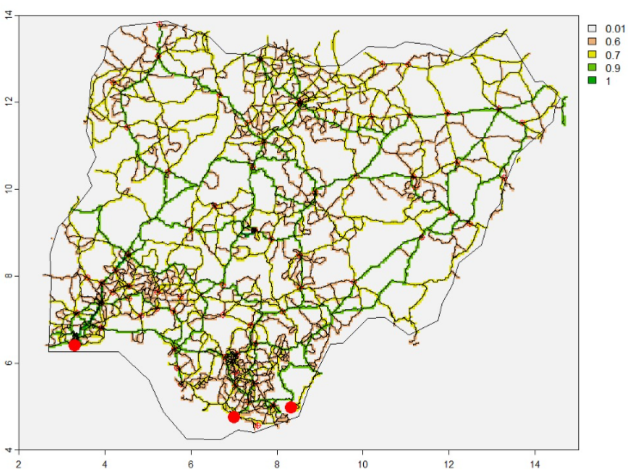

Figure 4: Nigeria full map

In Figure 4 we present a country level plot for Nigeria summarising the information obtained in the previous steps. Our plot has all the roads in the country, with different colour by type of route along with the weight, and finally all the ports that were considered for the country with a big red circle. In Figure 5 we present a map of the whole of Africa, where for each country we include in our study we show the road routes from the settlements in the country to the nearest port.

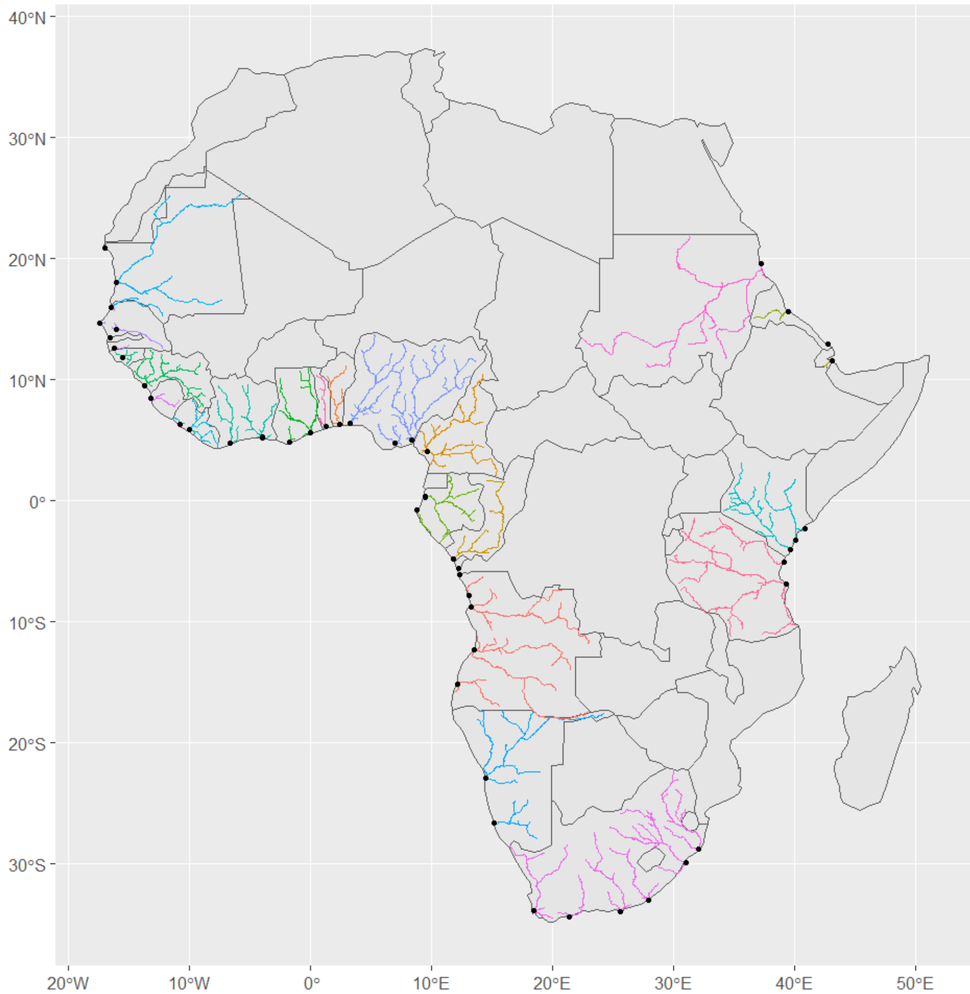

Figure 5: Shortest distances across Africa

3.2 Econometric analysis

We are interested if the $AGOA$ policy had heterogeneous impacts on cities across Africa dependent on their distance to the closest port. To investigate this we set up the following econometric model:

$$Nightlights_{it} = \alpha_i + \beta_1 AGOA_{it} + \beta_2 Distance_i + \beta_3 (AGOA : Distance)_{it} + \beta_4 Population_i + \beta_5 (Country : Year)_{it}$$

Here we run an OLS regression where $Nightlights$ is the total night lights in an area, $AGOA_t$ is a dummy representing if the country was part of $AGOA$ in period t, $Distance$ is the minimum distance to the nearest port as constructed in the previous section, $Population$ is the maximum population of the area over our sample period[4], and $(Country : Year)$ are dummies accounting for country specific effects over time such as a localised recession.

Our variable of interest here is the interaction between $AGOA$ and $Distance$ which we will refer to as the $AGOA$ Distance Interaction term. While $AGOA$ picks up the area wide effect of joining the $AGOA$ agreement and $Distance$ measures the impact of distance from ports on night-lights in general, the interaction will account for the $AGOA$ specific heterogeneous impacts based on the distance from the closest port.

Figure 6 displays the results of our baseline regressions. In the baseline column we only have the $AGOA$ and $Distance$ variables, while in each column after we add different controls until we have our full specification as outlined above. Focusing on the $AGOA$ variable, we find that being part of $AGOA$ has a positive effect on nightlights, until time dummies are included, where we find that being part of $AGOA$ has a negative impact on nightlights. This can be explained as follows: countries were generally part of the $AGOA$ agreement in the later part of our sample, so when excluding time dummies, the $AGOA$ dummy is simply picking up that the level of nightlights tends to increase over time. Once the time effect is accounted for, the impact of $AGOA$ turns negative. Although we would have expected to find a positive coefficient for this variable, it is possible that $AGOA$ only positively impacted areas close to ports, but had a negative impact on the aggregate, a theory we investigate later in the report. All other covariates have coefficients as expected, with population being associated with an increase in nightlights and the distance to ports having a negative association with nightlights. Now analysing our variable of interest, we find that the $AGOA$ Distance Interaction is negative and statistically significant in three of the four regressions. This means that as the distance from the nearest port increases, the impact of the $AGOA$ policy worsened for areas further away from ports. This provides evidence in favour of the hypothesis of this research project, that being further away from ports meant it was harder for settlements to reap the benefits from the country wide $AGOA$ agreement.

[4]We do not vary population over time in our panel data as we only had access to town level population data for one period of time. For this reason, we assume that the relative population between areas in our sample remains stable over the period of analysis.

	Dependent variable:			
	Night lights			
	Baseline	Population	Country dummies	Year dummies
	(1)	(2)	(3)	(4)
AGOA	661.474^{***}	701.613^{***}	485.024^{***}	-271.675^{***}
	(118.584)	(86.921)	(76.825)	(95.483)
Distance	-0.001^{***}	-0.0004^{***}	-0.001^{***}	-0.001^{***}
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Population		0.004^{***}	0.004^{***}	0.004^{***}
		(0.00004)	(0.00003)	(0.00003)
AGOA Distance Interaction	-0.0002	-0.0003^{**}	-0.0002^{*}	-0.0002^{*}
	(0.0002)	(0.0001)	(0.0001)	(0.0001)
Constant	$2,538.450^{***}$	$1,147.035^{***}$	754.100^{***}	$-148,136.300^{***}$
	(84.011)	(63.114)	(93.646)	(11,350.830)
Observations	11,748	11,748	11,748	11,748
R^2	0.022	0.475	0.619	0.624
Adjusted R^2	0.022	0.474	0.618	0.623
Residual Std. Error	3,952.455 (df = 11744)	2,897.081 (df = 11743)	2,470.355 (df = 11722)	2,452.223 (df = 11721)
F Statistic	87.305^{***} (df = 3; 11744)	$2,650.854^{***}$ (df = 4; 11743)	760.455^{***} (df = 25; 11722)	748.791^{***} (df = 26; 11721)
Note:				*p<0.1; **p<0.05; ***p<0.01

Figure 6: Baseline Regressions

To further explore the heterogeneous impacts of the *AGOA* policy we run other specifications of our regression analysis which are reported in Figure 7. Here, all models include every covariate previously discussed, but we vary the observations included. The baseline model is the same as above, while for the cities model we focus only on those areas with a population greater than 50,000. For the non-coastal model we focus only on areas that are further than 1km away from the nearest port. Finally, we run a pseudo treatment model, which acts as a robustness check. Here we apply our method to Tunisia and Morocco, two north African countries which have never been eligible for *AGOA*, creating a pseudo treatment where they both joined *AGOA* in 2001. In this specification, we should not find any effect from *AGOA*; if we do, it would suggest the effect from *AGOA* we identify in the other specifications may be picking up some other unobservable factor in our data.

We can see that the effect of the *AGOA* Distance Interaction seems to be stronger when focusing only on cities. This can be explained as in our original data we have lots of small towns which are unlikely to have large scale production for exporting, and so are unlikely to be impacted by the *AGOA* policy. By isolating the effect for larger towns and cities, we find stronger evidence that joining *AGOA* benefited cities closer to ports more so than cities further inland. When focusing only on non-coastal settlements, we find the *AGOA* Distance Interaction term becomes insignificant. This supports our previous theory that the *AGOA* policy may have had a negative effect overall, but a positive effect for those close to ports, as we loose our effect when excluding them from the regression. This means the coastal cities play a key role in the effects we are finding in the other specifications, as they likely saw large benefits from the *AGOA* agreement. Finally, in the pseudo treatment regression, we find that neither the pseudo *AGOA* dummy or the *AGOA* Distance Interaction term had a statistically significant effect on nightlights in the *non-AGOA* nations. We also find

	Dependent variable:			
	Night lights			
	Baseline	Cities	Non coastal	Pseudo
	(1)	(2)	(3)	(4)
AGOA	-271.675***	-372.824**	-286.638***	-126.541
	(95.483)	(147.191)	(97.598)	(122.128)
Distance	-0.001***	-0.001***	-0.001***	0.001***
	(0.0001)	(0.0002)	(0.0001)	(0.0002)
Population	0.004***	0.003***	0.004***	-0.0001
	(0.00003)	(0.00004)	(0.00004)	(0.00005)
AGOA Distance Interaction	-0.0002*	-0.0004**	-0.0002	0.0003
	(0.0001)	(0.0002)	(0.0001)	(0.0003)
Constant	-148,136.300***	-214,893.900***	-146,250.200***	-27,809.980*
	(11,350.830)	(17,737.990)	(11,476.070)	(15,515.590)
Observations	11,748	5,983	11,506	1,012
R^2	0.624	0.671	0.616	0.109
Adjusted R^2	0.623	0.670	0.615	0.104
Residual Std. Error	2,452.223 (df = 11721)	2,878.134 (df = 5957)	2,450.699 (df = 11479)	820.143 (df = 1005)
F Statistic	748.791*** (df = 26; 11721)	486.309*** (df = 25; 5957)	708.062*** (df = 26; 11479)	20.484*** (df = 6; 1005)
Note:				*p<0.1; **p<0.05; ***p<0.01

Figure 7: Further specifications

the R^2 is significantly lower in the pseudo treatment regression, which is as expected as the $AGOA$ policy should have no explanatory power for nightlight changes in these nations. The findings from the pseudo treatment gives us confidence that the $AGOA$ based effects we are finding in the other regressions are robust.

4 Conclusion

In our research proposal and through the preliminary analysis, we identified statistically significant differences in the economic impact of the $AGOA$ policy on settlements, depending on their proximity to ports. This differentiation offers a more insightful view on the dynamics of trade benefits within African countries. Additionally, by accounting for the varied types of roads within these countries, our approach allows for a more nuanced comprehension of the real-world circumstances that influence economic development.

Further research could be done in different ways. For instance, by expanding the pool of countries considered and using *non-$AGOA$* states, a counterfactual can be built for a more robust study. Another path can be to challenge the main model assumption (nightlights as GDP) and establish if this relationship still holds for other relevant socio-economic indicators like population density, urbanization or poverty/inequality. Finally, the research could be extended to other trade agreements or policies of similar nature. If the effects are consistent, it would support our investigation and validate the conclusions from this project, thus making it more robust.

References

[1] Office of the United States Trade Representative. African Growth and Opportunity Act (AGOA). https://ustr.gov/issue-areas/trade-development/preference-programs/african-growth-and-opportunity-act-agoa, 2023.

[2] AGOA Eligibility - Trade.gov. https://legacy.trade.gov/agoa/eligibility/#:~:text=GuineaBissau'seligibilityrestoredDecember,benefitsonDecember15,2016, 2023.

[3] African Union. Africa's Blue Economy is a vehicle for sustainable development. https://au.int/es/node/36807, 2019.

[4] Klaus Desmet and Joseph F Gomes. Ethnic remoteness reduces the peace dividend from trade access. Technical report, National Bureau of Economic Research, 2023.

[5] J. Vernon Henderson, Adam Storeygard, and David N. Weil. Measuring economic growth from outer space. *American Economic Review*, 102(2):994–1028, 2012.

[6] Natural Earth Data - Borders, Ports, Populated Places. https://www.naturalearthdata.com/downloads/10m-cultural-vectors/, 2023.

[7] European Commission, Joint Research Centre (JRC). African intra transport roads. https://www.arcgis.com/home/item.html?id=ba1cf90a739f41f4b91b26441929918a, 2023.

[8] National Geophysical Data Center. DMSP-OLS Nighttime Lights Time Series. https://ngdc.noaa.gov/eog/dmsp/downloadV4composites.html, 2023.

[9] World Bank. GDP (current US)., 2022.