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Abstract

This study uses nightlight time data and machine learning techniques to predict industrial development in Africa. The results provide the first evidence on how machine learning techniques and nightlight data can be used to predict economic development in places where subnational data are missing or not precise. Taken together, the research confirms four groups of important determinants of industrial growth: natural resources, agriculture growth, institutions, and manufacturing imports. Our findings indicate that Africa should follow a more multisector approach for development, putting natural resources and agriculture productivity growth at the forefront.

JEL Classification: I32; O15; O40; O55

Keywords: Industrial growth; Machine learning; Africa

1. Introduction

This study is motivated by at least two main tendencies in the scholarly and policy literature pertaining to the development of sub-Saharan Africa (SSA). These tendencies include the challenges of extreme poverty and low productivity in the region in light of sustainable development goals (SDGs) and gaps in the existing literature. The tendencies are elucidated in the following passages.

First, building on evidence that approximately half of the countries in SSA failed to reach the millennium development goals' (MDGs) extreme poverty targets at the turn of 2015 (Asongu & Kodila-Tedika, 2017; Tchamyou, Erreygers, & Cassimon, 2019), studies are consistent with the position that the SDG target of reducing extreme poverty levels in the region to a critical mass of below 3% by 2030 will be daunting unless countries adopt substantial policy initiatives, *inter alia*, boosting industrial development and reducing the prevailing levels of inequality that unfavorably moderate the negative responsiveness of extreme poverty to economic growth (Bicaba, Brixiova & Ncube, 2017; Tchamyou, 2019a, 2019b; Asongu & le Roux, 2017, 2019). The literature also maintains that whereas average levels of extreme poverty will decline by 2030 (Chandy, Ledlie & Penciakova, 2013; Yoshida, Uematsu, & Sobrado, 2014), the objective of substantially reducing poverty in light of the SDG target can be most feasibly achieved if the average economic growth rates experienced between the years 2000 and 2010 are maintained (Ravallion, 2013). The premise of this study on the importance of industrial development in poverty reduction builds on these narratives and is also motivated by a gap in the literature.

Second, the literature on the issues relevant to this study comprises three main strands: productivity; value added across economic sectors; and the use of nightlight satellite images to assess nexuses between macroeconomic factors and poverty outcomes. In the first strand, contemporary scholarship related to productivity in Africa has largely been concerned with, *inter alia*, the foreign investment–driven ramifications of productivity (Fanta & Minkina, 2017; Dunne & Masiyandima, 2017); issues relating to gender and changes in the supply of labor (Elu & Price, 2017); connections between exports and the manufacturing sector (Cisse, 2017); and education and the degree to which children take part in the labor market (Ahouakan & Diene, 2017). Within this strand of the literature, Fedderke and Mengisteab (2017) examined output gaps with relation to the productivity of potential output, while Uduji and Okolo-Obasi (2018a, 2018b) were concerned with the relevance of the female gender in agricultural productivity. Kreuser and Newman (2018) examined connections between productivity, manufacturing sectors, and productivity growth across sectors, while Maryan and Jehan (2018) were concerned with the relevance of information technology in facilitating the convergence of productivity. Bokpin, Ackah, and Kunawoto (2018) investigated the relationship between financial access and productivity, whereas Meniago and Asongu (2019) assessed how value chains across various sectors of the economy moderate foreign investment to enhance productivity and economic growth.

In the second strand, the contemporary literature on value chains, which fundamentally focuses on the three main economic sectors, has failed to engage the problem statement being considered in this research. This includes research on the agricultural sector (Van Rijsbergen, Elbers, Ruben, & Njuguna, 2016; Lutz & Olthaar, 2017; Lutz & Tadesse, 2017; Olthaar & Noseleit, 2017; Metzlar, 2017; Vermeire, Bruton, & Cai, 2017), the manufacturing sector (Banga, Kumar, & Cobbina, 2015; Ruben, Bekele, & Lenjiso, 2017; Van Lakerveld & Van Tulder, 2017), and the service sector (Beerepoot & Keijser, 2015).

In the third strand, as expounded in Section 2, contemporary literature on the use of nightlight images to predict development outcomes is sparse on the African continent. Moreover, the specific scope of this research is not apparent in the literature. Some research has focused on the application of satellite data in economic studies (Donaldson & Storeygard, 2016) within the frameworks of, *inter alia*, measuring rural electrification (Dugoua, Kennedy, & Urpelainen, 2018) and the fight against poverty (Blumenstock, 2016); assessing poverty levels (Pan & Hu, 2018; Zhao et al., 2019); predicting local wealth (Weidmann & Schutte, 2017); and estimating subnational gross domestic product (Wang et al., 2019). The common theoretical framework underpinning the highlighted literature is premised on the broad consensus that the application of nightlight data to measuring urban development reflects the intuition that proxies related to national measures of urbanization in developing countries can inform scholars about the theoretical linkages between poverty rates and urbanization.

The rest of this study is structured as follows. Section 2 covers the intuition for using nightlight data as a proxy for industrial growth and the literature on the nexuses between macroeconomic factors and poverty outcomes. Section 3 is concerned with the data and methodology, while Section 4 discloses the empirical results. Section 5 concludes with implications and future research directions.

2. Intuition and the extant literature

2.1. Using nighttime light information as a proxy for industrial growth

In light of the prior literature (Chen & Nordhaus, 2011; Blumenstock, 2016; Donaldson & Storeygard, 2016; Yamada & Otchia, 2019; Zhao et al., 2019), this research employs satellite data on nightlights from the Defense Meteorological Satellite Program (DMSP), within the remit of the Space and Missile Systems Center at the Los Angeles Air Force Base in California, USA. A growing body of literature documents the relevance of nightlight data (especially from the DMSP) as a proxy for economic growth in developing countries (Ravallion & Chen, 1999; Nordhaus, 2006; Henderson, Storeygard, & Weil, 2012; Johnson, Larson, Papageorgiou, & Subramanian, 2013; Keola, Andersson, & Hall, 2015; Yamada & Otchia, 2019). These studies motivate the use of this alternative measurement of economic activity in the absence of data of quality and quantity in developing countries, especially in light of ineffective data collection agencies, poor coordination, and communication facilities, as well poor data collection practices (Kodila-Tedika, 2014). For instance, Shortland, Christopoulou, and Makatsoris (2013) showed that the relationship between nightlight intensity and economic development withstands empirical scrutiny in Somalia, where data have not been available due to political strife and decades of civil war.

According to Weidmann and Schutte (2017), using nightlight data as a proxy for economic prosperity is typically consistent with the intuition that the wealth of nations can be assimilated to nighttime illumination. Three main mechanisms can substantiate the underlying connections. First, access to a power generator or power grid is contingent on access to finance and financial investment, made by citizens with access to financial and economic resources. Second, as argued by Henderson, Storeygard, and Weil (2011), the intensity of nightlight reflects economic activity within a country and, by extension, the wealth of a nation. Third, consistent with Hodler and Raschky (2014), street lamps which indicate nighttime illumination could also be traceable to preferential treatment by the state of particular regions and elements of society.

Irrespective of the channels under consideration, high nightlight emissions are likely to be positively correlated with the wealth of nations from an aggregate perspective. The preceding inference is contingent on the fact that an absolute correlation between high nightlight intensity and aggregate economic wealth can be problematic from the perspective of inclusive economic development if the attendant light intensity is exclusively skewed towards wealthier fractions of society. Moreover, other elements of asymmetry could build on the facts that, on the one hand, people benefiting from an economic activity correlated with nightlight intensity may not necessarily be living in locations where such lights are apparent and, on the other that commercial centers characterized by bright light may not necessarily be home to rich people. Hence, some arguments might be put forward to substantiate the fact that nightlight intensity in a given location may not be directly at the service of the population. An eloquent example is the presence of an oil refinery, which requires few staff and near which, residential areas are not always apparent for obvious security reasons. In light of these clarifications, the association between nightlight intensity and economic development needs to be substantiated with empirical evidence.

2.2.The extant literature

Consistent with Weidmann and Schutte (2017), the existing literature on the importance of nightlight intensity in development outcomes has varied across the years. Much earlier research from Elvidgeet al. (1997) established a correlation between economic output and area illumination. However, it is worthwhile to note that the established correlation maybe due to country size, given that large countries are typically also associated with major economic activities and hence emit more light intensity at night. It is for this underlying reason that later studies, such as that of Henderson, Storeygard, and Weil (2011), have taken on board this critique and confirmed the established relationship.

Another strand of empirical literature, which focuses on economic output at the level of subnational units (i.e., provinces, regions, and states), has confirmed findings on the positive connection between nightlight intensity and aggregate economic development levels. Studies in this strand have established connections between nightlight intensity and economic development in China (Pan & Hu, 2018), India (Dugouaet al., 2018), and Sweden (Mellander, Stolarick, Matheson, & Lobo, 2013). Other studies include Sutton, Elvidge, and Ghosh (2007), which focused on four countries (i.e., China, India, Turkey, and the USA) to confirm the mainstream nexus. Blumenstock (2016) investigated how poverty can be fought using data and established that African countries, mostly characterized by limited data availability, can build on recent progress by using nightlight observations within the framework of machine learning techniques to assess poverty.

Using these data, Alesina, Michalopoulos, and Papaioannou (2016) constructed a measurement to assess inequality between ethnic groups. Cederman, Weidmann, and Bormann (2015) employed a similar strategy, also triangulating the data with nightlight information in order to address concerns pertaining to weaknesses in the sources of data. Kuhn and Weidmann (2015) demonstrated that the underlying approach can be extended to assessing intra-group inequality, while Hodler and Raschky (2014) used nighttime illumination in studying ethnic favoritism.

Weidmann and Schutte (2017) used light emissions for the prediction of local wealth, showing that light emissions can adequately predict the wealth of nations, especially when estimating new localities in a known country and generating estimates for previously unobserved countries. Wang et al. (2019) examined and mapped subnational GDP in Uganda by combining multiple sources of data, notably nighttime light (NTL) data from the Suomi National Polar-orbiting Partnership Visible Infrared Imaging Radiometer Suite (NPP-VIIRS), population data sources from the Global Human Settlement Layer (GHSL), observations on market prices for several types of commodities, and information on the production of the agricultural sector. This combination of data has led to a gridded dataset for the country's GDP at sub-national levels that can capture heterogeneity in economic activities in the country.

3. Data

In this section we describe our data sources and discuss nighttime light data as proxy for industrial development.

3.1. Nighttime lights data

Our nighttime light data come from the National Oceanic and Atmospheric Administration (NOAA). These well-known data contain yearly frequency cloud–free nightlight pixels, each corresponding to less than 1 square kilometer. The nightlight imagery are recorded by satellite F10 for the period 1992–1994, F12 for 1994–1999, F14 for 1997–2003, F15 for 2000–2007, F16 for 2004–2009, and F18 for 2010–2013. Following typical practice, we aggregate nightlights by taking cell-level weighted averages across satellites in years with overlapping satellite coverage. Weights are given by the number of cloud-free days. The data go from 0 to 63, with higher values implying more intense nighttime light. We employ data for 5,968 second administrative regions (ADM2) in 46 African countries. The term region refers to the subnational administrative units (counties, districts, or municipalities) that represent the lowest level of territorial division in Africa. The sub-regional level is highly relevant for industrial development, as many industries; especially those related to natural resources, are located at specific places and can be correlated with existing minerals. We concentrate on the mean lights and calculate annual growth rates at the ADM2 level. Figure 1 shows an increasing trend since 2004, which slows down in 2008 and 2012.

Consistent with the narratives in Section 2, extensive research has shown that light intensity arguably acts as a viable proxy for economic activities at subnational levels. Many developing countries are debating whether nightlight intensity is the best proxy for agriculture, industry, or service output. We test these relations following the econometric approach in Henderson, Storeygard, and Weil (2012). Specifically, we estimate the equation

$$z_{it} = \psi x_{it} + e_{it}, \tag{1}$$

where z_{it} is real output (agriculture, industrial, service, total) and x_{it} is the intensity of nightlights. Since our goal in this analysis is simply to document the relationship between nightlights and components of GDP, we estimate equation (1) in log-linear form using aggregate data at country level. We include year fixed effects to control for differences in light sensitivity across satellites, technological advances, and energy costs. We also control for country fixed effects to eliminate cultural differences in the use of nightlights and national conditions for generating electricity across countries.

Table 1 presents the basic results of our regressions of GDP growth and its sectoral composition on nightlights, for balanced panel data of 46 African countries over 21 years. We report the within-country R^2 (i.e., coefficient of determination) of these regressions for purposes of comparison with previous research. The first column shows that nightlights explain 84% of within-country variation in economic growth, with the corresponding nightlight elasticity of GDP being about 0.26. In column 2, we include the squared term to test a quadratic form fit. We find that the predictive power of the nightlights remains constant and the nightlight elasticity of GDP increases to 0.28. Henderson et al. (2012) and other researchers have found similar coefficients with higher R^2 using worldwide samples. Columns 3 and 4 present the corresponding results for agricultural GDP growth. The associated nightlight elasticities of agricultural growth vary between 0.24 and 0.36, and the within-country R^2 is 0.58. When we evaluate whether nightlights are correlated with manufacturing growth, we find a positive and statistically significant estimated elasticity of 0.26. Surprisingly, the within-country R^2 is smaller than for agriculture growth. The next two columns show the results for industrial growth. Again, we find a positive and statistically significant nightlight elasticity of industrial growth, which varies between 0.51 and 0.85. The within-country R^2 is quite high compared to those pertaining to agricultural- or manufacturing-specific regressions. Finally, the last two columns present the results for service growth. While we find a within-country R^2 of 0.78, the nightlight elasticity of service sector growth is positive but not statistically significant. These results are very important because they are consistent with our main interest of establishing that nightlights can be used as a proxy for industrial growth. The corresponding predictors are discussed in the next section.

3.2.Predictors

In line with the theories of industrialization and their empirical applications, we define four sets of explanatory variables, covering natural resource endowment, the composition of domestic output and expenditure, demographics and human capital, institutional measures, and trade. ADM2 also measures variables related to natural resource endowment and infrastructure, such as road and port infrastructure, oil and gas fields, land use, and mines. Data on mineral facilities in each subnational region come from the Mineral Resource Data System of the United States Geological Survey (USGS 2005) and contain 24 types of minerals. We compute an ADM2-level measure of mineral endowment as the first principal component of the 24 different types of mines.[1] We include the oil and gas variable, which takes a value of one if

[1] The list comprises aluminum, as bestos, barium/barite, beryllium, boron/borates, chromium, copper, diamond, gold, iron, lead, manganese, mica, nickel, phosphorus/phosphates, platinum, silver, sulfur, strontium, tin, tungsten,

parts of an oil or gas field overlap with the area of a sub-national region, as in Lujala, Rød, and Thieme (2007). To test the claim that mergers matter for local industrial development, we exploit geographic data from the Center for International Earth Science Information Network (CIESIN) (2013) to include many road variables, such as the length of highways, primary roads, secondary roads, tertiary roads, local/urban roads, and trails. We further use data from the World Port Index of 2011 to construct a binary indicator variable for ports, which assumes a value of one if a port is located in a subnational region.[2] We also use unique information that measures land structure in terms of the percentage of land use that is artificial, cropland, grass, tree, shrubs, herbaceous, mangroves, sparse, bare soil, snow, and water, respectively. We take the first principal components of these eleven variables to create a more continuous index of land structure. We further use the population size of sub-national regions, based on high-resolution data on the spatial distribution of the world population in 2000 from the Center for International Earth Science Information Network.

Data on macroeconomic conditions come from the World Bank Development Indicators. They include detailed information about economic growth, GDP composition, and expenditure. We focus, in particular, on agriculture, service, investment, total trade, imports, exports, mineral rents, fuel imports, foreign direct investment, government expenditure, military expenditures, manufacturing imports, manufacturing exports, terms of trade, inflation, money supply, aid, consumption, credit to the private sector, number of phones, rural population, and population growth. To examine the predictive capacity of governance, we obtained information on civil liberties and political rights from Freedom House, which has a publicly available database.[3] Our preferred dataset for the reel exchange rate is Darvas (2012).[4] Finally, we use the Chinn-Ito index (Chinn & Ito, 2006) to measure the degree of capital account openness. The Chinn-Ito index is the broadest measure of financial openness, and also covers restrictions on the current account of the balance of payments and on the foreign exchange market. More specifically, Chinn and Ito (2008) create a composite measure with annual frequency from four dummy variables, using a principal component approach. These four binary indicators are (1) the openness of a country's capital account; (2) the openness of the current account; (3) the stringency of requirements for the repatriation and/or surrender of export proceeds; and (4) the existence of multiple exchange rates for capital account transactions. The Chinn-Ito index is an aggregate indicator and does not differentiate between inflow and outflow controls, but it is

uranium, and zinc.

[2] World Port Index, Maritime Safety Information, National Geospatial-Intelligence Agency, http://msi.nga.mil/NGAPortal/MSI.portal?_nfpb=true&_pageLabel=msi_portal_page_62&pubCode=0015

[3] https://freedomhouse.org

[4] The REER is the nominal effective exchange rate of the focal country (which, in turn, is a geometrically weighted average of the bilateral exchange rates between this country and its trading partners) multiplied by the consumer price index of the focal country in period t and divided by the geometrically weighted average of the consumer price indexes of its trading partners for the same period.

available for a relatively large number of countries (182) for a long period (1970–2013). Appendix A1 summarizes the variables and their sources, and Appendix A2 presents descriptive statistics for our sample.

4. Machine learning as a tool to predict industrial development

Machine learning techniques have found a broad application in many areas of empirical economics. McKenzie and Sansone (2019) and Kleinberg et al. (2018) have had promising results as to the predictive accuracy of these methods. In this paper, we use a random forest algorithm (Breiman, 1996; 2001) to predict industrial development proxied by nightlight data at the sub-national level. The random forest is a tree-based algorithm that uses machine learning techniques for classifying and supervised regression. This section provides a very brief summary of this tool; a more comprehensive review can be found in Basuchoudhary et al. (2018).

A random forest model is a collection of tree predictors $h(\mathbf{x};\theta_k), k = 1, \dots, K$, where x represents the inputs vectors (of length p) with an associated random vector X, and where θ_k are independent and identically distributed random vectors. The random forest prediction is an unweighted average over the collection:

$$\bar{h}(\mathbf{x}) = \left(\frac{1}{K}\right)\sum_{k=1}^{K} h(\mathbf{x};\theta_k).$$

The random forest technique is flexible, data-driven, and efficient for constructing predictive models to identify the observable predictors serving as the most important explanatory variables of industrial development. Among the range of machine-learning algorithms, the random forest stands out for its ability to deal with missing data, outliers, and complex nonlinear relationships between variables, as well as to estimate the accuracy of a classification independently of an external validation dataset via the Out-of-Bag (OOB) method. Studies have found that the random forest can better predict economic outcomes than other algorithms (Basuchoudhary et al., 2018).The excellent predictiveness of random forests makes them multidisciplinary. The random forest model's predictive ability allows variables to be sorted according to their importance in predicting the dependent variable.

In this paper, we use the bootstrap technique to obtain n samples from the original training data. Following standard practice, we first separate the data into two random subsamples of countries. The first is used to train the algorithm and build the models, while the second is used to evaluate the model's performance by testing its out-of-sample predictive accuracy. In our case, about 70% of the data is used to grow a classification tree and 30% is left to obtain unbiased estimates of correct classification rates and feature importance. Then, the random forest algorithm separately grows 1000 unpruned classification trees from bootstrap samples of the original training data.[5] Each decision tree was grown by selecting 10 of the *n* predictor variables, for the best possible split of the sample. Instead of random sampling, the algorithm uses the mean squared error at each split point (internal node) as the splitting criterion. Each tree votes to indicate its decision about the class of the object, and then the forest classifies behaviors (predictions for the test data) based on a majority vote from the 1000 trees. Finally, to assess the accuracy of the predictions, we compare the OOB with the OLS estimations.

5. Findings

5.1. Explaining levels of nightlight intensity

This section presents the main results of the paper. Figure 2 presents the results on variable importance obtained from the random forest approach, with relative importance on the horizontal axis and the 40 most important predictors in descending order from the top on the vertical axis. The variable importance measures how great a role a given variable plays in reducing the error of the out-of-sample prediction across the forest, there used as an our predictability indicator. The top five ranked predictors are minerals, GDP growth, local/urban roads in the second subnational region, agriculture value added, and the length of trails in the SN2 region. These variables show the importance of natural resources, local infrastructure, and agriculture growth as conditions for industrial development. The GDP growth exhibits the conditional growth hypothesis, implying that national growth can lead to regional growth. The next five most important predictors are military expenditure, GDP per capita, government expenditure, political rights, and manufacturing imports. In addition to political rights, the presence in this group of two variables related to expenditure indicates the importance of public institutions in fostering industrial development policy. The presence of agriculture, infrastructure construction, and manufacturing imports in the top ten variables indicates that Africa has not successfully gone through the process of structural transformation. We also find that the service sector is not among the most important variables, as detected by the random forest strategy. This is interesting as the service sector in Africa has been deemed low productive. In the literature, service is important in the positive structural transformation whereby resources move from low agriculture and manufacturing sectors to a higher productive service sector. These findings indicate that growth has been simultaneously driven by natural resources and agriculture. This is surprising because in theory, resources should move from one sector to another. Minerals have been attracting resources not attracted by agriculture. In fact, minerals are capital-intensive and agriculture is labor-intensive.

[5] Estimation and cross validation are carried out using the Random Forest Algorithm in Stata. See Zou and Schounlau (2018).

5.2.Explaining the growth of nightlight intensities

Next, we examine the extent to which predictors explain growth rates in nightlight intensity, using the same predictors as in the previous section. Figure 3 shows the importance of each variable, ranked from most to least important. We can see three distinct groups, according to their importance in determining nightlight growth. The first constitutes the six most important predictors: fuel imports, inflation, exports, money, manufacturing imports, and terms of trade. The second group contains height important predictors with relatively less predictive power than the first group. It includes military expenditure, manufacturing exports, the number of phones, FDI, rural population, government expenditure, and government expenditure. Finally, the third group, which is nearly as important as the second group, includes variables such as minerals, GDP per capita, agriculture value added, aid, and GDP growth. This package of natural resources and agricultural transformation is also important in explaining nightlight intensity, as discussed in the previous section.

5.3.The role of natural resources

Our machine learning results point to a natural-resource–led pattern of industrial development, reflected empirically in the high importance of the minerals and resources variables. The presence of manufacturing imports as an important predictor also shows symptoms of the Dutch Disease. Here, we explore minerals in a more granular way by decomposing this one variable into 23 different types of mines. The results from running the random forest algorithm for these variables are presented in Figure 4. We find that chromium mines reflects the most important predictor of nightlight intensity, followed by gold, silver, phosphate, and nickel. Chromium demand is mainly driven by the stainless steel industry in China, with South Africa and Zimbabwe being the largest suppliers in Africa. Since South Africa has, on average, a high mean of nightlight intensity, we believe our results are driven by the growth of this industry in this country. The demand for gold and silver has also increased in recent years. The next group includes copper, lead, beryllium, tin, and manganese. Zinc, iron, diamond, and uranium have played minor roles in industrial development.

6. Interpreting our findings through the lens of industrial policy and structural change

Industrial policy is generally regarded as a set of well-coordinated measures targeted at specific industries—such as manufacture and/or agriculture and high productive services—in order to foster structural change toward a particular development path. Economists suggest that African countries should not mimic paths, modes, and specific policies of Asian economies, given that the initial conditions differ and Asian economies followed highly unusual and distinctive paths of growth (Otchia, 2015). In our machine learning prediction analysis, we confirm that Africa should create a multipronged development strategy to accelerate structural transformation, sustain growth, and create jobs. Our findings that natural resources remain an important predictor of industrial development in Africa suggest that development strategies in the continent should make natural resources more inclusive through better management of revenues from natural resources and exchange rates.

On the impact of structural change, existing studies have found that a positive structural transformation starts with productivity growth in the agricultural sector. This leads to growth in income and demand for manufactured products, resulting in a reallocation of resources to higher productive activities. The literature (Diao & McMillan, 2014; McMillan & Harttgen, 2014) suggests that structural changes in Africa were growth-reducing, moving resources from high productive sectors to lower productive ones. These findings have been used to explain the rise of the service sector as a result of labor movement from the agricultural and manufacturing sectors to the service sector. Our findings, however, indicate that agriculture remains an important sector for African industrial development. This is because investment in manufacturing and minerals did not crowdout investment in the agricultural sector, meaning that Africa is attracting investment in both agricultural and nonagricultural sectors. Since these sectors differ in terms of resource endowment, Africa can develop by promoting labor-intensive industries simultaneously with capital- or technology-intensive sectors, as there is no competition and reallocation of resources between these industries. Our findings are consistent with the development theory that calls for a multisector approach—in agriculture, natural resources, manufacturing, and services—to attain growth similar to the old manufacturing export–led strategy (Stiglitz, 2018).

Studies reported by the African Development Bank (2018) suggest considerably higher growth in regional industrial development due to the improvement of local infrastructure. The expansion of domestic infrastructure reported in these studies could increase global GDP by anywhere from 2.6 to 4.7 percent. Overall, local infrastructure development may therefore have a higher impact on industrial development. In our case, the differences in findings on the importance of local compared to national infrastructure appear to be more closely related to the data structure used. Compared to existing studies, we used very detailed infrastructure data at ADM2 levels, combined with machine learning techniques, which gives higher precision and higher quality predictions. Our findings that roads linking ADM2 regions are strong predictors of industrial development suggest this instrument is very relevant for Africa. Finally, our findings are consistent with the idea that development states play a key role in industrial development.

7. Conclusion

In this study, we use nightlight time data and machine learning techniques to predict industrial development in Africa. We begin by assessing the extent to which nightlight data are the best proxies for agriculture, manufacturing, or service output. We find that nightlight data explain 84% of within-country variation in economic growth and represent a better proxy for industrial development. We also find a strong and non-statistically significant correlation between nightlight data and service sector output. This suggests that nightlight data can be used as a reliable proxy for industrial development at the sub-national level, where data is usually imprecise or unavailable.

We then exploit machine learning techniques to identify the best predictors of industrial development. In a first step, we use nightlight data to predict the most important determinants of industrial development in Africa. We identify minerals, GDP growth, local roads, and agriculture value added as the most important predictors, followed by the level of GDP per capita, government expenditure (military and all), political rights, and manufacturing imports. In a second step, we predict industrial growth using the increase in the intensity of nightlights as our proxy. We find that fuel imports, inflation, exports, money supply, and manufacturing imports are the most important determinants. Another group of important determinants is the number of phones, FDI, rural population, government expenditure, service, minerals, and agriculture value added. In the last step, we make use of our rich and detailed data on mines to identify important predictors of growth with respect to nightlight intensity. We identity chromium and gold mines as important variables, followed by silver, phosphate, and copper mines.

These results provide the first evidence about how machine learning techniques and nightlight data can be used to predict economic development in places where subnational data are missing or imprecise. Taken together, our research confirms four groups of important determinants: natural resources, agriculture growth, institutions, and manufacturing imports. Our findings indicate that Africa should follow a more multisector approach for development, putting natural resources and agriculture productivity growth at the forefront.

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Figure 1: Evolution of night lights intensity in Africa

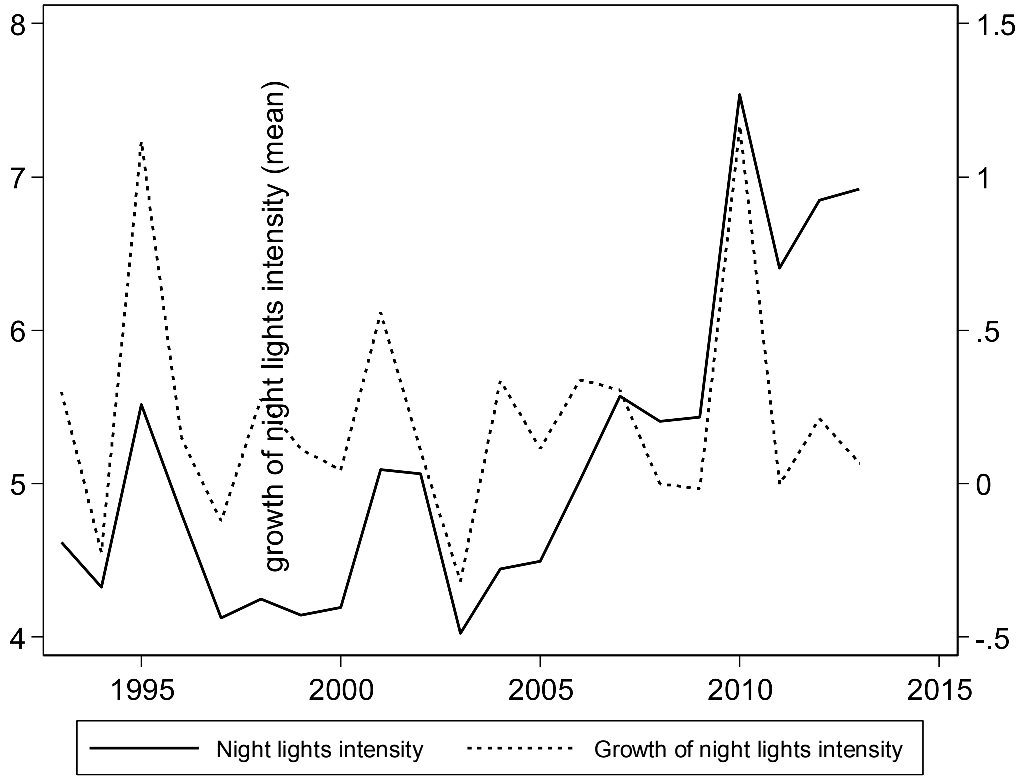

Figure 2: Explaining Night lights intensities in level

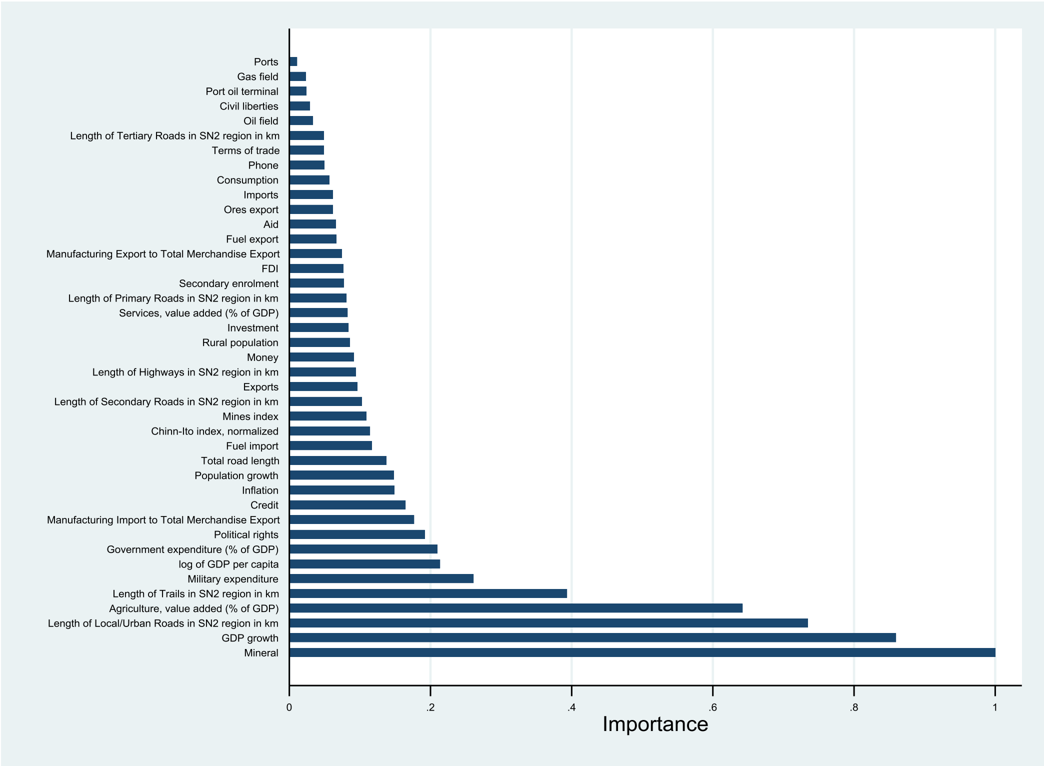

Figure 3. Explaining the growth of night lights intensities

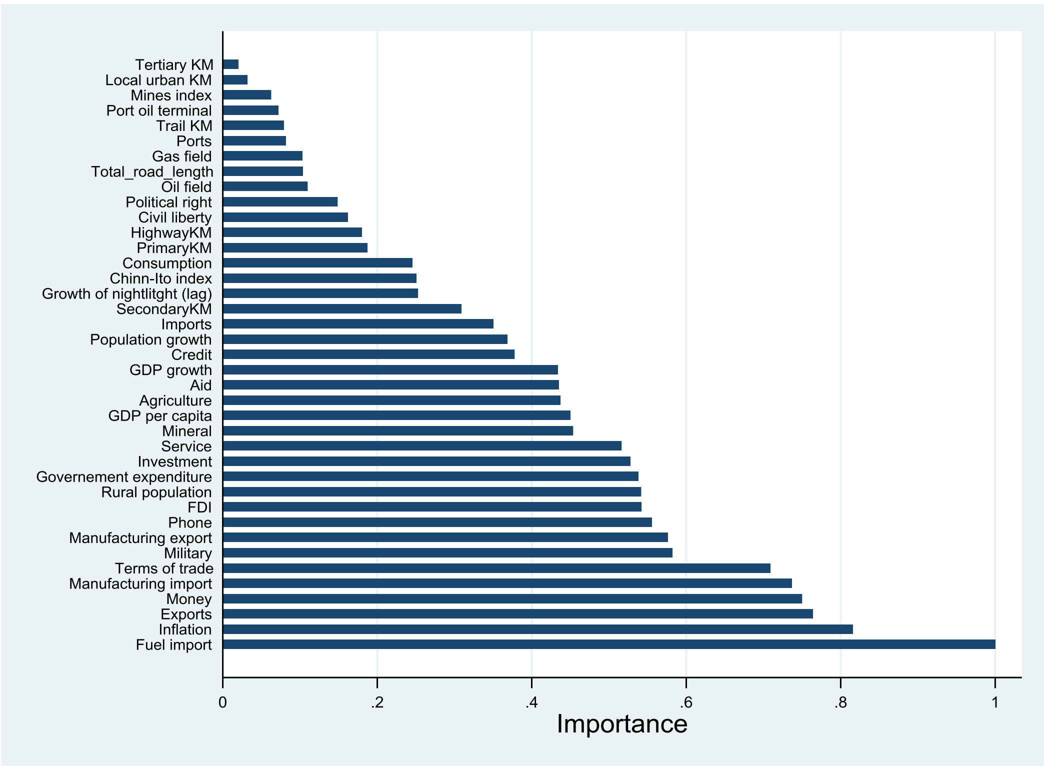

Figure 4. Explaining the growth of night lights intensities

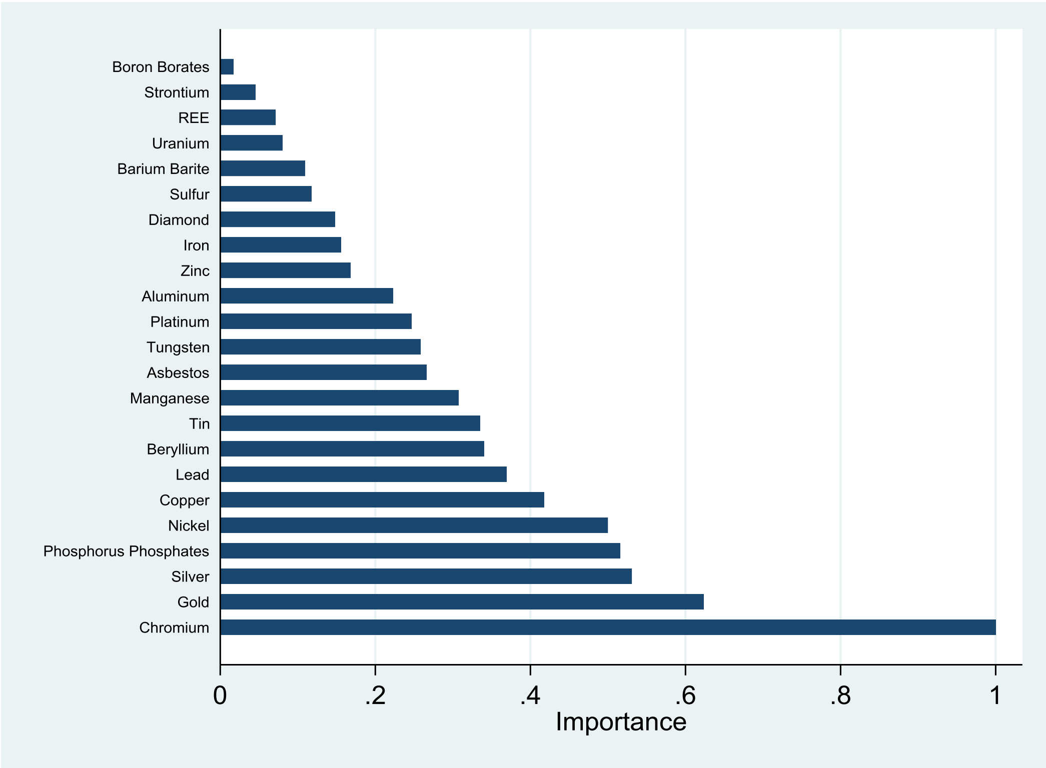
Boron Borates
Strontium
REE
Uranium
Barium Barite
Sulfur
Diamond
Iron
Zinc
Aluminum
Platinum
Tungsten
Asbestos
Manganese
Tin
Beryllium
Lead
Copper
Nickel
Phosphorus Phosphates
Silver
Gold
Chromium
0
.2
.4
.6
.8
1
Importance

Table 1.

	ln (GDP)		ln (Agriculture)		ln (Manufacturing)		ln (Industry)		ln (Service)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
ln (lights/area)	0.259**	0.282*	0.236*	0.356***	0.257*	0.095	0.513***	0.847***	0.268	0.641
	[0.108]	[0.165]	[0.126]	[0.121]	[0.137]	[0.204]	[0.135]	[0.231]	[0.254]	[0.438]
ln(lights/area) sq		-0.002		-0.010		0.014		-0.029		-0.032
		[0.013]		[0.012]		[0.016]		[0.019]		[0.039]
Observations	800	800	800	800	800	800	788	788	770	770
Countries	46	46	46	46	46	46	46	46	45	45
(Within country) R^2	0.837	0.837	0.576	0.579	0.536	0.538	0.683	0.693	0.780	0.782

Notes: All specifications include country and year fixed effects. Robust standard errors, clustered by country, are in brackets.

***Significant at the 1 percent level.

**Significant at the 5 percent level.

*Significant at the 10 percent level.

Appendix A1: Variables' definition and sources

Variables	Definitions	Sources
mines	(sum) mines	USGS 2005
ports	(sum) ports	CIESIN (2013)
port_oil_term~l	(sum) port_oil_terminal	CIESIN (2013)
HighwayKM	Length of Highways in SN2 region in km	CIESIN (2013)
PrimaryKM	Length of Primary Roads in SN2 region in km	CIESIN (2013)
SecondaryKM	Length of Secondary Roads in SN2 region in km	CIESIN (2013)
TertiaryKM	Length of Tertiary Roads in SN2 region in km	CIESIN (2013)
Local_UrbanKM	Length of Local/Urban Roads in SN2 region in km	CIESIN (2013)
TrailKM	Length of Trails in SN2 region in km	CIESIN (2013)
total_road_le~h	(sum) total_road_length	CIESIN (2013)
oil_field	Oil field	CIESIN (2013)
gas_field	Gaz field	CIESIN (2013)
ka_open	Chinn-Ito index, normalized	Chinn & Ito (2006)
nciliberty	Civil Liberties	Freedom House
nporight	Political Rights	Freedom House

Variables	Definitions
service	Services, value added (% of GDP)
govexpend	Government expenditure (% of GDP)
manufexport	Manufacturing Export to Total Merchandise Export
manufimport	Manufacturing Import to Total Merchandise Export
tot	Terms of trade
lgdppc	log of GDP per capita
agri	Agriculture, value added (% of GDP)
gdppcgr	GDP per capita growth
fuelimport	Fuel import
inflation	Inflation
fdi	FDI
inv	Investment (% of GDP)
aid	Net official development assistance received
consumption	Consuption (% of GDP)
exports	Exports (% of GDP)
imports	Imports (% of GDP)
credit	Domestic credit provided by financial sector (% of GDP)
money	Broad money (% of GDP)
mineral	Mineral revenue
military	Military expenditure

phone	
ruralpop	Rural population
popgrowth	Population growth

Appendix A2: Descriptive statistics

	Learning sample					Test sample				
	Obs	Mean	Std. Dev.	Min	Max	Obs	Mean	Std. Dev.	Min	Max
gmlight	69,072	0.17	2.25	-341.27	82.81	29,838	0.19	1.85	-65.96	177.67
mines	68,631	0.53	2.70	0.00	87.00	29,619	0.54	2.66	0.00	87.00
secenrol	50,341	56.37	25.40	5.21	107.59	21,795	56.20	25.44	5.21	107.59
ports	68,631	0.05	0.29	0.00	7.00	29,619	0.05	0.28	0.00	7.00
port_oil_t~l	68,631	0.02	0.19	0.00	6.00	29,619	0.03	0.18	0.00	6.00
HighwayKM	42,765	4.94	24.19	0.00	405.78	18,557	4.72	23.30	0.00	405.78
PrimaryKM	42,765	27.84	71.42	0.00	864.50	18,557	27.32	71.18	0.00	864.50
SecondaryKM	42,765	54.72	149.57	0.00	1761.23	18,557	53.95	149.25	0.00	1761.23
TertiaryKM	42,765	61.28	267.07	0.00	5099.27	18,557	60.79	271.71	0.00	5099.27
Local_Urba~M	42,765	1.20	7.72	0.00	246.56	18,557	1.21	7.48	0.00	246.56
TrailKM	42,765	96.66	500.81	0.00	6791.77	18,557	100.11	503.77	0.00	6791.77
total_road~h	42,765	517.81	1332.37	0.01	29310.42	18,557	524.71	1397.61	0.04	29310.42
oil_field	68,631	0.11	0.31	0.00	1.00	29,619	0.11	0.31	0.00	1.00
gas_field	68,631	0.07	0.25	0.00	1.00	29,619	0.07	0.25	0.00	1.00
service	60,219	43.64	9.41	12.44	82.59	26,034	43.68	9.45	12.44	78.56
govexpend	66,426	14.13	5.93	0.91	69.54	28,744	14.08	5.87	0.91	69.54
manufexport	59,852	17.90	24.02	0.00	95.68	25,839	18.04	24.06	0.00	95.68
manufimport	59,920	68.40	8.53	29.32	92.99	25,876	68.34	8.58	29.32	92.99
tot	67,492	0.02	0.21	-0.83	0.47	29,156	0.02	0.21	-0.83	0.47
lgdppc	68,733	7.62	0.92	5.09	9.92	29,695	7.61	0.92	5.09	9.92
agri	61,120	17.95	12.24	0.89	79.04	26,404	18.00	12.21	0.89	79.04
oresexport	59,870	6.78	14.65	0.00	88.81	25,850	6.80	14.58	0.00	88.81
fuelexport	59,150	55.12	44.27	0.00	99.66	25,505	54.74	44.38	0.00	99.66
gdppcgr	68,679	1.82	4.71	-62.23	140.50	29,669	1.78	4.39	-62.23	140.50
fuelimport	59,920	8.25	8.12	0.01	42.50	25,876	8.32	8.20	0.01	42.50
inflation	65,630	24.57	397.37	-9.80	23773.13	28,300	27.81	486.90	-9.80	23773.13
fdi	65,872	2.44	4.75	-8.59	161.82	28,457	2.40	4.42	-8.59	103.34
inv	66,470	24.03	7.66	-2.42	59.72	28,755	24.03	7.71	-2.42	59.72
aid	68,825	739000000.00	1150000000.00	-16800000.00	11300000000.00	29,731	737000000.00	1170000000.00	-11600000.00	11300000000.00
consumption	66,470	72.53	18.16	16.71	241.97	28,755	72.56	18.05	16.71	241.97
exports	67,492	31.17	12.03	4.23	89.69	29,156	31.12	12.05	4.23	89.69
imports	67,492	30.10	13.66	7.24	236.39	29,156	30.05	13.39	7.24	236.39
credit	67,891	25.42	34.92	0.00	160.12	29,333	25.40	34.77	0.00	160.12
money	67,891	40.26	22.52	0.02	151.55	29,333	40.08	22.46	0.02	151.55
mineral	68,971	0.81	2.73	0.00	46.62	29,799	0.82	2.88	0.00	46.62
military	66,506	2.29	1.84	0.00	34.38	28,656	2.27	1.77	0.00	34.38
phone	69,009	4.28	3.95	0.00	31.07	29,803	4.27	3.96	0.00	31.07
ruralpop	69,028	22900000.00	26200000.00	59465.00	92600000.00	29,823	22900000.00	26300000.00	60678.00	92600000.00
popgrowth	69,028	2.12	0.80	-6.18	7.92	29,823	2.12	0.80	-6.18	7.92
ka_open	68,740	0.21	0.18	0.00	1.00	29,686	0.21	0.17	0.00	1.00
nciliberty	69,053	3.52	1.28	1.00	7.00	29,829	3.51	1.29	1.00	7.00
nporight	69,053	3.10	1.75	1.00	7.00	29,829	3.08	1.74	1.00	7.00