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Services and economic development in Africa

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Introduction

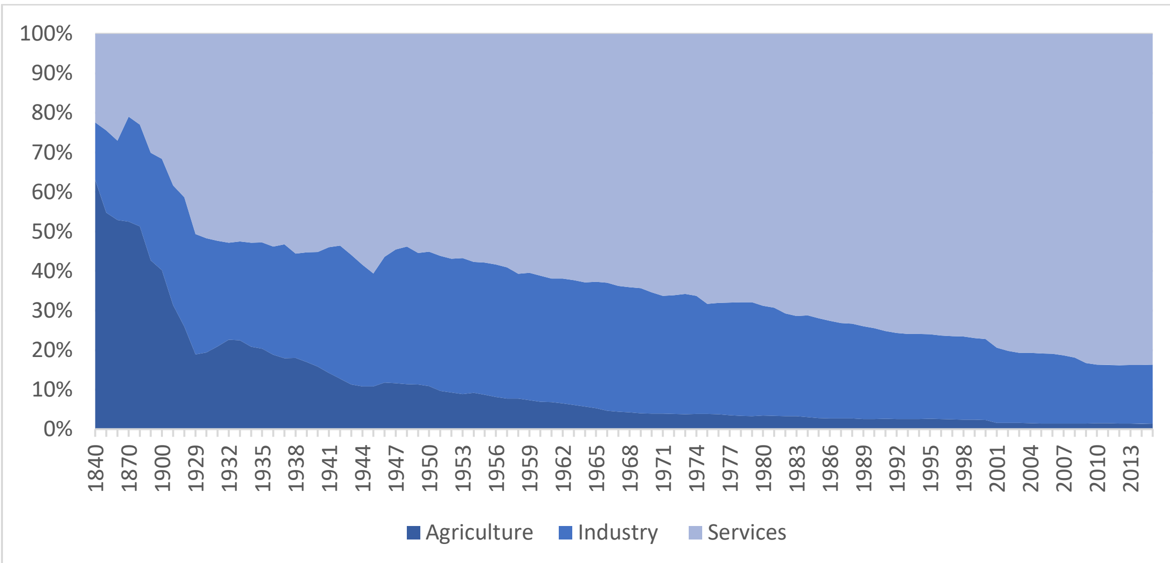
Economic development is generally associated with a shift of the workforce from the agricultural to non-agricultural sectors, a process commonly referred to as structural transformation (Herrendorf, Rogerson, et al., 2014). The traditional path associated with structural transformation is illustrated in Figure 1: economic development involves a steady reduction in the share of agriculture-related employment as workers leave the land and shift into industry, mostly manufacturing (Kravis et al., 1983; Schettkat & Yocarini, 2006). Some of the workforce goes to services activities, resulting in a net expansion of overall employment in services, but the rate of increase in manufacturing is greater and drives both employment and output dynamics. There are also important intra-sectoral reallocations, e.g., away from personal household services towards industry and other services. The changes in broad aggregate sectoral shares are accompanied by large intra-sectoral reallocations. As per capita income increases, at some point the share of manufacturing in total employment peaks and the share of services expands further.

This 'traditional' path of economic growth and development may be less applicable to lower-income countries today than it was in the past. Insofar as China and Asia more broadly will continue to be the world's dominant factory for the near future and technological change (automation, additive manufacturing, etc.) combined with policy pressures on multinational firms to reshore or near-shore production may imply less scope for developing countries to significantly expand manufacturing. An important stylized fact in this regard is that developing countries are moving into services at a faster rate than was observed in previous periods, e.g., East Asian economies in the 1970s and 1980s. The associated 'premature deindustrialization' (Rodrik, 2016) is a source of concern insofar as it implies that low-income countries today cannot use the traditional path to increase per capita incomes. The argument is not that developing countries are staying too focused on agriculture and not moving resources to more productive sectors. It is that they are moving into services and prematurely deindustrializing as a result of technological change and domestic (trade) policies in major economies.

A key argument as to why this may be detrimental to growth prospects is that services do not offer the same prospects for sustained productivity growth as manufacturing does and that services activities offer less potential for positive spillover effects (innovation; linkages; clusters; etc.).

Another concern is that many services are on average more skill-intensive than the assembly-type tasks that featured prominently in manufacturing activities that drove growth in successful countries in the past, therefore offering less scope to provide jobs for unskilled labor than manufacturing.

Figure 1. The standard story – sectoral employment shares & economic growth



Note: Data cover employment in the US and is originally sourced from (Herrendorf, Rogerson, et al., 2014)
Source: Authors' elaboration on Our World in Data

There is a vibrant and unsettled debate on whether and how the services sector can become the new engine of jobs creation in developing countries. Alternative models of structural transformation without industrialization have been proposed, and research undertaken that analyzes the experiences of countries in Africa and Latin America.[1] These include both cases in which growth in income and productivity has been recorded *within* the agricultural sector and, cases in which the development of services sectors can substitute for industrialization as a channel for growth (Lagakos & Shu, 2021). Arguments that services can play a role similar to that played by the manufacturing sector in past examples of successful development are based on the view that, due to the changes occurring in the organization of international production, the reduction in transport costs and opportunities offered by new technologies, the nature of services is changing

[1] Dihel & Goswanmi (2016) provide a number of case studies of specific services that involve trade between African countries. See also Balchin et al., (2016).

dramatically. Many services activities are (increasingly) tradable, have experienced high productivity growth, and can achieve economies of scale (Gervais & Jensen, 2019; Hsieh & Rossi-Hansberg, 2019; Loungani & Mishra, 2014). Structural transformation is in part an inter-sectoral dynamic – from low productivity agriculture and informal services to higher productivity work in the formal sectors – both goods and services – but as important are sectoral shifts within sectors. Within services resource allocation shifts are a driver of productivity growth in the same way as in goods-producing sectors. Young (2014) finds that average productivity growth in services is similar to that in other sectors.

Recent work has emphasized the importance of diversification into non-manufacturing activities for the generation of jobs in Africa (Newfarmer et al., 2018). Thanks to revolutions in transport and technologies, industries "without smokestacks", such as horticulture, agro-processing, tourism, e-commerce, digitally enabled business, health and education services, have the potential to drive sustainable demand for jobs, together with rising productivity, leveraging the increasing tradability of many services products. Services are very heterogeneous in terms of skill intensity, tradability and scope for productivity growth. Some services offer great scope for the type of productivity dynamics that have characterized manufacturing, others do not. To some extent, the debate about services versus manufacturing is a semantic one – what matters is value added and employment generation. Many manufacturing activities are services-intensive, and servicification of manufacturing has been increasing over time. Conversely, many services depend on manufactured inputs and machinery, be it computer hardware, telecom infrastructure, airplanes, trucks etc. The question is whether a services-centric economic development strategy can support employment and generate the productivity growth needed for sustainable development of low-income countries in Africa and elsewhere, in a context where the type of export-led manufacturing strategy that was used by successful countries in the past is constrained.

This paper documents and analyzes the structure of employment in thirteen African economies at the administrative unit level and relates employment in services to indicators of economic development commonly used in the literature, including nighttime lights and a set of economic and geographic covariates. Our aim is to provide a fine-grained overview of who works in services and where and how this has changed over time. The data we use come from different sources. The main source is the IPUMS International Database published by the Minnesota Population Center. We extract data for all African countries for which at least two censuses are available in IPUMS, subject to one key condition: the presence of at least two temporal observations of the variable called "INDGEN" – the disaggregated industrial classification of employed persons. This has 12 industries that roughly conform to the services sectors in the International Standard Industrial Classification (ISIC).

We compile data from IPUMS on about 56 million individuals covering 1,546 administrative units in 13 African countries for either two or three census waves. Our sample is representative of the Africa region. It includes both low income countries whose GDP per capita is about US$1,000 (Malawi, Mozambique), middle income countries such as Mauritius; resource rich countries (Botswana, Zambia), more diversified economies (South Africa and Morocco), landlocked countries (Rwanda) and countries with sea borders and a strong tourism industry (Mauritius, Tanzania). Combined, the sample countries account for 31.1% and 44.1% of Africa's total population and GDP, respectively.[2]

The paper has two parts. The first presents a descriptive snapshot of changes in the composition of employment in Africa over time. The second provides correlations between services and proxies for economic development. The descriptive analysis is conducted at the sub-national level and is broadly in line with existing evidence (e.g. Newfarmer et al., 2018) showing that structural transformation in Africa is mostly directed towards the services sector, with manufacturing being less dynamic. Digging deeper into specific services sectors, we assess both graphically and by means of multivariate analyses which activities within the broad aggregate of services have been growing faster in terms of employment in recent decades. This reveals that employment in trade (wholesale and retail) services is leading the trend. We also observe that growth in services is associated with a shift to higher skilled types of services—although in most cases they start with very low levels of employment.

[2] Data cited in text is from the IMF WEO (April 2021 edition). Figures for GDP are based on the PPP values for the year 2019 (the last non-estimated figure), and 2015 for population (the latest non-estimated values).

Broad sectoral employment shares and employment in services sectors correlate with characteristics of the administrative units that are the geographic focus of analysis. We show that services are more likely to develop in urban and densely populated areas as well as in areas with higher access to national and international markets. Compared to manufacturing, persons employed in services are on average more educated (36.5% have secondary or tertiary degree vs. 18% in manufacturing) and engage in higher skilled occupations. Services also employ a relatively large (40%) share of women (twice as large as in the manufacturing sector). There are no striking differences with other sectors in terms of age groups or migration status. Following (Duernecker & Herrendorf, 2020) we show that there has been a shift over time towards occupations related to the production of *intangible* value added, and among these towards activities that can be classified as higher skilled. The shift to occupations associated with production of intangibles overlaps with instances where administrative units demonstrate growth in the share of employment generated by the secondary sector, suggestive of servicification.

We conclude the more descriptive part by developing a classification that clusters specific services industries into high- and low-skills groups. We group industries according to the level of education and intensity of more complex types of occupations of individuals. The two clusters are: (1) "high skilled, complex occupation" (high skills) industries, including education, finance, health, business, public services, other business and unspecified services; and (2) "low skilled, simple occupations" (low skills) sectors, including transport, trade and distribution-related activities, accommodation, and private household services.

Armed with this wealth of micro data, the second part of the paper reports correlations between services and economic development, which we proxy with nightlight luminosity. Our main results are five-fold.

1. There is no association between the aggregate service sector and economic development.
2. There is a great deal of heterogeneity within services. In particular, we document a strong positive association between high skills services and economic development, whereas low skills services correlate negatively with economic development.

3. Health services, public services, and, to a lesser extent, business services are positively associated with economic development. Conversely, transport and private household services are negatively correlated with development indicators.
4. The correlation between high skills services and development is particularly strong in areas with low incidence of malaria, with natural resources, and with good mobile phone coverage. These associations point to a mediating role of market conditions and technology in the relation between services and economic development.
5. The association between services – both high and low skills – and spatial inequality measures is weak, a finding that requires further investigation.

1. Data

We use four types of data for the analysis:

A. Geolocalized employment data across sectors, including up to 12 services sectors;
B. Geolocalized indicators of economic development;
C. Relevant features of the economic environment that could shape the relationship between services activities and economic development;
D. Measures of spatial economic inequality.

This information is merged into one panel dataset, identified at the ADMIN-wave pair, covering 1,546 administrative units in 13 African countries: Benin, Botswana, Egypt, Ghana, Malawi, Mali, Mauritius, Morocco, Mozambique, Rwanda, South Africa, Tanzania and Zambia. The data span either two or three waves, depending on availability of census waves in the IPUMS International Database.[3] The final panel comprises 3,846 observations[4] and 55,976,623 individuals spanning the period 1982-2013.

1.A Employment and Occupation Data

Employment data come from the IPUMS International Database (Minnesota Population Center, 2019). IPUMS reports information for a repeated cross-section of representative individuals,

[3] Information on available waves and all variables is reported in the Online Technical Appendix. An online tool that provides graphs and maps on sectoral and occupational dynamics in Africa over available census waves in the IPUMS International database can be found at: https://globalgovernanceprogramme.eui.eu/services-and-economic-development-in-africa/

[4] When including Mauritius. The number of observations is 3,727 when Mauritius is excluded in analyses using the spatial Gini coefficient and all Alesina et al., (2021) variables.

covering a variable fraction of a country's total population.[5] We aggregate individual-level information to the lowest available administrative designation for each country, in order to obtain a dataset defined at the ADMIN-wave level.[6] We only extract data for African countries for which at least two census waves report the "INDGEN" variable,[7] which provides a disaggregated sectoral employment classification, including up to 12 specific services industries.[8]

Given the abundance of temporal inconsistencies in the administrative designations in the IPUMS International Database, reflecting frequent redistricting by national authorities, we rely instead on the temporally and spatially consistent shapefiles provided by Alesina et al., (2021), to which we collapse all indicators included in our analyses. Figure 2 plots the 1,546 unique administrative units employed in the analysis, showing that these are broadly comparable in terms of surface area. Larger administrative entities located in Morocco, Mali and Egypt correspond to mostly uninhabited and/or desert areas). As the Alesina et al. (2021) dataset does not include shapefiles for Mauritius;, we rely on the administrative designations provided by IPUMS International for this country.

We calculate ADMIN-wave level sectoral shares for each of the 17 levels of the INDGEN variable,[9] weighting each individual-level observation by the survey weights provided by IPUMS

[5] Coverage fractions and total number of surveyed individuals in each census wave are reported in the Online Technical Appendix.

[6] This operation amounts to aggregating data at the second administrative level for most countries, excluding Botswana, for which the sole administrative division available for aggregation is the first. The second-level administrative unit corresponds to Districts in a majority of cases, with the exception of Benin ("Communes"), Malawi ("Traditional Authorities"), Mali ("Circles"), Mauritius ("Municipal Wards/Village Council Areas"), Morocco and Rwanda ("Provinces").

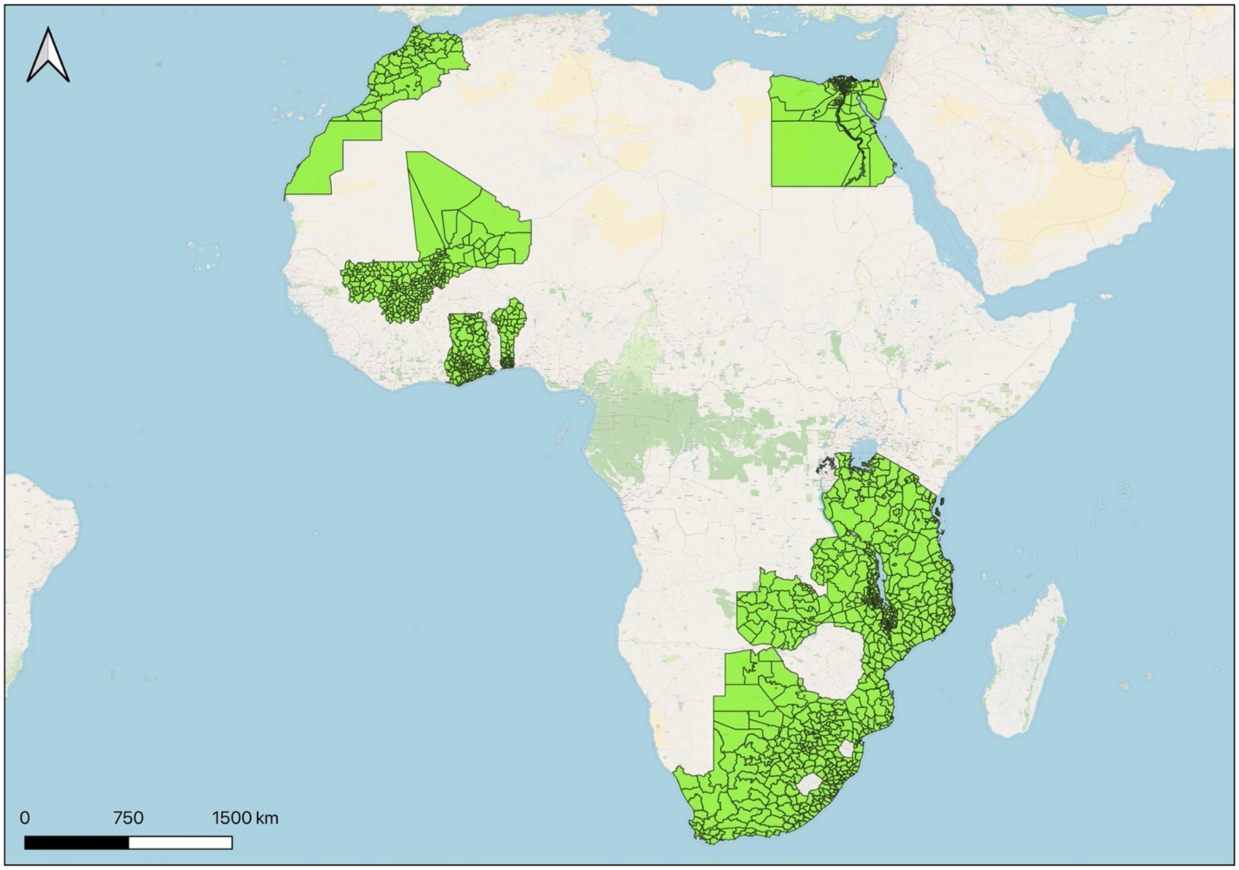
[7] The "INDGEN" variable refers to a disaggregated sectoral classification with 17 levels "roughly conforming to the International Standard Industrial Classification (ISIC)."

[8] There is only one data point for sectoral employment in IPUMs for Burkina Faso, Cameroon, Guinea, Kenya, Lesotho, Senegal, Sierra Leone, South Sudan, Sudan, Uganda, and Zimbabwe, precluding us from including these African countries. We also exclude Liberia and Togo due to the very long time period between the two survey waves reported in the IPUMs dataset (1974 and 2008 for Liberia and 1970 and 2010 for Togo).

[9] The categories are: (1) Agriculture, fishing and forestry; (2) Mining and extraction; (3) Manufacturing; (4) Utilities (electricity, gas, water and waste management); (5) Construction; (6) Wholesale and retail trade; (7) Hospitality (hotels and restaurants); (8) Transportation, storage and communications; (9) Financial services and Insurance; (10) Public Administration and Defence; (11) Services, not specified; (12) Business services and real estate; (13) Education; (14) Health and social work; (15) Other services; (16) Private household services; (17) Other industry, not elsewhere classified. The "Other services" category includes the following: (a) miscellaneous personal and community services n.e.c., e.g. sanitary services and entertainment activities; (b) repairs not clearly for business functions and undifferentiated repairs; and (c) rental activities not of a business nature.

International. This results in 17 distinct variables measuring the share of each sector in an administrative unit's total recorded sectoral employment.[10]

Figure 2. Administrative units for all countries included in the analysis



Source: Author's elaboration on IPUMS and Alesina et al. (2021)

We repeat the same procedure for individual-level occupational characteristics, reported by IPUMS International in the "OCCISCO" variable. This comprises 11 categories detailing the dwelling covered by each surveyed person within their occupational remit.[11] We thereby obtain

[10] The IPUMS International Database includes "Not in Universe" (NIU) responses. In order not to distort the resulting sectoral shares, we decide to drop NIU observations from the dataset.

[11] IPUMS codes occupations according to the major categories in the International Standard Classification of Occupations (ISCO) scheme for 1988. For someone with more than one job, the primary occupation is typically the one in which the person had spent the most time or earned the most money. The 11 categories are: (1) Legislators, senior officials and managers; (2) Professionals; (3) Technicians and associate professionals; (4) Clerks; (5) Service workers and shop and market sales; (6) Skilled agricultural and fishery workers; (7) Crafts and related trades workers; (8) Plant and machine operators and assemblers; (9) Elementary occupations; (10) Armed forces; (11) Other occupations, unspecified or not elsewhere classified.

11 distinct occupational shares for each administrative unit, detailing the incidence of each dwelling on total employment. The OCCISCO variable is available in all included census waves, besides Rwanda's first census (1991).

1.B Geolocalized Indicators of Economic Development

We leverage a burgeoning literature in the field of Economic Geography, dating back to Henderson et al., (2012), in constructing disaggregated indicators of economic performance based on remotely sensed data, primarily night-time lights (NTLs). NTLs have been shown to be a useful proxy for economic growth and output, especially for developing countries.[12] One frequent caveat against the use of NTLs in longitudinal economic analyses concerns time-series inconsistencies in NTLs trends due to satellite intercalibration issues (Gibson et al., 2021).[13] A recently published dataset by Li et al. (2020) has attempted to mitigate these issues and is therefore viable for timeseries and panel analyses. Li et al. employ two generations of satellite instruments, the pioneering DMSP-OLS (which collected data between 1992 and 2013) and its successor, VIIRS (still in orbit), in order to construct a longer data series spanning 1992-2018. Their dataset improves on pre-existing NTL data products on two fronts: first, they intercalibrate the internal 1992-2013 DMSP-OLS time series at the global scale; second, they reduce discrepancies between the DMSP and VIIRS data series by converting the VIIRS radiance information to DMSP-like NTL data, thereby providing the scientific community with a dataset exhibiting temporal consistency and extending the span of historical DMSP NTL data to 2018, at the cost of losing some granularity.[14]

The full (1992-2018) dataset from Li et al. (2020) is used to compute zonal statistics at the second administrative level for each ADMIN-wave pair in our sample, resulting in two main variables: mean NTLs and the Sum of Lights (SoL). These are divided by each ADMIN's total population to

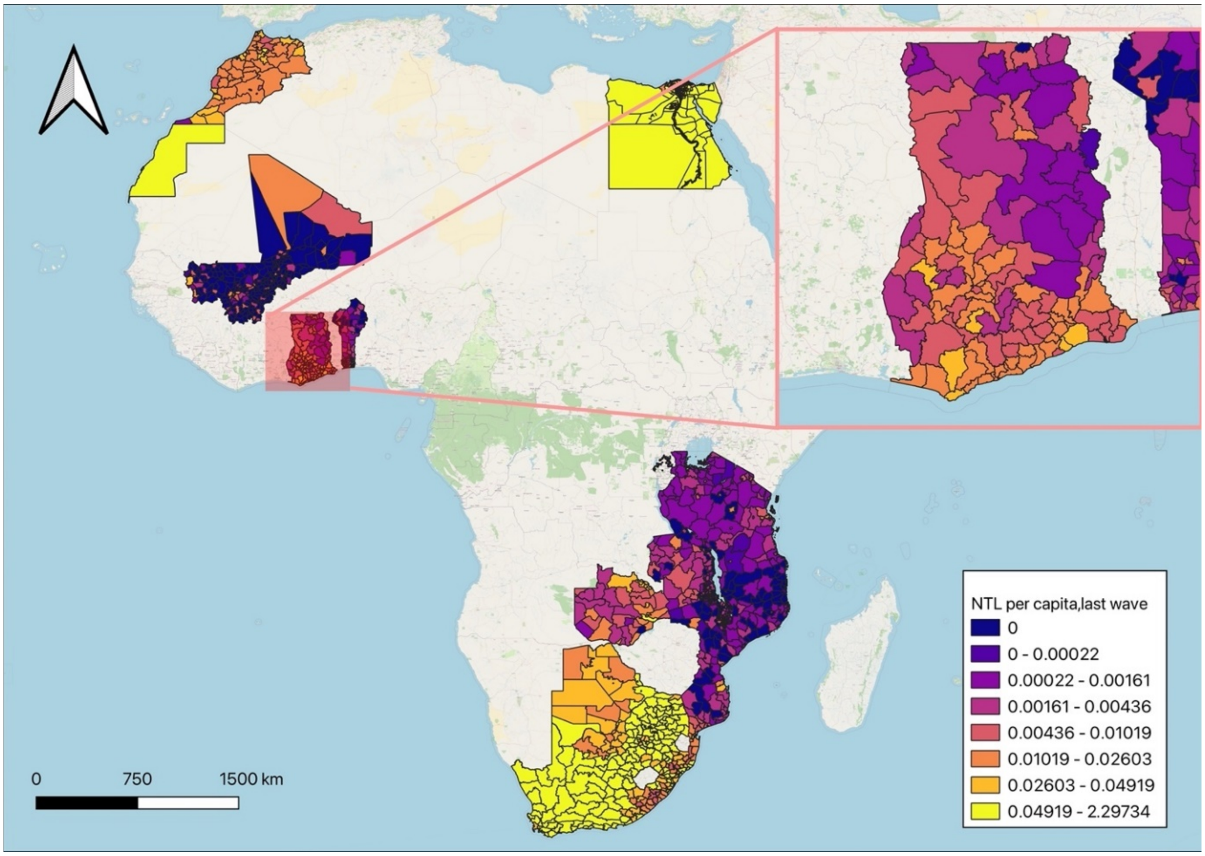
[12] In developed countries, the top-level saturation of the NTLs data due to the widespread presence of night-time illumination masks cross-sectional and temporal heterogeneity, while this effect is less pronounced for developing countries presenting large swaths of unlit territory.

[13] DMSP-OLS, the NOAA program which has produced the frequently used 1992-2013 NTLs time series, has launched six individual satellites whose orbits have progressively lowered over time and whose sensors are not perfectly identical, resulting in inconsistencies when employing their measurements across years.

[14] Due to the conversion between VIIRS and DMSP NTL, the target resolution is DMSP-OLS, which is coarser than VIIRS. Some caveats remain, mostly due to uncertainties in NTL pixels with values lower than 10.

obtain a nightlights per capita measure. Figure 3 illustrates the sub-national variation in this variable, revealing substantial variation both between- and within-countries.[15]

Figure 3. **Nightlights per capita, latest reported census wave**



Source: Author's elaboration on Li et al. (2020)

1.C Economic and geographic covariates

A first set of economic controls include in our dataset are derived from the information included in the IPUMS International Database. We collapse individual-level information to the second administrative level with the same weighting procedure described in Section 1A, therefore again obtaining ADMIN-wave shares for each category of each variable.

We use the following indicators in the analysis: (1) shares of urban and rural population; (2) a set of socio-economic indicators, including the average age in each administrative unit, and the share

[15] The relatively high value for Western Sahara reflects relatively high values of NTL (which is summed across pixels) and a small population.

of male and female individuals; (3) a range of linguistic and ethnicity variables, including the shares of each major religion, share of primary languages spoken and shares of ethnic composition – which we also leverage to construct indices of linguistic and ethnic fractionalization as in Alesina et al. (2003); (4) an array of literacy covariates, consisting of school attendance shares, literacy rates, shares of educational attainment categories (no primary school; primary school; secondary education; university education), and average years of schooling;[16] and (5) the share of migrants, calculating shares of native and migrant individuals over total population.[17]

We also use aggregate two additional sets of economic and geographic covariates. We obtain data on 2G and 3G mobile phone coverage and internet penetration from Manacorda & Tesei, (2020). As their dataset consists of 50Km^2 square grid cells covering the whole African continent, we first rasterize the information contained in their dataset, and then compute zonal statistics for 2G and 3G mobile phone coverage and internet penetration at our preferred administrative level.[18] In addition, we derive indexes for the mean stability of malaria transmission; the presence of oil fields and diamond mines and a range of geographic indicators from Alesina et al. (2021). The latter are available at the same administrative unit level we employ in our analyses.

[16] The variables considered are those in caps, followed by a short description. SCHOOL (school attendance): the data is largely comparable across waves, with slight differences in the age of the respondents and hence in the composition of the universe. Small differences can also be found with respect to the inclusion of correspondence courses, adult literacy classes, and non-traditional studies. LIT (literacy) : "Samples provide differing criteria with respect to the level of ability that should constitute literacy", and the standards can vary across samples-waves. EDATTAIN (educational attainment): in order to ensure comparability across samples and waves, IPUMS International applies the UN standard 6-3-3 classification (primary, lower secondary, higher secondary schooling). For countries reporting only degree rather than grade, the answer is classified to the corresponding category. YRSCHOOL (years of schooling): top-coded differently across samples, with a maximum of 18+ years. In our sample, Botswana 1991 is top-coded at 17+, Botswana 2001, all Mauritius and all South Africa at 13+, while the remaining country-wave pairs are all top-coded at the standard 18+.

[17] In order to harmonize the migration variable, which is not universally coded across the IPUMS surveys, we assume that an individual is categorized as native to an administrative unit if their previous residence, their residence 10 years prior, 5 year prior or the year prior to the survey is either in the same major administrative unit, or in the same major and same minor administrative unit; we categorize an individual as a migrant if their previous residence (in general), their residence 10 years prior, 5 year prior or the year prior to the survey are in the same major but different minor administrative unit, or in a different major administrative unit, or abroad. In doing so, we follow Hohmann (2018).

[18] All data download, cleaning, and aggregating operations, including spatial and zonal calculations, are performed in R version 4.1.0 by way of the `tidyverse`, `sf`, `raster` and `exactextractr` packages.

1.D Remotely-sensed spatial inequality measurements

Our fourth and final set of variables capture measures of spatial inequality, which represent one of the latest developments in the use of remotely sensed socioeconomic data. In particular, we exploit the Li et al. (2020) harmonized NTLs dataset described in section 1.B in conjunction with the recently released LandScan dataset (Oak Ridge National Laboratory, 2019), a 1Km^2 pixel-level raster population database covering 2000-2018, and the Gridded Population of the World v3 (Center for International Earth Science Information Network-CIESIN-Columbia University et al., 2005) dataset, a 4.6Km^2 pixel-level raster population database for the years 1990 and 1995. We calculate 1Km^2 pixel level NTLs sums for 1992-2018 from the Li et al. (2020) dataset, and population counts for 1990, 1995 and 2000-2018 using LandScan and GPW v3 and calculate population counts for 1992-1994 and 1996-1999 by linearly interpolating population values from 1990 to 1995 and from 1995 to 2000. This results in a pixel-level population and nightlights panel dataset comprising over 10 million observations for the countries in our sample.

To obtain remotely-sensed measures of inequality, we employ the procedure described in Elvidge et al. (2012) and further refined by Mirza et al. (2021) as follows: we first calculate average lights per person (LPP),[19] by dividing pixel-level NTLs by pixel-level population counts; we then calculate inequality in the distribution of LPP for each administrative units by calculating Gini coefficients for the range of pixels contained in each administrative unit in our sample. Figure C1 in Appendix C presents results on the distribution of the inequality at the administrative level for the year corresponding to the last census wave available.

2. Services in African Structural Transformation

Structural transformation in many African countries has a distinct pattern. The decline in agricultural employment has been argued to have been accompanied by increases in industries often characterized by low productivity (McMillan et al., 2014), with relatively few large, export-

[19] As in Mirza et al., (2021) we first censor both pixel-level NTLs and population in order to exclude zeroes, an operation which prevents placing excessive weight on uninhabited regions or places without detectable NTLs.

oriented manufacturing companies that have not created significant employment. Most African firms are small and medium sized, and often are informal (Hagen Kruse et al.).[20]

The shift towards services is evident in our sample of subnational units in Africa, too. Figure 4 plots decadal changes in employment shares across the three major sectors – primary, secondary and tertiary.[21] It shows that the drop in primary activities goes mostly hand in hand with an increase in services. Importantly, this pattern of services constituting a major source of employment growth is consistent across our sample, i.e. independent on the stage of development (e.g. Egypt vs. Malawi) or on the presence of natural resources (Botswana vs. Benin). The data also reveal that the share of the secondary sector generally increases during the period, with many instances in which employment shares in the secondary sector increase from an initial low base, offset by instances where administrative units with initially high shares of secondary sector employment experience a reduction in over time. Most of the instances where the share of industry increases are in the lower tail of the scatterplot. Conversely, administrative units where industry (the secondary sector) accounts for more than 25 percent of employment in the first wave often see a decline, consistent with Rodrik (2016). Appendix Figure C2 replicates the scatter plot for agriculture, manufacturing and services, showing a virtually identical picture as Figure 4.

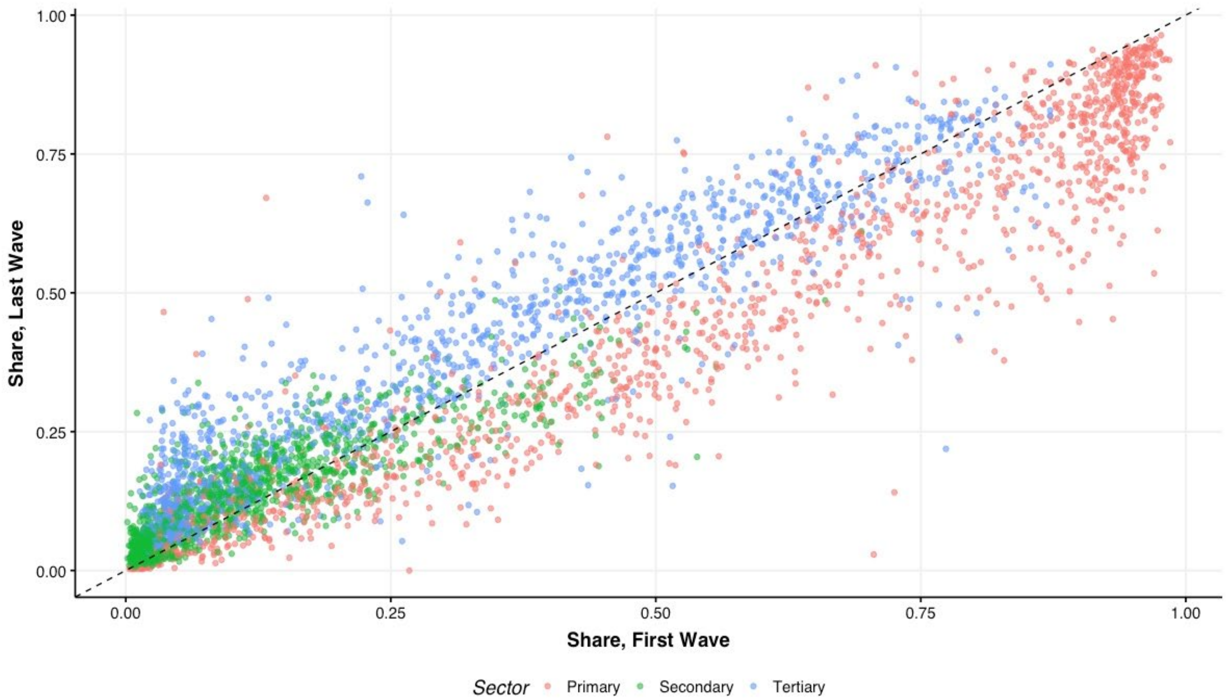
The fact that we observe increases in the share of industrial employment in many administrative units suggests secondary sector activities demonstrate dynamism. Whether these activities can grow the share of industrial employment over time is of course an open question. An important research (and policy) question suggested by these descriptive data is what drives the growth in secondary activity at the lower end of the distribution, and whether and how it is distinct from the economic activities that are associated with instances of administrative units that report high shares of industrial employment in the first wave and lower shares in the second wave.[22]

[20] For instance, a recent work by Diao et al. (2021) shows that manufacturing employment in Ethiopia and Tanzania is mostly determined by small and informal firms with stagnant productivity growth.

[21] Primary spans agriculture and mining; secondary includes utilities, manufacturing and construction; tertiary spans all services sectors.

[22] These data pertain to shares and are not informative about the associated absolute levels of employment in a given sector of interest.

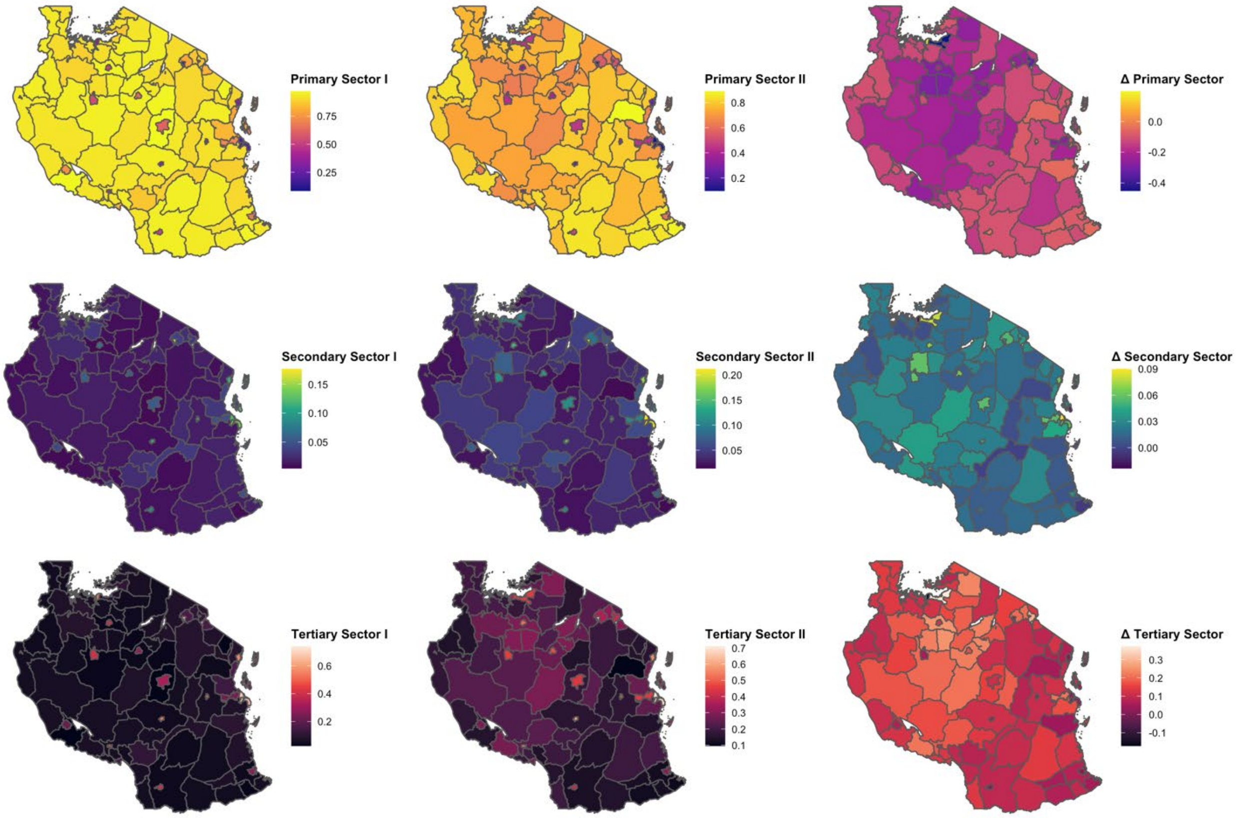
Figure 4. Structural transformation at the sub-national level



Note: Each dot represents an administrative unit that is observed over two successive waves of the census.
Source: Author's elaboration on IPUMS.

The online Appendix provides country specific maps plotting changes in sectoral employment over time. An illustration of these maps is provided in Figure 5, reporting data for Tanzania. It shows how structural change happened across administrative areas within the country over the decade spanning the two most recent population censuses (2002 and 2012). With the exception of a few areas, including the capital and other important cities, the rest of the country has been characterized by drops in the share of agricultural employment that went together with an increase of employment within the services sectors. As is the case for the sample overall (Figure 4), there is also an increase in the share of the secondary sector.

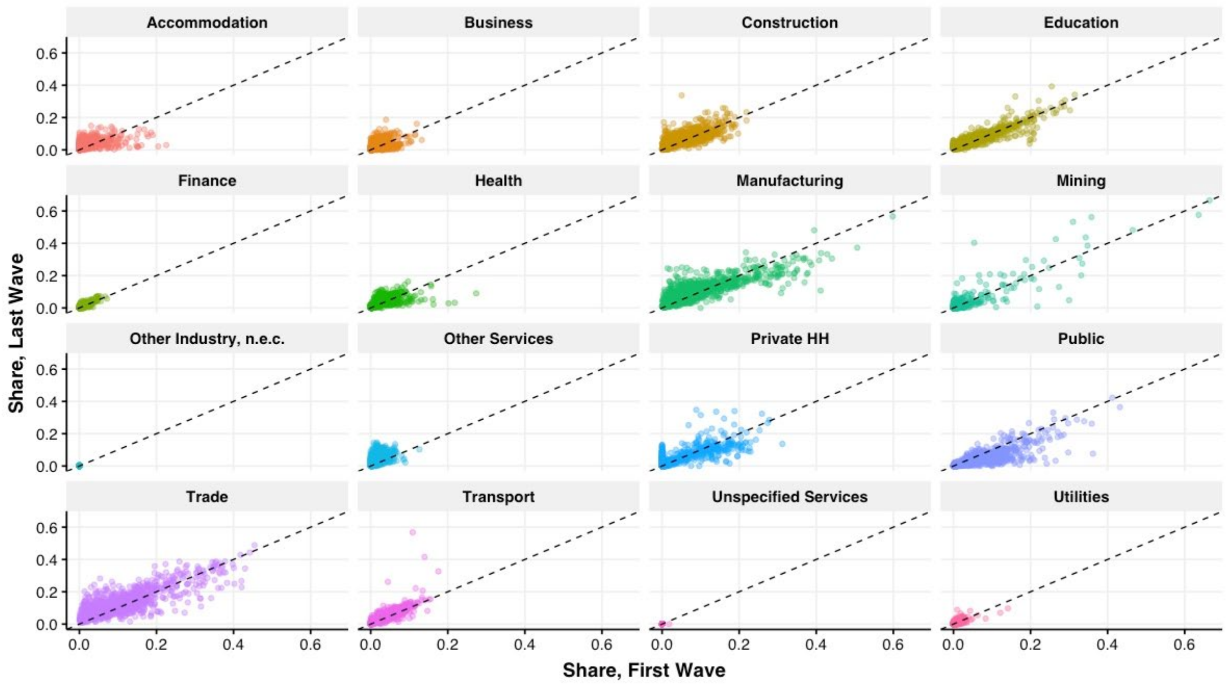
Figure 5. Sectoral dynamics in Tanzania between 2002 (I) and 2012 (II)



Note: the maps report administrative units' share of employment in the three main sectors. The first column reports maps covering the first (I) wave of the census (2002); the second column the next (II) wave; and the third column the difference between the two periods.
Source: Author's elaboration using IPUMS.

Figure 6 reports details for each of the 2-digit industries belonging to the services sector, in addition to other sectors for comparison. Again, all the graphs report information for the entire database and show changes that occurred in the most recent wave compared to the prior one. A few industries within services appear to explain the trends observed in the previous figure. This is most visible in the case of trade. Other services activities (e.g. business and financial services) also rise, but since they start from a very small base, their growth is more difficult to assess through visual inspection. Country-specific figures, reported in the online Appendix show interesting heterogeneity across sectors over time (e.g. a visible drop in public sector employment in Botswana, Tanzania and South Africa).

Figure 6. Structural transformation at the sub-national level: sector specific data



Note: Each dot represents an administrative unit that is observed over two successive waves of the census. Agricultural sector is excluded to allow a better visualization of smaller industries (given that all industries share the same values in the Y-axis).
Source: Author's elaboration using IPUMS.

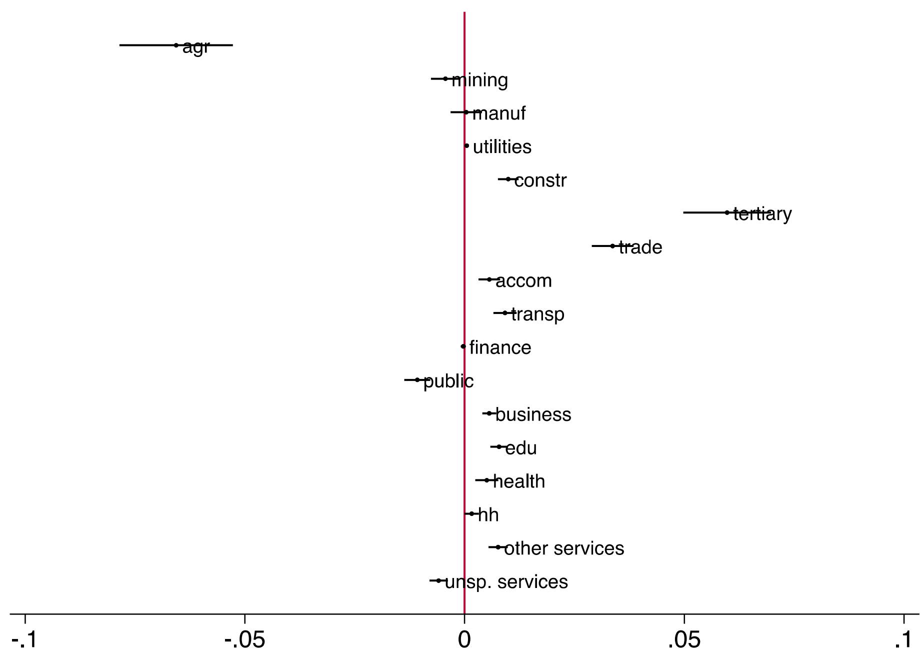
Premature de-industrialization and the rise of services at the sub-national level

To get a better sense of the trends discussed above and the rate of change we replicate a specification proposed by Rodrik (2016) and adopted in other papers (Hagen Kruse et al. 2021), linking sectoral employment to time trends, as follows:

$$Emp\_share_{it} = \beta_0 + \beta_1 pop_{it} + \beta_2 pop_{it}^2 + \beta_3 ntl\_pc_{it} + \beta_4 ntl\_pc_{it}^2 + \theta_i D_i + \gamma_t post\_2000_t + \varepsilon_{it} \quad (1)$$

where the dependent variable is the employment share in agriculture, manufacturing and in all the industries comprising services. All regressions control for both demographic factors and income by means of the inclusion of (log) population and per capita night light and their squared terms, as well as for location i (administrative unit) fixed effects. The variable of interest is γ_t, which takes the value of 1 if the survey was run after 2000 and 0 otherwise. The estimated coefficient of this dummy gives us the size of the common shock to all sectors considered in the post-2000 period relative to pre-2000. Results are summarized in Figure 7, which reports the estimated γ_t using coefficients for all the regressions considered. Full results are reported in Appendix Tables A1 and A2. This exercise reveals the drop in agricultural employment has been substantial. On average, across all administrative units, agricultural shares of employment experienced a 6.6 percentage point (p.p.) decline compared to the pre-2000 period. While the changes in manufacturing have been substantially zero, the tertiary sector as a whole has shown an average increase of almost 6 p.p. Within the tertiary sector most industries grew compared to the previous decade. The trade sector records the greatest increase, while the relative size of the public sector shrinks.

Figure 7: Time trends across sectors



Note: Each point is the estimated γ_t, along with its 90% confidence interval, of different specifications based on equation (1).

Correlates of services employment

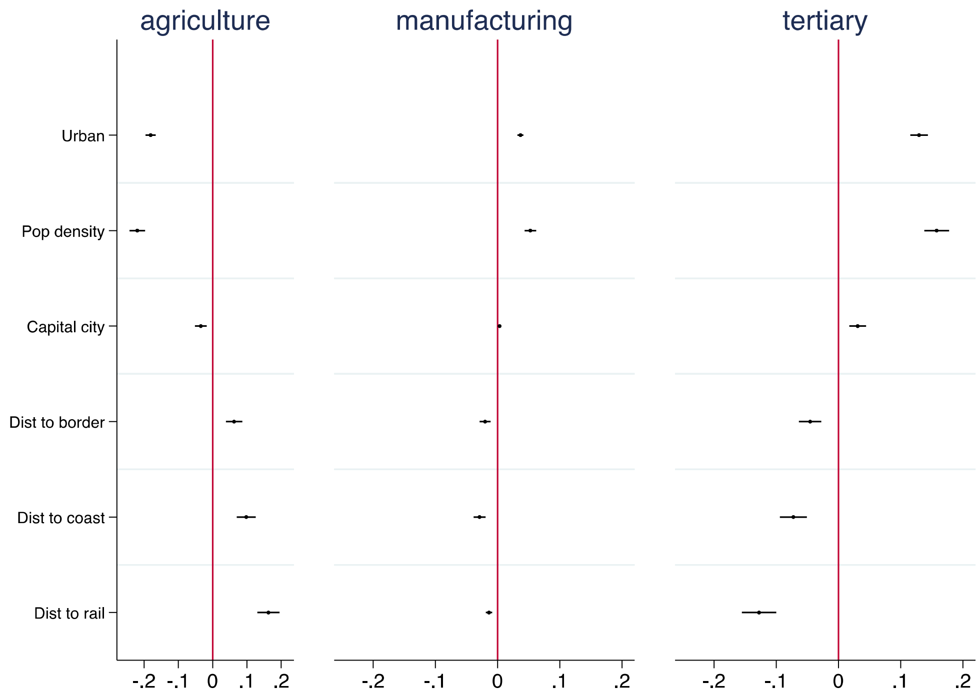
To explore whether the distribution of employment across sectors is correlated with specific characteristics of administrative areas, we exploit information on: (1) urbanization, measured as the share of the population living in urban areas; (2) population density; (3) a dummy indicating whether the area hosts the administrative capital of the country; and (4) the distance from the district centroid to the nearest border, coast and colonial railroad. Data on the first three variables are taken from the census data, while the distance measures are from Alesina et al. (2021). The technical Appendix provides detailed definitions of the variables considered, along with their summary statistics.

The variables we examine here are mostly related to historical and geographic factors identified by the existing literature as relevant drivers of African long run economic development (see Michalopoulos & Papaioannou (2020), for a review). By shaping the direction of economic development, these factors might have determined the distribution of economic activities, and hence been linked with the contemporaneous size of certain types of services. The correlations presented below are useful indicators of potential drivers of services development, but the analysis does not imply anything about causal identification. Results, based on unconditional estimates accounting for country and wave fixed effects are summarized in Figures 8 and 9. Figure 8 plots the major differences across the three main sectors of the economy. Figure 9 reports results for specific services. All coefficients are standardized to facilitate comparison across the different estimations.

For each variable there is a (symmetric) difference between agriculture and the other sectors, which is more evident for services than for manufacturing. The characteristics of the administrative units appear to shape the distribution of economic activities within each country. Services (and, to a lesser extent, manufacturing) are more concentrated in urban areas, and in more densely populated parts of the country, including in particular areas in and around the capital city, where most administrative activities are concentrated.[23] Similarly, connectivity matters. Services employment is less likely to be high in areas far away from, in order of relevance: a border, a coast (where most of external trade happens) and a (colonial) railway. Surprisingly, these variables seem to matter less (though they keep the expected sign) for the location of manufacturing employment.

[23] Public sector jobs in capital city are on average more than two times larger than in other areas of the country.

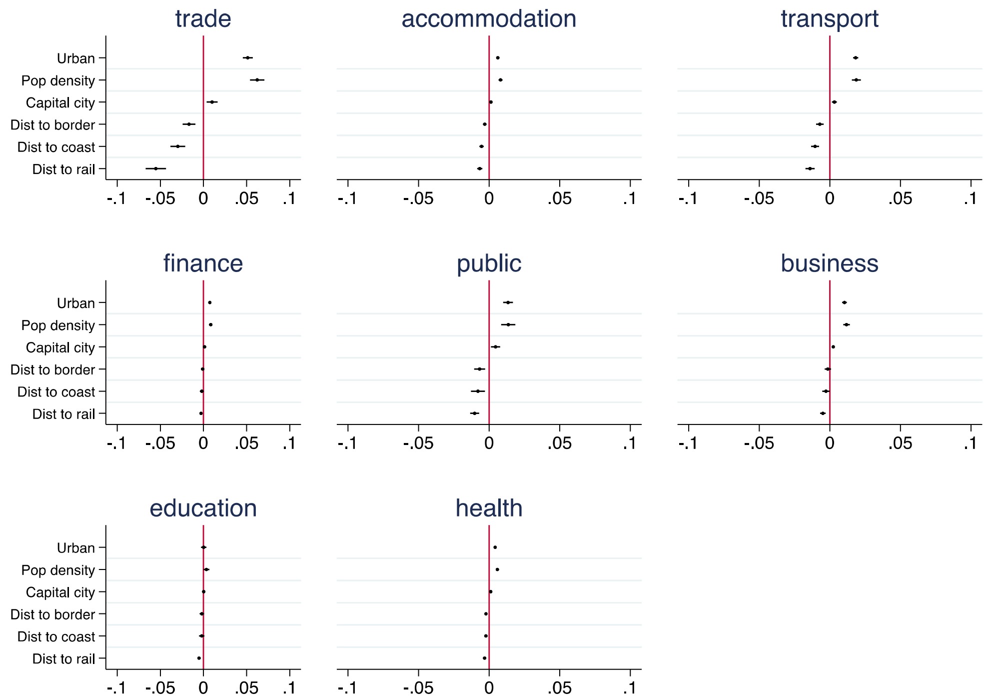
Figure 8. Correlates of sectoral employment



Note: Each point is the estimated coefficient, along with its 90% confidence interval, of a specification in which the outcome of interest (the share of employment in agriculture, manufacturing and services) is regressed against one of the following variables: urban (the share of urban population on total within each district); pop density (the ration of a district's population on its area); capital city (a dummy taking 1 if the district hosts the administrative capital of the country); dist to border (the log of the distance, in km, from a district's centroid to the closest border); dist to coast (the log of the distance, in km, from a district's centroid to the closest coast); dist to rail (the log of the distance, in km, from a district's centroid to the closest colonial railroad). All regressions include country and wave fixed effects, and standard errors are clustered at the district level.

Figure 9 reports the same correlations for specific services industries. Most of these industries tend to show the same pattern observed for the tertiary sector as a whole (Figure 8). There is however some heterogeneity that it is possibly worth highlighting. Trade and transport activities are most likely to be clustered in more densely populated and urban areas, and in better connected ones. On the other hand, geography seems to matter less for public services such as health and education.

Figure 9. Correlates of sectoral employment within services



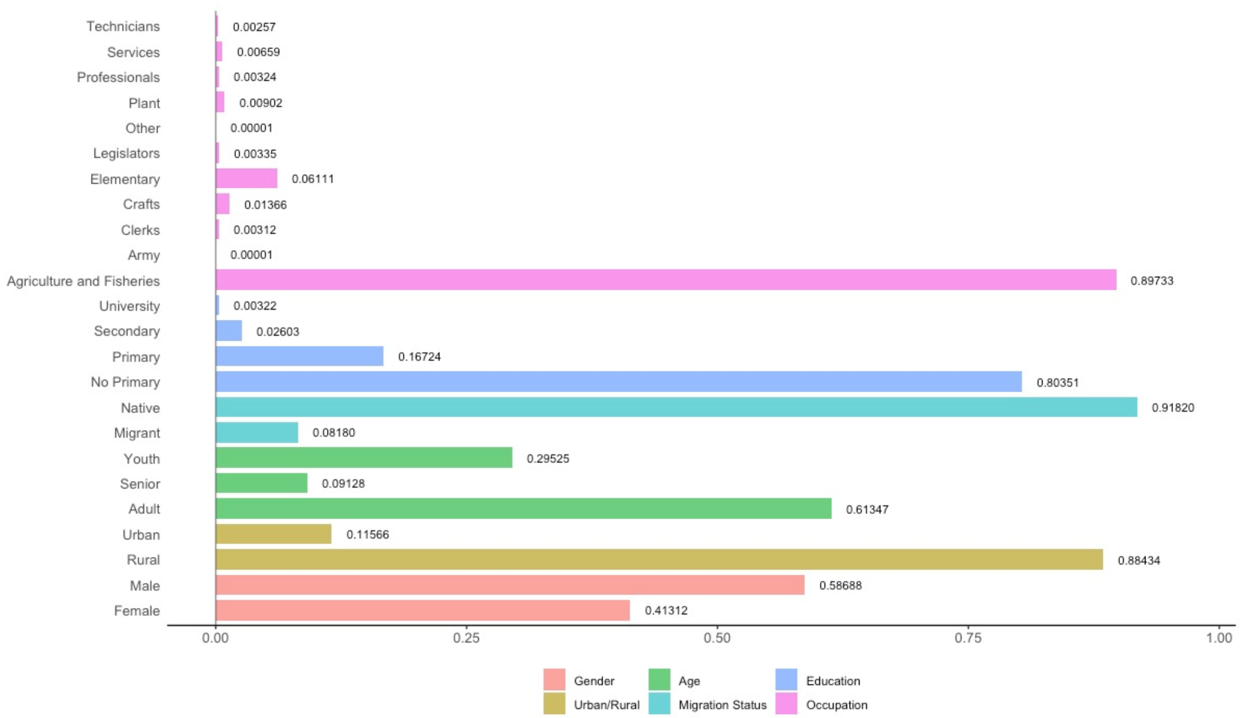
Note: Each point is the estimated coefficient, along with its 90% confidence interval, of a specification in which the outcome of interest (the share of employment in each of the services industries reported) is regressed against one of the following variables: urban (the share of urban population on total within each district); pop density (the ration of a district's population on its area); capital city (a dummy taking 1 if the district hosts the administrative capital of the country); dist to border (the log of the distance, in km, from a district's centroid to the closest border); dist to coast (the log of the distance, in km, from a district's centroid to the closest coast); dist to rail (the log of the distance, in km, from a district's centroid to the closest colonial railroad). All regressions include country and wave fixed effects, and standard errors are clustered at the district level. Regressions on undefined industries (other and unspecified services) are not included.

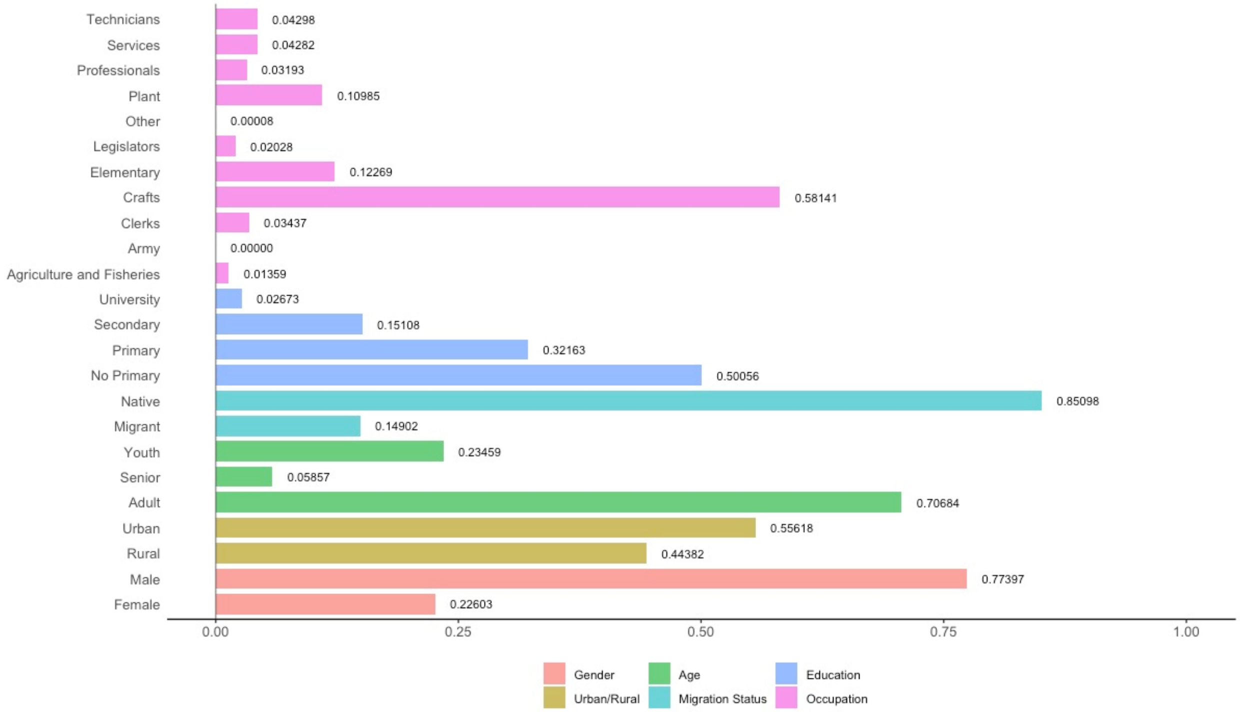
Who works in services?

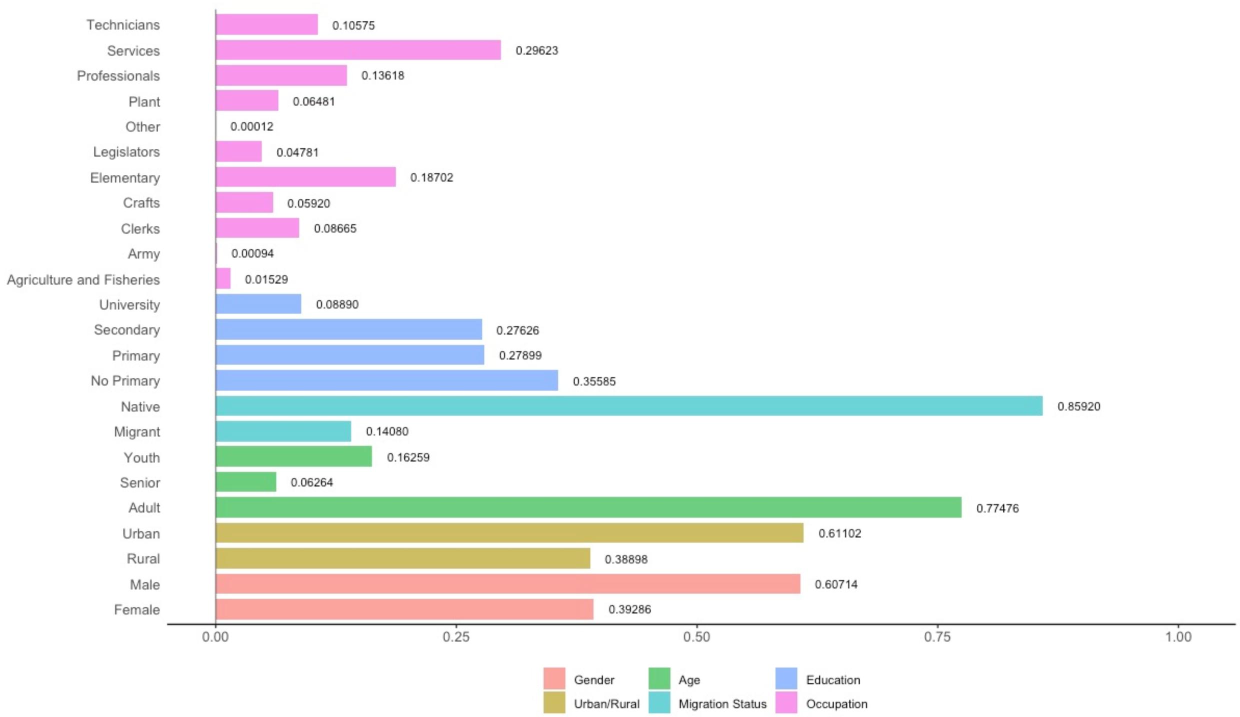
While services are important sources of employment in Africa, surprisingly little is known about their characteristics as well as their composition. For instance, previous research has shown that heterogeneity across services in terms of both skills and productivity plays a role in explaining cross-country differences in economic growth (Buera & Kaboski, 2012; Duarte & Restuccia, 2020). How much of this heterogeneity can be identified with the existing data, and how does it help to identify the potential contribution of sectors and industries to economic development?

In this section, we provide a snapshot based on the individual information available from IPUMS regarding the characteristics of people employed in services. We focus on the following characteristics: gender; urban/rural residence; age cohorts; migration status; education and occupation. Data were collapsed over the latest two waves. Figure 10 summarizes the average values across all the countries included in our sample. Some patterns emerge with respect to the type of occupation (some of the more skilled ones are concentrated in the tertiary sector) and education. Regarding the latter, 8.9% of those employed in the services hold a university degree (2.8% in manufacturing) and 27.6% have a secondary school level (15.1% in manufacturing). Services employ a relatively higher share of women, some 40%, almost double that for the secondary sector. On the other hand, industry and services show relatively similar patterns in terms of the share of migrant workers employed (around 14% of the workers are internal migrants). Finally, younger cohorts of workers are less represented in services, compared to both the primary and secondary sectors.

Figure 10. Sectoral composition (%) by groups for primary (top panel); secondary (middle panel) and tertiary activities (bottom panel)







Source: Authors’ elaboration on IPUMS

The online Appendix provides all the possible decompositions of the previous graphs by industries and country-industry pairs. As far as the industries within services are concerned, education, public administration, financial and business services employ a relatively large share of high educated individuals. Private household services, health and accommodation are female-dominated activities. Again, the majority of services industries employ a low share of youth or migrants.

Occupations

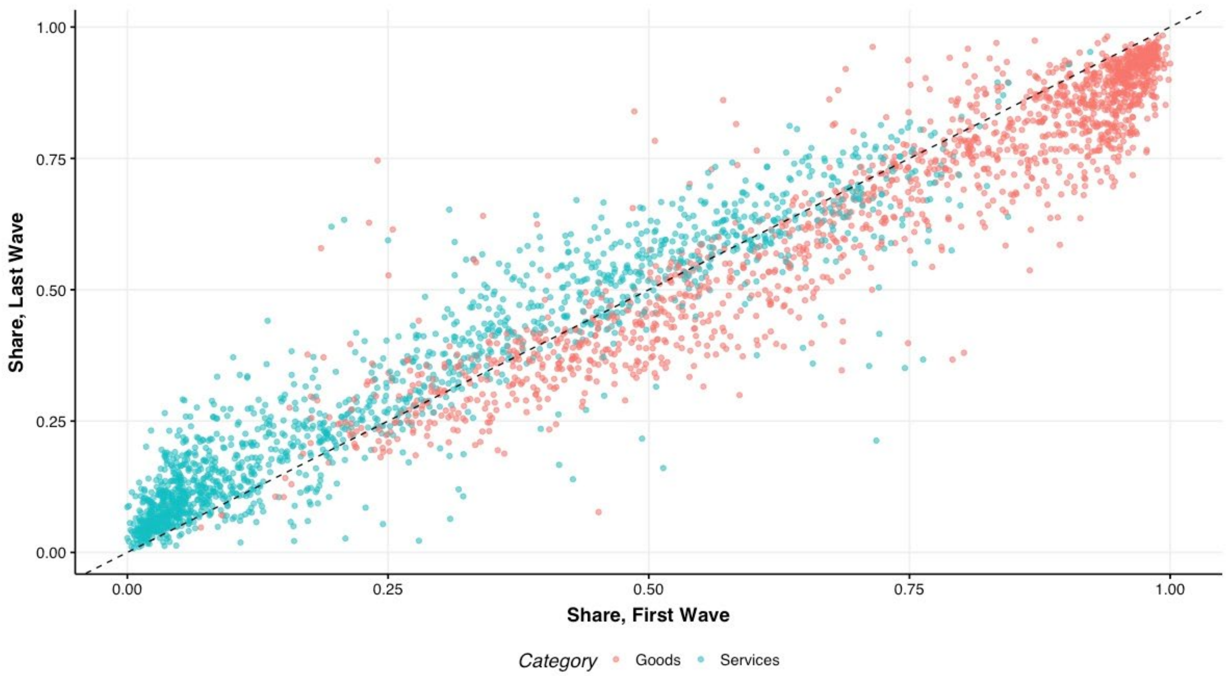
There is a rising emphasis on the role of occupations as opposed to industries or sectors in the literature on structural transformation (Lagakos & Shu, 2021). Industries are not necessarily precise categories. For instance, individuals formally employed in the manufacturing sector might perform services-related functions. There is evidence of this potential misclassification from developed countries (Berlingieri, 2014), and data shown in the previous section seem to confirm that this is an issue that can also be relevant in our sample of African countries (for instance, fig. 10 shows that some of the workers formally employed in the manufacturing sector are in fact performing service-related occupations as clerks, professionals or technicians, or craft workers in the services).

Duernecker & Herrendorf (2020) have proposed a distinction between categories of occupations that broadly map into the traditional distinction among the main economic sectors, although they are not necessarily attached to a specific sector. The categories are (1) *goods occupations*, which are related to the production of *tangible* value added; and (2) *services occupations*, which are related to the production of *intangible* value added. Employing census data for a large group of (developed and developing) countries, they show that the typical pattern of structural transformation (i.e. an increase in services as GDP per capita grows) holds also when using such classification. Given that they employ the same data we use in this report, we can replicate their exercise for our sample, and check whether results remain consistent.[24] Figure 11 shows that this is indeed the case. The shift towards intangible activities is evident for the last decades, and this pattern seems true for almost all the individual countries in our sample, with the exception of Benin

[24] Concerning our sample, goods occupations include agriculture and industry (elementary, crafts and plant) occupations. Services occupations include the following: armed forces; clerks; elementary services; legislators; professionals; services; technicians.

and Mali. In these two countries, while services are on the rise, goods occupations –especially those related to agriculture—have also kept going up over the last decade.

Figure 11. Structural transformation at the occupational level



Note: Each dot represents an administrative unit that is observed over two successive waves of the census.
Source: Author's elaboration on IPUMS

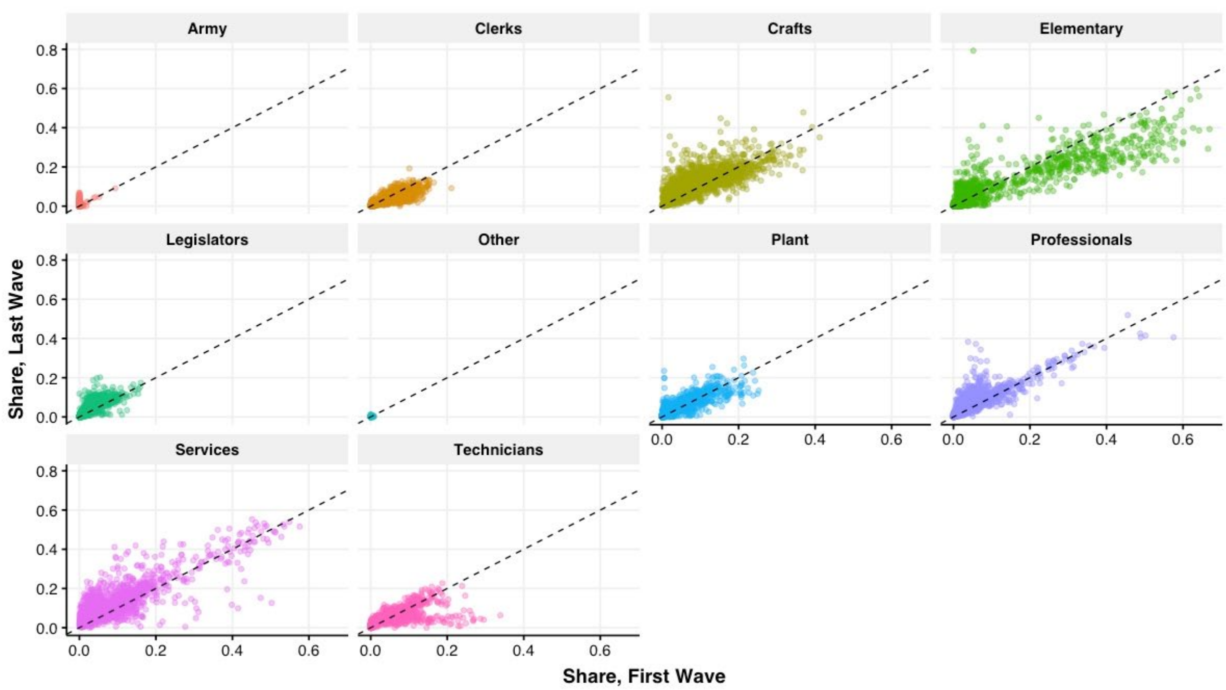
The results plotted in Figure 11 suggest that the increases in the shares of secondary sector employment registered by many administrative units reported in Figure 4 involve intangible (services) occupations. To check if this is the case, we run two exercises. First, we replicate Figure 11 with data relative to the manufacturing sector only.[25] Doing this allows us to observe more clearly that service occupations are growing the most in relative term during the most recent decade (see Figure C3 in Appendix C). Second, we run a simple regression in which we link changes in sectoral employment to changes in specific types of occupation. For the manufacturing sector, we find that a 1 percentage point increase in intangible occupations correlates with employment

[25] Considering the whole sample, the share of services (goods) occupations among those employed in manufacturing is about 30% (70%).

growth (see Table A3 in Appendix A), while this is not the case for tangible occupations.[26] This pattern would be consistent with the general trend towards servicification of economic activity in manufacturing (e.g., Beverelli et al. 2017). Insofar as this is the case, it may be one factor explaining the patterns of growing and declining shares of secondary sector employment observed across administrative units in the 13 countries in our sample. This is a question where further research using more granular information and firm-level data is needed.

Figure 12 plots changes in each occupation covered in our data for the whole sample of countries and over the last two decades. We observe a drop in elementary types of occupations, and a rise of those generally accounted for as high-skilled, such as professionals, managers (the "legislators" category) and other services occupations.

Figure 12. Occupation specific change



Source: Author's elaboration on IPUMS
Note: Each dot represents an administrative unit that is observed over two successive waves of the census. The agri-fish occupation is excluded to allow a better visualization of smaller occupations (given that all share the same value in the Y-axis).

[26] Running the same regression on agriculture and services reveals that changes in employment shares are strongly correlated with the two types of occupations, tangible and intangible.

3. Clustering services

Economic characteristics, such as tradability, potential productivity growth, economic spillovers, scalability, and skill intensity can vary substantially across services activities. The literature suggests several approaches to cluster individual services sectors in terms specific properties depending on the relevant application. Research on services and global value chains, including the spillover-effects of services trade policy to downstream industries that use services as intermediate inputs, focus on the group of so called "production" or "producer" services. This includes R&D, financial, business, transport, telecommunication and wholesale trade services, which are used as inputs in virtually all modern production processes (Markusen, 1989; Francois, 1990; Beverelli et al., 2017). Fan et al. (2021) test the hypothesis of services-led growth in India using a structural model that explicitly distinguishes between consumer and producer services, dividing services sectors in two categories depending on whether their output is absorbed more by consumer demand or downstream production. An alternative approach is taken by Eckert et al. (2020), who investigate the drivers of urban bias growth in the US by identifying a cluster of "skilled, scalable" services based on each sector's reliance on high skilled-labor and ICT capital. This group includes professional, scientific and technical services; management services; information services and financial services. Eckert et al. (2020) show that US cities' comparative advantage in skilled services is a factor behind higher growth in urban areas.

As we are interested in the relationship between services and economic development, we propose to cluster services sectors in terms of employment characteristics which are both measurable in our data and relevant for economic development. These are: i) intensity in high skilled-labor, as captured by the share of employees with a university degree in a sector; and ii) intensity in complex occupations, measured through the share of legislators/senior officials/managers, professionals and technicians employed in each sector.[27]

[27] The shares are computed at the level of the whole sample. Education categories in the data are identified using IPUMS classification and include: less than primary; primary; secondary; and university. Occupational categories listed by the IPUMS classification are: legislators, senior officials and managers; professionals; technicians and associate professionals; clerks; service workers, shop and market sales; skilled agriculture and fishery workers; crafts and related trade workers; plant and machine operators and assemblers; elementary occupations; armed forces; other

Figure 13: Services sectors, skills and occupations

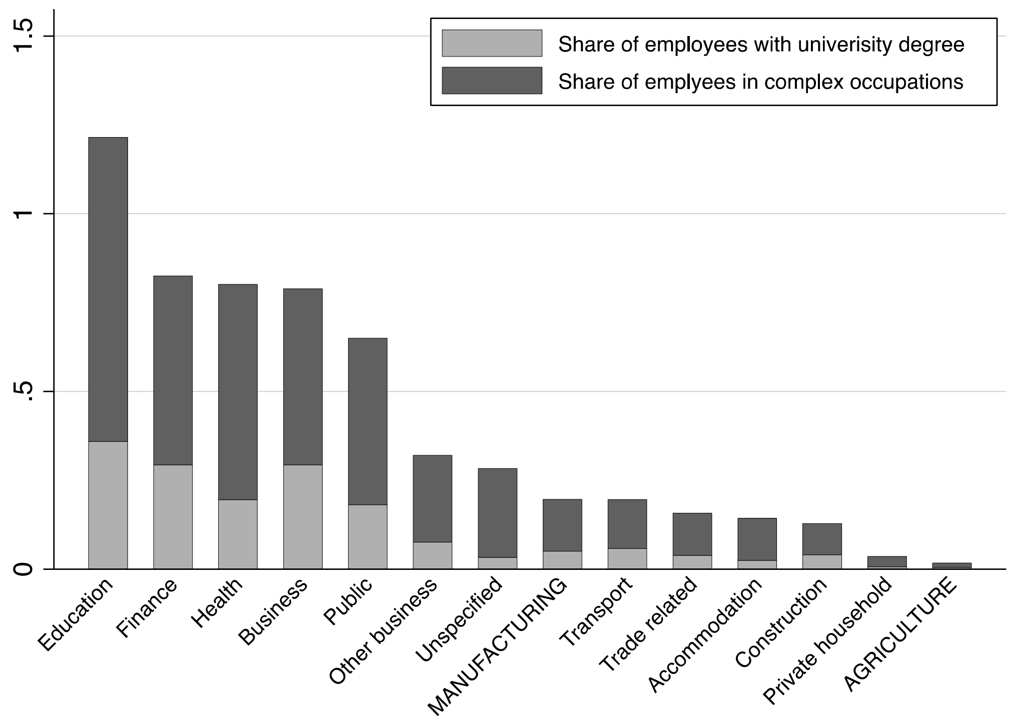


Figure 13 plots all services sectors identified in our database ranked in terms of the share of high skilled workers and complex occupations. The chart also reports the same figure for manufacturing and agriculture. We use manufacturing as a divide to identify two groups of services sectors: the cluster of "high skilled, complex occupation" (high skills) sectors, including education, finance, health, business, public services, other business and unspecified services; and the cluster of "low skilled, simple occupations" (low skills) sectors, including transport, trade related, accommodation, and private household services. According to our metric, seven services sectors rely more on skilled-labor and complex occupations than manufacturing. Agriculture has the lowest high skilled labor and complex occupation intensity. While our approach is somewhat discretionary, within the framework of our application it is fairly robust to alternative definitions of the ranking used to identify the two clusters.[28]

occupations unspecified or nec. According to our definition we consider as complex occupation legislators, senior officials and managers; professionals; and technicians and associate professionals.

[28] We computed 12 other rankings based on the following metrics: 1. share of employees with university degree; 2. share of employees with university or secondary degree; 3. share of complex occupations; 4. share of complex occupation including clerks; 5. share of employees in resident in urban areas (urban workers); 6. share of employees with university or secondary degree plus share of complex occupations; 7. share of employees with university or secondary degree plus share of complex occupations plus share of urban workers; 8. share of employees with

4. Services and development

In this section, we report partial correlations between measures of economic development and services activities. The latter are variously measured by the share of workers employed in the service sector as a whole; employment in high skills services and low skills services, using the taxonomy developed in the previous section; and disaggregating services into 2-digit industries. We also show how interactions between service activities and other variables commonly associated with economic development—the presence of good institutions and of technology, for instance—correlate with growth. Finally, we report correlations between spatial inequality and service activities to explore to what extent services cluster in urban areas.

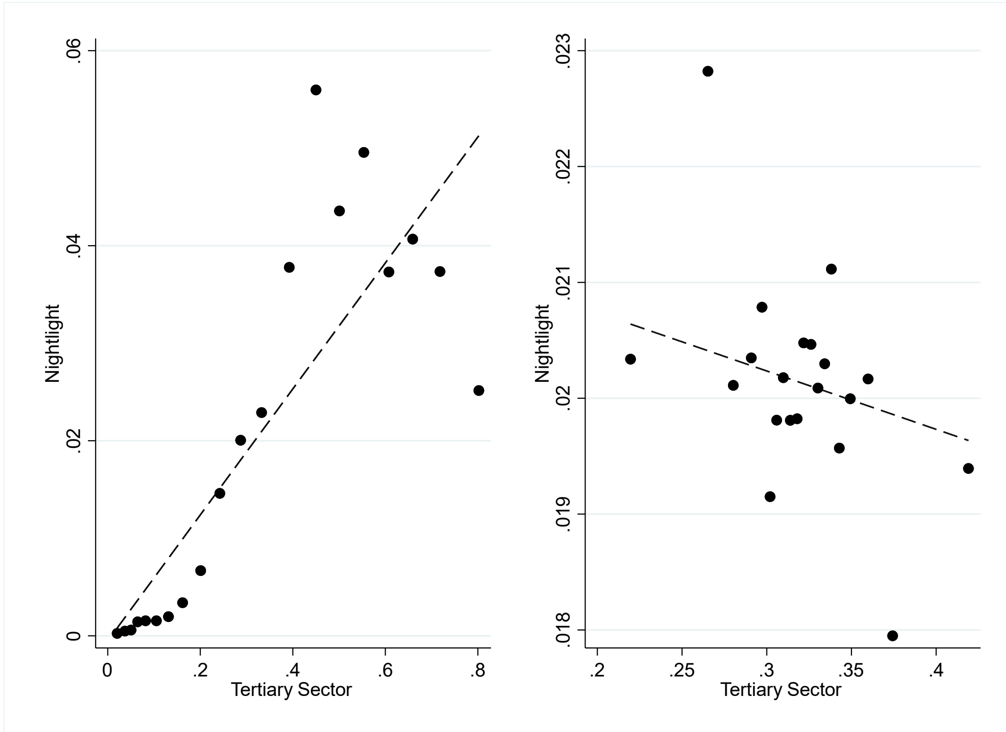
Baseline analysis

Before running multivariate regressions, Figure 14 shows correlations between nightlight *per capita*, our proxy of economic growth, and the share of the tertiary sector, using binned scatterplot. The panel on the left is a barebones correlation, whereas the panel on the right accounts for ADMIN and wave fixed effects. The take away messages are clear-cut: 1) there is a strong positive association between growth and services *across* administrative units; and 2) there is a negative (weaker) correlation between growth and services *within* units.[29]

university or secondary degree plus share of complex occupations including clerks; 9. share of employees with university or secondary degree plus share of complex occupations including clerks plus share of urban workers; 10. share of employees with university degree plus share of complex occupations plus share of urban workers; 11. share of employees with university degree plus share of complex occupations including clerks; 12. share of employees with university degree plus share of complex occupations including clerks plus share of urban workers. If we take the average score across all 13 rankings, the 7 high skills sectors correspond to the 7 highest ranked sectors according to the average ranking.

[29] In Appendix B, we report the same figures for the primary and secondary sector (Figures B1 and B2). There is always a negative (positive) correlation between nightlight and primary (secondary) sector with our without fixed effects.

Figure 14 Correlation between nightlight and share of the tertiary sector



Note: binned scatterplot. The graph on the left shows a simple correlation. The graph on the right shows correlations accounting for ADMIN and wave fixed effects.

We begin our reduced form analysis by estimating the following baseline model:

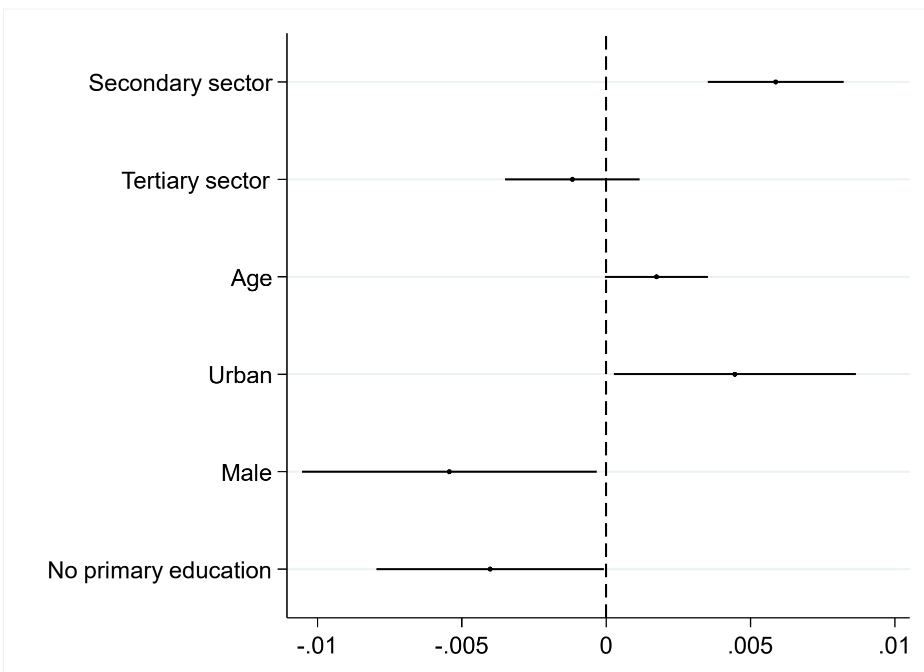
$$Nightlight_{it} = \alpha + \delta_i + \tau_t + \beta_1 Secondary\ Sector_{it} + \beta_2 Tertiary\ Sector_{it}$$
$$+\beta_3 Z_{it} + \varepsilon_{it}, (2)$$

where nightlight *per capita* is the outcome, i.e. sum of nightlights in a ADMIN divided by its population.[30] We observe this outcome in each ADMIN *i* and in each wave *t*. *Secondary Sector* and *Tertiary Sector* are share of worker employed in respectively industry and services in each ADMIN and in each wave. Thus, the share of workers employed in the primary sector is the baseline category in these regressions. Z is a matrix including our controls (share of people living in urban areas, share of male population, average age in an ADMIN, and share of people without primary education), δ and τ are ADMIN and wave fixed effects, and ε are the residuals.

[30] Our results are similar if we rely on the measure of nightlight created by Li et al. (2020) (see Appendix Figure B3 and B4).

We run OLS regressions weighted by population. We cluster the standard errors at the level of the ADMIN unit. For ease of comparison among covariates, we standardize all the right hand-side variables.[31] We report here only the results of the baseline model. Appendix B reports all model specifications, i.e. with and without fixed effects as well as with and without controls (see Table B1). The estimation sample includes around 3,000 observations, depending on the model. Our unit of analysis is district-census wave. The results of this baseline model are reported in Figure 15. Regions with a large share of workers employed in the secondary sector grow significantly faster that regions with a large share of workers employed in agriculture. There is no significant association between share of the tertiary sector and economic growth. Education and urbanization are positively associated with growth, while the share of male population is negatively associated with growth. Overall, we find little evidence that the service sector as a whole is an engine of economic development in African countries.

Figure 15 Main results by sector



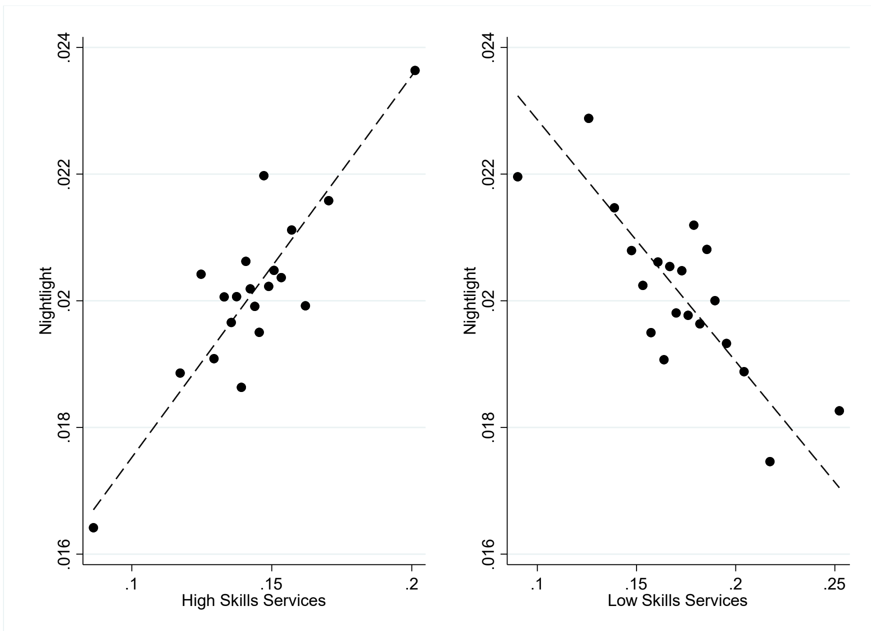
Note: OLS regression weighted by population with standard errors clustered by ADMIN units. The outcome variable is nightlight *per capita*. The model includes ADIMN and wave fixed effects. The number of observations is 2,909 and the R^2 is 0.965. 90% C.I.

[31] All the relevant outcome variables and independent variables are described in Section 1 above.

By macro service clusters

These foregoing findings may reflect the heterogeneity within the service sector. Distinguishing between high skills services and low skills services, using the categorization developed above,[32] Figure 16 reports correlations between nightlights *per capita* and high skill services and between nightlight *per capita* and low skills services, using binned scatterplot and accounting for ADMIN fixed effects. The panel on the left indicates a strong positive association between growth and high skills services, the panel on the right shows a strong negative association between growth and low skills services.

Figure 16 Correlation between nightlight and high skill/ low skills services



Note: binned scatterplot. The graph on the left shows a correlation between nightlight and high skills services. The graph of the right shows a correlation between nightlight and low skills services. Both correlations account for ADMIN and wave fixed effects.

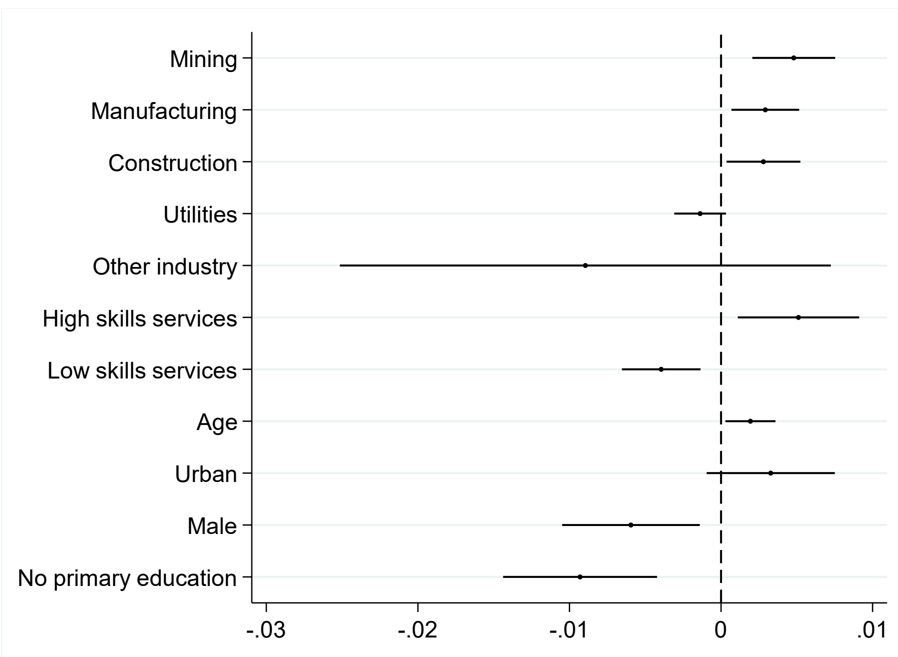
We investigate these associations more systematically, using the following model specification:

$$Nightlight_{it} = \alpha + \delta_i + \tau_t + \beta_1 Mining_{it} + \beta_2 Manufacturing_{it} + \beta_3 Utilities_{it} + \beta_4 Other\ Industry_{it} + \beta_5 High\ skills\ Services_{it} + \beta_6 Low\ skills\ Services_{it} + \beta_7 Z_{it} + \varepsilon_{it}, \quad (3)$$

[32] High skills services include education, finance, health, business, public, other business, and unspecified services, which employ a larger share of workers either with higher education or performing complex occupations than manufacturing does. Low skills services include transport, trade, accommodation, and private household services, which employ less high-skilled workers than manufacturing does.

where all the main variables have been already described and the baseline category is share of workers employed in agriculture. The coefficients of interest are β_5 and β_6. We again run OLS regressions weighted by population with standard errors clustered by ADMIN units. All covariates are standardized. There is a positive significant relationship between economic growth and share of workers employed in high skills services (Figure 17).[33] The magnitude of the positive correlation is in line and in fact larger than the magnitude of the positive correlation between nightlight and manufacturing. On the contrary, there is a negative significant association between economic growth and share of workers employed in low skills services. These results help understand the null effect of the baseline analysis. Note that we account for the share of people with no primary education, which is negatively correlated with development. Thus, our macro service clusters are not a mere proxy of education in this model.

Figure 17. Main results: high skill services vs. low skill services



Note: OLS regression weighted by population with standard errors clustered by ADMIN units. The outcome variable is nightlight *per capita*. The model includes ADIMN and wave fixed effects. The number of observations is 2,909 and the R^2 is 0.967. 90% C.I.

[33] We report tables with all model specifications in Appendix Tables B1-B2.

By individual service industries

To determine which service industries are more associated with economic growth, we run our main model including 2-digit industries. In particular, the model specification is as follows:

$$Nightlight_{it} = \alpha + \delta_i + \tau_t + \beta_1 Mining_{it} + \beta_2 Manufacturing_{it} + \beta_3 Utilities_{it} + \beta_4 Other\ Industry_{it} + \beta_5 X_{it} + \beta_6 Z_{it} + \varepsilon_{it}, \qquad (4)$$

where X is a matrix including 2-digit service industries. We rely on the same model specification as for the previous analyses and we standardize all the covariates.

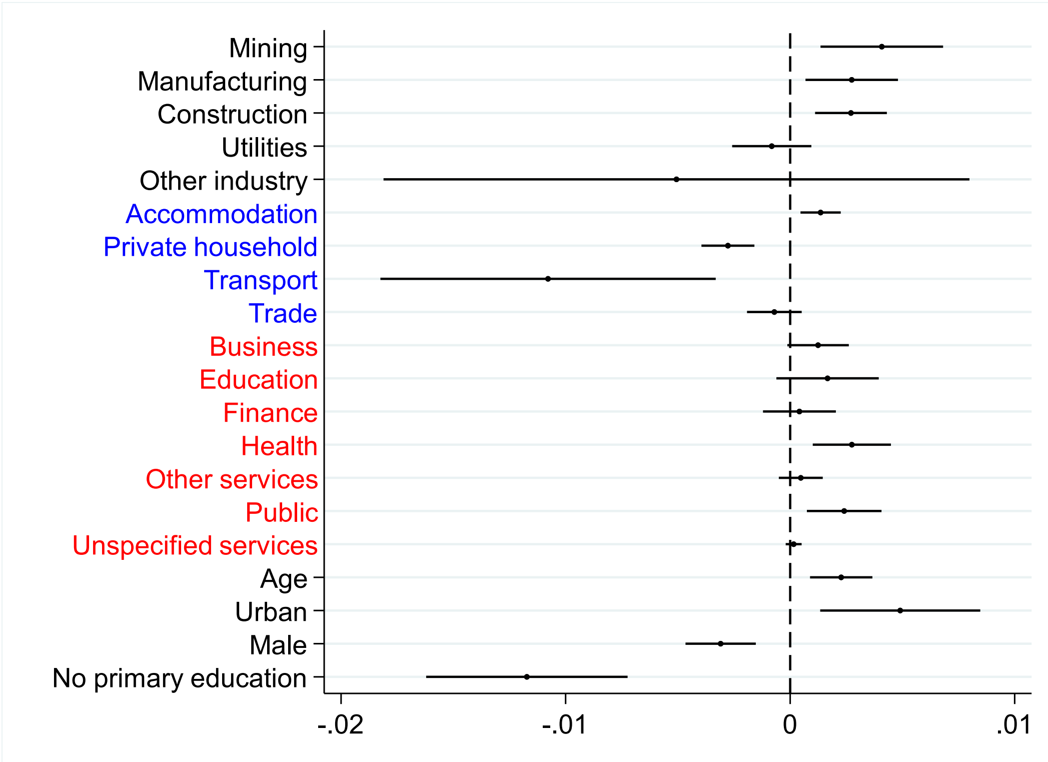
Figure 18 reports the results of this analysis.[34] To ease the reading of the results, high skills services are highlighted in red, whereas low skills services are highlighted in blue. Strikingly, all the high skill service industries are positively associated with economic growth, though only health and public services are significant. Conversely, private household services, transportation, and trade, which are low skills services, are negatively correlated with growth, though only the first two variables are significant. Accommodation, which are also low skill, are an exception, being correlated positively with growth. Concerns about strict reverse causality are severe in the case of these two industries, as they may be more an outcome of development rather than a driver. In sum, our categorization of service clusters based on the level of education and occupational complexity of their workers appears to explain patterns of development in these African countries.

Investigating heterogeneity across economic environments

The effect of services on development may be affected by heterogeneity across economic environments. We are interested in three dimensions of this heterogeneity: 1) the mediating effect of (lack of) economic activities at the baseline, which we capture with the incidence of malaria; 2) the mediating effect of natural resources, which we capture with the presence of diamond mines and oil extraction; 3) the mediating effect of technology, proxied by mobile phone coverage. The logic is to assess how heterogeneity in the economic environment mediates the effect of high and low skills services.

[34] Appendix Table B3 reports all model specifications.

Figure 18 Main results by industry



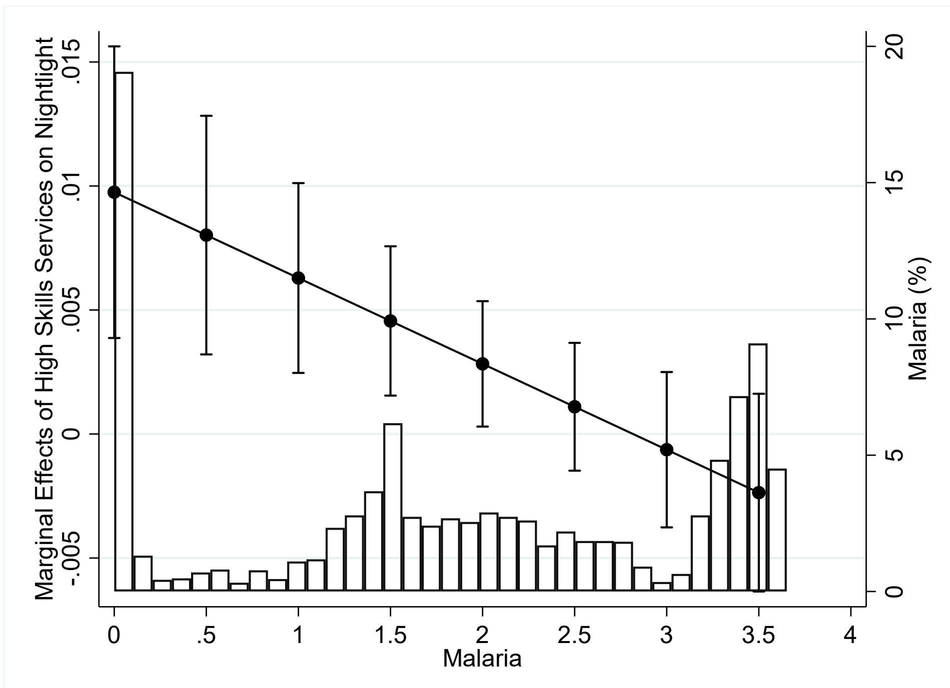
Note: OLS regression weighted by population with standard errors clustered by ADMIN units. The outcome variable is nightlight *per capita*. The model includes ADIMN and wave fixed effects. The number of observations is 2,909 and the R^2 is 0.972. 90% C.I.

To analyze this heterogeneity, we interact each mediating variable, e.g., the incidence of malaria, with share of high and low skills services as well as with the other industries, e.g., mining and manufacturing. We then run the same model specification as described in the previous analyses. That is, we include the same set of controls as well as ADMIN and wave fixed effects. We rely on OLS regression weighted on population, clustering the standard errors at the level of ADMIN units. To ease the interpretation of the interaction terms, we show the results graphically.[35] We focus on the interaction between high skills services and mediating variables. We start with the incidence of malaria, where low values correlate with thriving economic activities (Acemoglu, Johnson, and Robinson 2001).

[35] We report the figures with coefficients and confidence intervals in Appendix Figures B5-B7.

Figure 19 reports the marginal effect of high skills services on nightlight *per capita* for different level of incidence of malaria. The positive correlation between high skills services and growth is only significant for low incidence of malaria. On the contrary, for incidence of malaria (roughly) above the mean, the correlation between high skills services and growth is no longer significant, i.e. the line of the marginal effect crosses the 0. In sum, we find convincing evidence that the presence of economic activities at the baseline mediates the positive association between high skills services and development.[36]

Figure 19 High skills services and growth: Mediating effect of the incidence of malaria



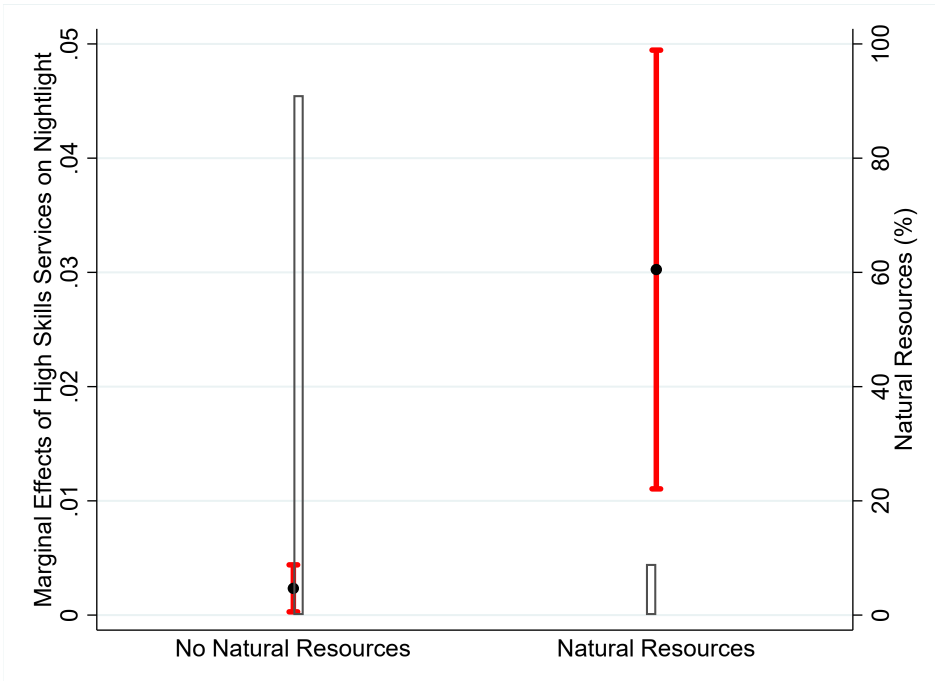
Note: OLS regression weighted by population with standard errors clustered by ADMIN units. The outcome variable is nightlight *per capita*. The model includes ADIMN and wave fixed effects. The number of observations is 2,829 and the R^2 is 0.970. 90% C.I.

Turning to the mediating effect of natural resources, we interact high skills services with a dummy scoring one if there is at least one mine of diamond in the ADMIN unit. Figure 20 reports the marginal effect of high skills services on nightlight *per capita* for units with and without mines of diamond. While the positive correlation between high skills services and growth is significant in

[36] Appendix Figure B8 shows that the incidence of malaria does *not* mediate the effect of manufacturing on development.

both regions with and without mines of diamond, the correlation is significantly stronger in regions with mines of diamond. This finding suggests that the presence of natural resources and related wealth provides the demand for the expansion of the high skills services, a result in line with Gollin et al. (2016).[37]

Figure 20 High skills services and growth: The mediating effect of natural resources



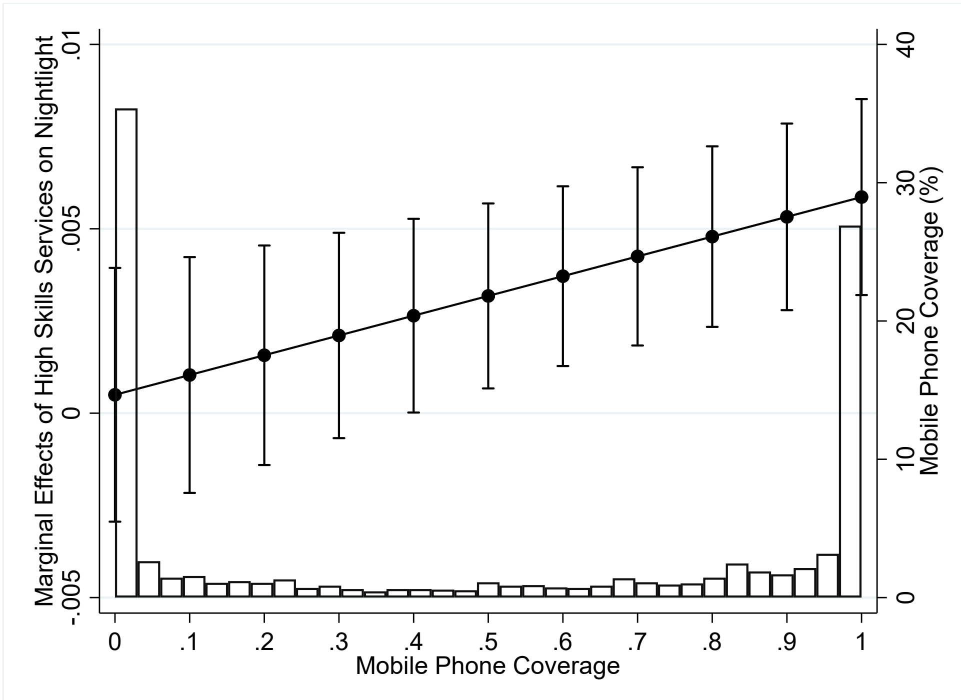
Note: OLS regression weighted by population with standard errors clustered by ADMIN units. The outcome variable is nightlight *per capita*. The model includes ADIMN and wave fixed effects. The number of observations is 2,811 and the R^2 is 0.966. 90% C.I.

Finally, we look at the mediating effect technology. Specifically, we interact high skills services with mobile phone coverage (Manacorda and Tesei 2020). The rationale is that technology provides the supply for the expansion of service activities. Figure 21 reports the marginal effect of high skills services on nightlight *per capita* for different levels of mobile phone coverage. The positive correlation between high skills services and growth is only significant for high values (i.e. roughly above the mean) of mobile phone coverage, whereas is not significant for low values of mobile phone coverage. This finding points to technology being an important

[37] Appendix Figure B9 shows that natural resources do *not* mediate the effect of manufacturing on development.

intervening variable to explain the positive association between some services activities and development.[38]

Figure 21 High skills services and growth: The mediating effect of technology



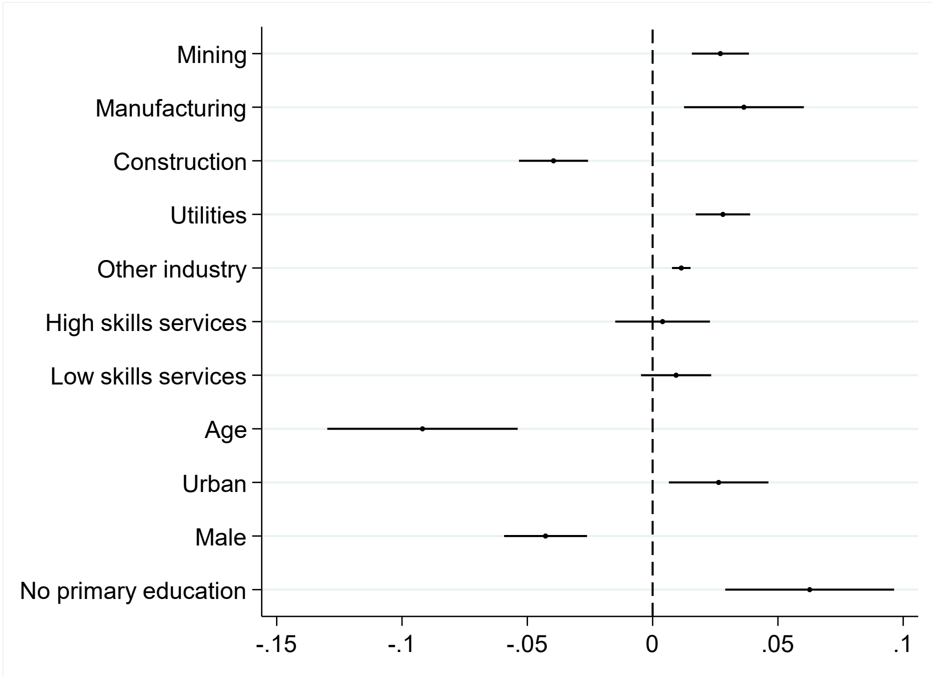
Note: OLS regression weighted by population with standard errors clustered by ADMIN units. The outcome variable is nightlight *per capita*. The model includes ADIMN and wave fixed effects. The number of observations is 1,958 and the R^2 is 0.975. 90% C.I.

Exploring the Effect of Services on Spatial Inequality

We conclude this section by exploring the effect of services on spatial inequality. We do so by running the model specification in equation 2, replacing nightlight with spatial inequality using the measure described in Section 1.D. Results are reported in Figure 22. They show a positive but weak correlation between both high and low skills services and spatial inequality, as expected. The correlation between manufacturing and spatial inequality is positive and significant. Since we lose many observations for which we do not have a measure of spatial inequality, the weak association between services and spatial inequality is preliminary and requires further investigation.

[38] Appendix B10 shows that technology mediate also the effect of manufacturing on development.

Figure 22 Services and Spatial Inequality



Note: OLS regression weighted by population with standard errors clustered by ADMIN units. The outcome variable is nightlight *per capita*. The model includes ADIMN and wave fixed effects. The number of observations is 736 and the R^2 is 0.914. 90% C.I.

5. Conclusion

This paper contributes to the literature on structural transformation and economic development by providing detailed data on changes in the composition of employment over time at the administrative unit level for thirteen African countries. This reveals novel evidence of structural transformation towards services sectors and service-related occupations at sub-national level, providing a fine-grained picture of changes in sectoral employment shares and occupations. The data reveal a clear shift towards services in all the countries in the sample. Across all the administrative units in our sample of countries there is a decline in the total share of employment in agriculture of six percentage points, offset by an equivalent increase in the share of employment in services sectors.

Although the overall share of secondary sector employment is stable, there is significant heterogeneity across sub-national units. The data reveal reductions in industrial employment shares in locations where such activity accounted for relatively high shares of total employment in the initial census year, but also numerous increases in areas where industry accounted for relatively low shares of total employment. There is weak evidence that manufacturing employment growth in these locations is associated with servicification, in the sense that employment in occupations associated with intangible outputs appears to grow in many regions where the share of employment in the secondary sector increases between two census waves.

Exploratory analysis of the relationship between services and economic development, using per capita nightlight luminosity as a proxy for growth, reveals no evidence that services as an aggregate are associated with economic development. There is however substantial heterogeneity across different services industries. Disaggregating the tertiary sector by skill intensity reveals that higher-skilled services are strongly associated with development. We distinguish between high and low skills services sectors by sorting services sectors by intensity of use of workers with a university degree and engaged in occupations that are more complex. Sectors that use these categories of workers more intensively than the average observed in manufacturing are classified as high skills. The strong positive association between high skills services sectors and development is mediated by incidence of malaria, natural resources and technology. Greater incidence of malaria, the presence of a mining facility and below average mobile phone coverage in an administrative unit reduces or undoes the significance of the positive association.

Overall, our work highlights an important role of services activities for employment, skills and economic development in Africa. It also suggests several areas on which future research could focus. One is to analyze the evolution within services across the sampled countries to understand better the relationship between high skills services and economic development. A corollary research question pertains to the role of services in explaining manufacturing employment dynamics, including analysis of the extent to which servicification is occurring in manufacturing. More broadly, insofar as high skills services are associated with development future research to assess the drivers of demand for such services and possible complementarities between services activities would seem apposite. Complementing the census data with firm-level information at the administrative unit level is a necessary condition for developing a better understanding of the role services play in structural transformation and the prospects for increasing productivity and employment generation.

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APPENDIX A

Table A1: Full results by main sectors based on equation (1)

	(1) Agriculture	(2) Mining	(3) Manufacturing	(4) Utilities	(5) Construction	(6) Tertiary
ntl_pc	-2.100***	0.198*	0.604***	0.00982	0.416***	0.881***
	(0.354)	(0.106)	(0.129)	(0.0151)	(0.0643)	(0.251)
ntl_pc^2	1.016***	-0.0535	-0.202*	0.0429***	-0.202***	-0.556***
	(0.321)	(0.0488)	(0.119)	(0.0112)	(0.0297)	(0.189)
pop	0.353***	0.0636	-0.0258	-0.0368***	-0.0758***	-0.314***
	(0.129)	(0.0697)	(0.0427)	(0.00591)	(0.0229)	(0.0890)
pop^2	-0.0190***	-0.00209	0.00192	0.00168***	0.00362***	0.0155***
	(0.00539)	(0.00281)	(0.00179)	(0.000256)	(0.000968)	(0.00374)
post_2000	-0.0656***	-0.00436***	0.000364	0.000494**	0.00993***	0.0597***
	(0.00657)	(0.00169)	(0.00182)	(0.000238)	(0.00120)	(0.00508)
Constant	-0.876	-0.442	0.0956	0.203***	0.415***	1.802***
	(0.780)	(0.427)	(0.254)	(0.0342)	(0.135)	(0.538)
Observations	3,135	3,135	3,135	3,135	3,135	3,135
R-squared	0.971	0.920	0.913	0.881	0.899	0.969

Notes: Estimates are based on equation (1). NTL_pc is the value of nighttime lights per capita. pop is the log of population. The squared term of both the former variables is included. Post_2000 is the variable of interest, a dummy taking 1 if the year of the census is successive to 2000. All regressions include district fixed effects. Robust standard errors in parenthesis. District. *** p<0.01, ** p<0.05, * p<0.1

Table A2: Full results by industries within services based on equation (1)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
VARIABLES	trade	accommodation	transport	finance	public	business	education	health	private_hh	other_services	unspec_service
ntl_pc	-0.0465	0.430***	-0.0739	0.0608***	-0.145	-0.0843**	0.256***	0.148***	-0.219***	0.625***	-0.0792***
	(0.104)	(0.0654)	(0.255)	(0.0149)	(0.110)	(0.0371)	(0.0560)	(0.0435)	(0.0790)	(0.0874)	(0.0242)
ntl_pc^2	-0.0776	-0.162***	-0.215	-0.0228**	0.148*	0.0553***	-0.0416	-0.0990***	0.108**	-0.307***	0.0143
	(0.0615)	(0.0235)	(0.144)	(0.00950)	(0.0860)	(0.0191)	(0.0351)	(0.0273)	(0.0503)	(0.0617)	(0.0127)
pop	-0.206***	-0.0286	-0.0670***	-0.00998*	0.256***	-0.00127	0.0597***	-0.0951***	-0.0949***	-0.111***	0.0222
	(0.0585)	(0.0226)	(0.0259)	(0.00530)	(0.0361)	(0.0186)	(0.0217)	(0.0232)	(0.0240)	(0.0239)	(0.0358)
pop^2	0.00812***	0.00195**	0.00328***	0.000562***	-0.0115***	0.000198	-0.00201**	0.00441***	0.00456***	0.00585***	-0.00167
	(0.00251)	(0.000958)	(0.00104)	(0.000216)	(0.00159)	(0.000790)	(0.000933)	(0.000918)	(0.00107)	(0.00102)	(0.00162)
post_2000	0.0337***	0.00562***	0.00919***	-0.000309	-0.0108***	0.00561***	0.00784***	0.00505***	0.00162*	0.00762***	-0.00591***
	(0.00242)	(0.00126)	(0.00135)	(0.000292)	(0.00150)	(0.000809)	(0.00102)	(0.00134)	(0.000829)	(0.00111)	(0.00106)
Constant	1.371***	0.0721	0.357**	0.0444	-1.362***	-0.00209	-0.386***	0.519***	0.510***	0.499***	-0.0234
	(0.343)	(0.135)	(0.163)	(0.0326)	(0.205)	(0.109)	(0.127)	(0.144)	(0.135)	(0.141)	(0.197)
Observations	3,135	3,135	3,135	3,135	3,135	3,135	3,135	3,135	3,135	3,135	3,135
R-squared	0.904	0.647	0.910	0.921	0.901	0.796	0.941	0.859	0.907	0.716	0.466

Notes: Estimates are based on equation (1). NTL_pc is the value of nighttime lights per capita. pop is the log of population. The squared term of both the former variables is included. Post_2000 i the variable of interest, a dummy taking 1 if the year of the census is successive to 2000. All regressions include district fixed effects. Robust standard errors in parenthesis. District. *** p<0.01, ** p<0.05, * p<0.1

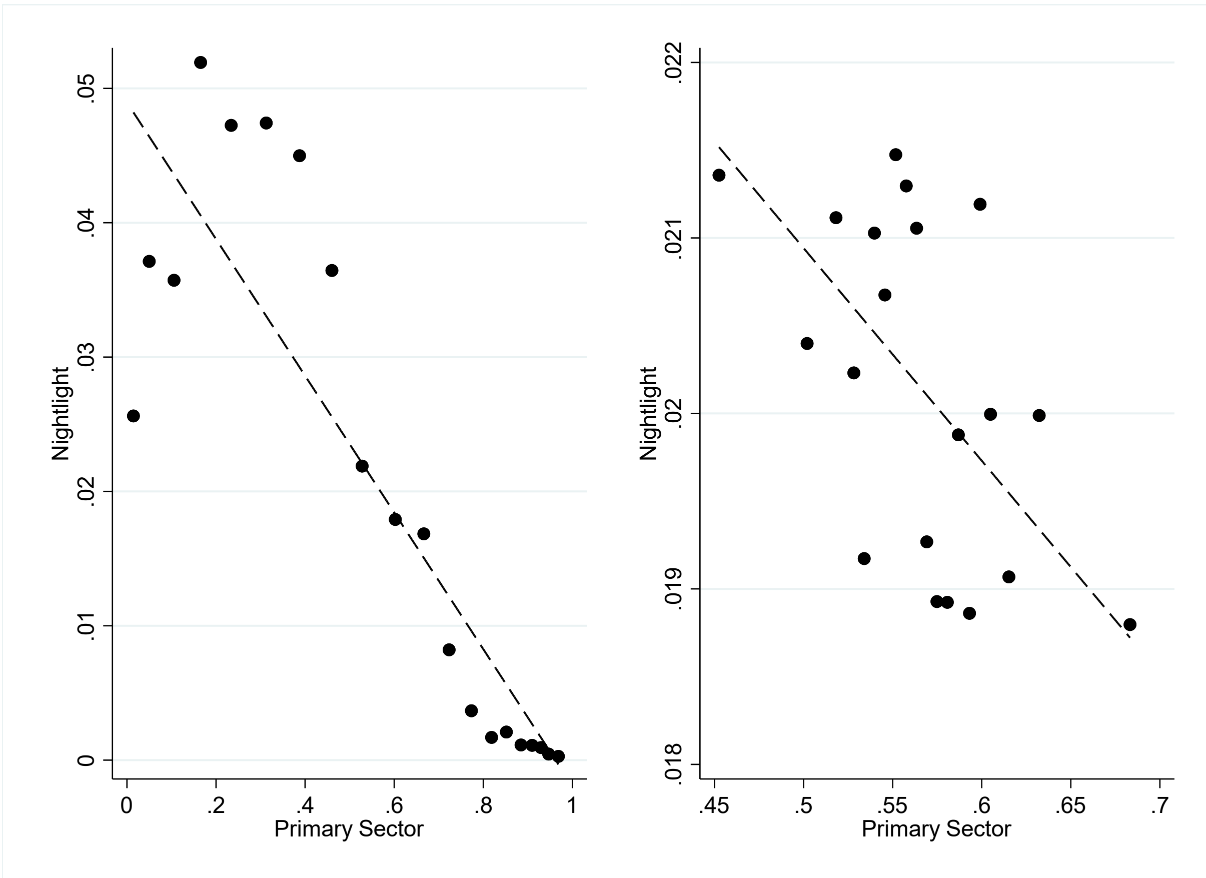
Table A3: Correlations between changes in sectoral employment and type of occupation

VARIABLES	(1) Agriculture	(2) Manufacturing	(3) Services
Goods (tangible) occupations	0.751***	0.180	-0.412**
	(0.245)	(0.129)	(0.186)
Services (intangible) occupations	-0.310	0.232*	0.523***
	(0.247)	(0.129)	(0.189)
Constant	-0.0396***	0.00844***	0.0211***
	(0.00204)	(0.00123)	(0.00125)
Observations	1,528	1,520	1,529
R-squared	0.712	0.210	0.867

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Notes: Each column reports a regression linking the first difference in the share of employment in one of the three sectors (agriculture, manufacturing, services) against the first difference in the share of workers classified into goods (tangible) or services (intangible) types of occupations according to the definition by Duernecker & Herrendorf (2020). The latter refers only to those employed within a specific sector. In order to compute the first difference in an homogenous manner, the estimation sample includes the two most recent waves for each country.

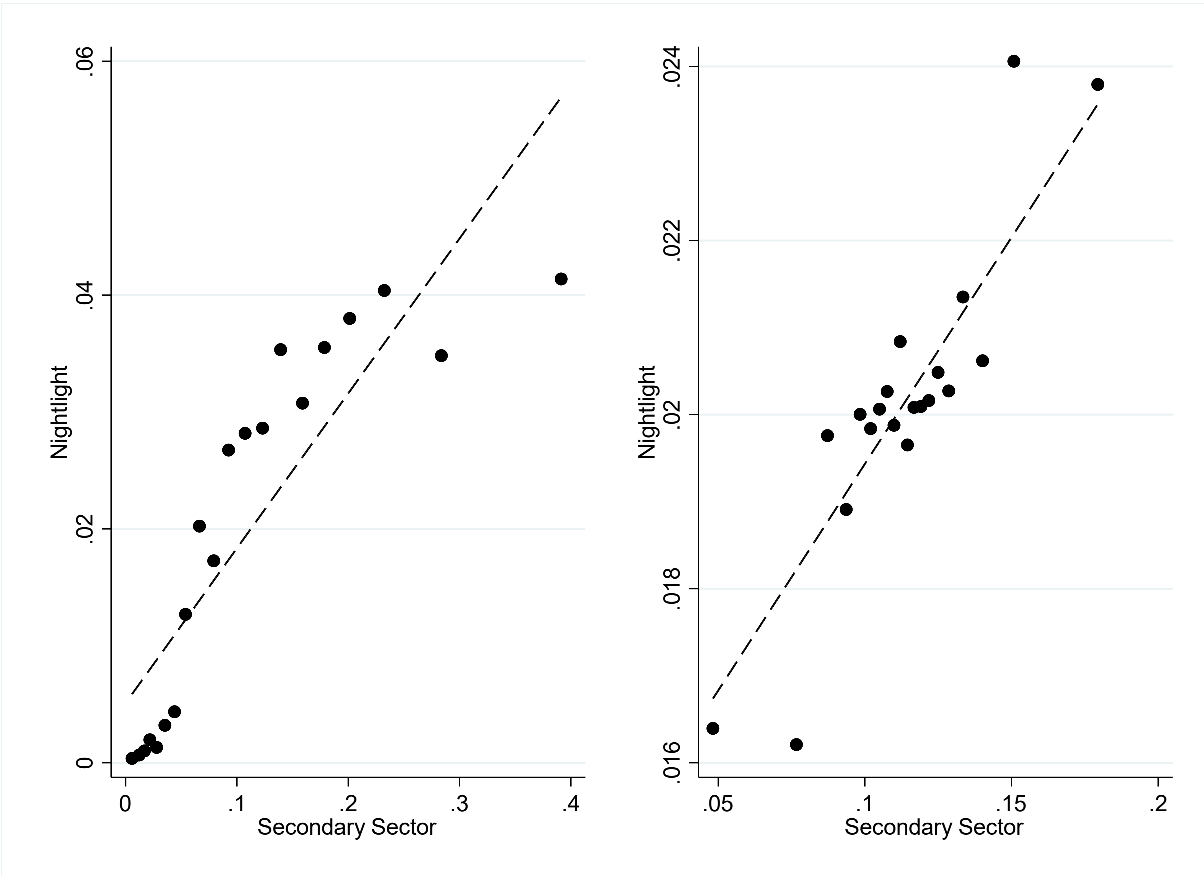
APPENDIX B: Services and development

Figure B1 Correlation between nightlight and share of the primary sector



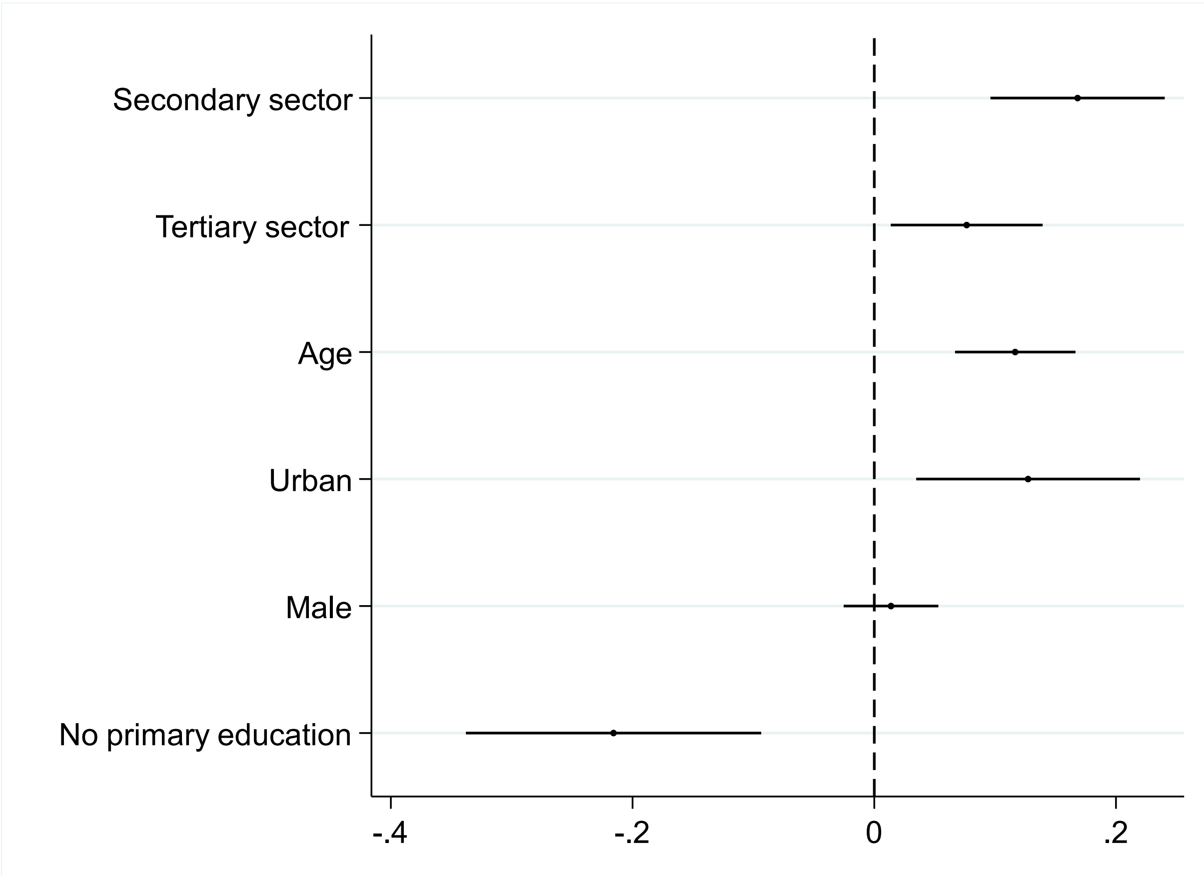
Note: binned scatterplot. The graph on the left shows a simple correlation. The graph of the right shows a correlation accounting for ADMIN and wave fixed effects.

Figure B2 Correlation between nightlight and share of the secondary sector



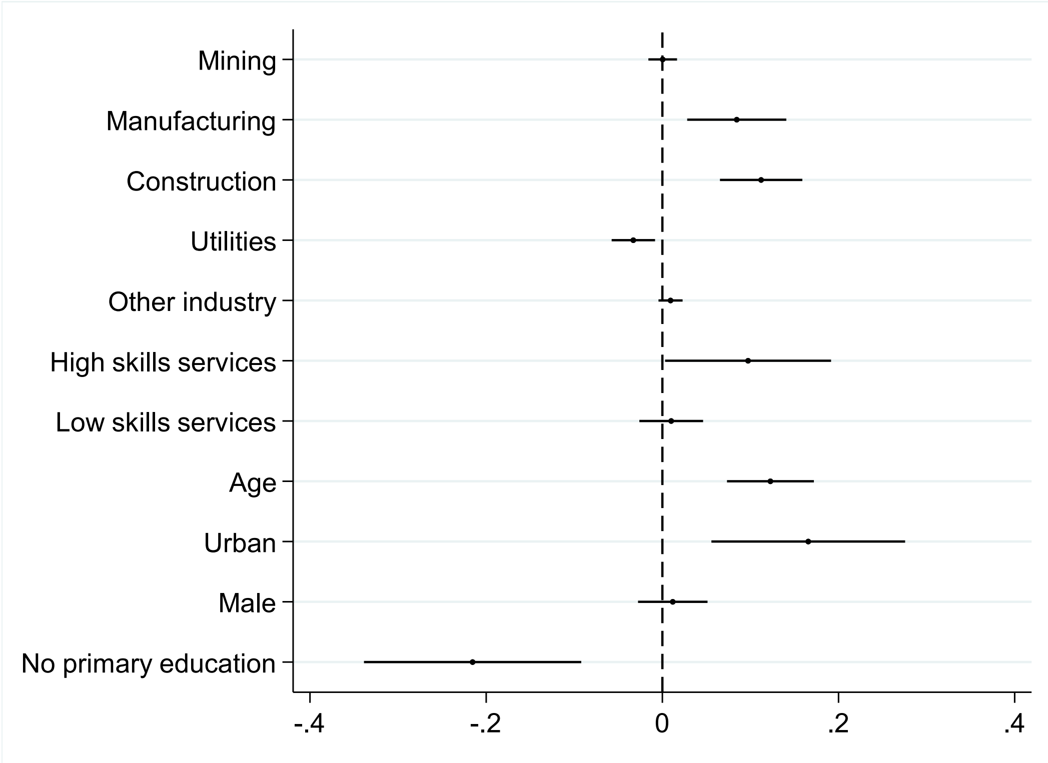
Note: binned scatterplot. The graph on the left shows a simple correlation. The graph of the right shows a correlation accounting for ADMIN and wave fixed effects.

Figure B3 Main results by sector (alternative measure of nightlight)



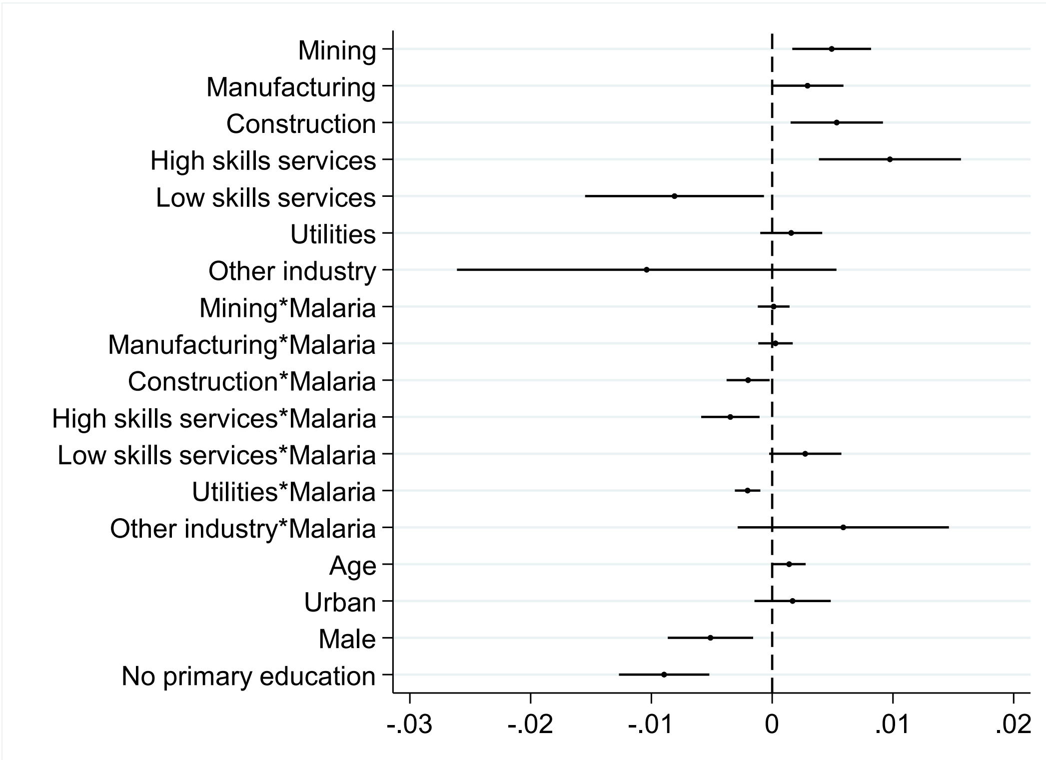
Note: OLS regression weighted by population with standard errors clustered by ADMIN units. The outcome variable is nightlight *per capita*. The model includes ADIMN and wave fixed effects. The number of observations is 2,909 and the R^2 is 0.971. 90% C.I.

Figure B4 Main results: high skills services vs. low skills services (alternative measure of nightlight)



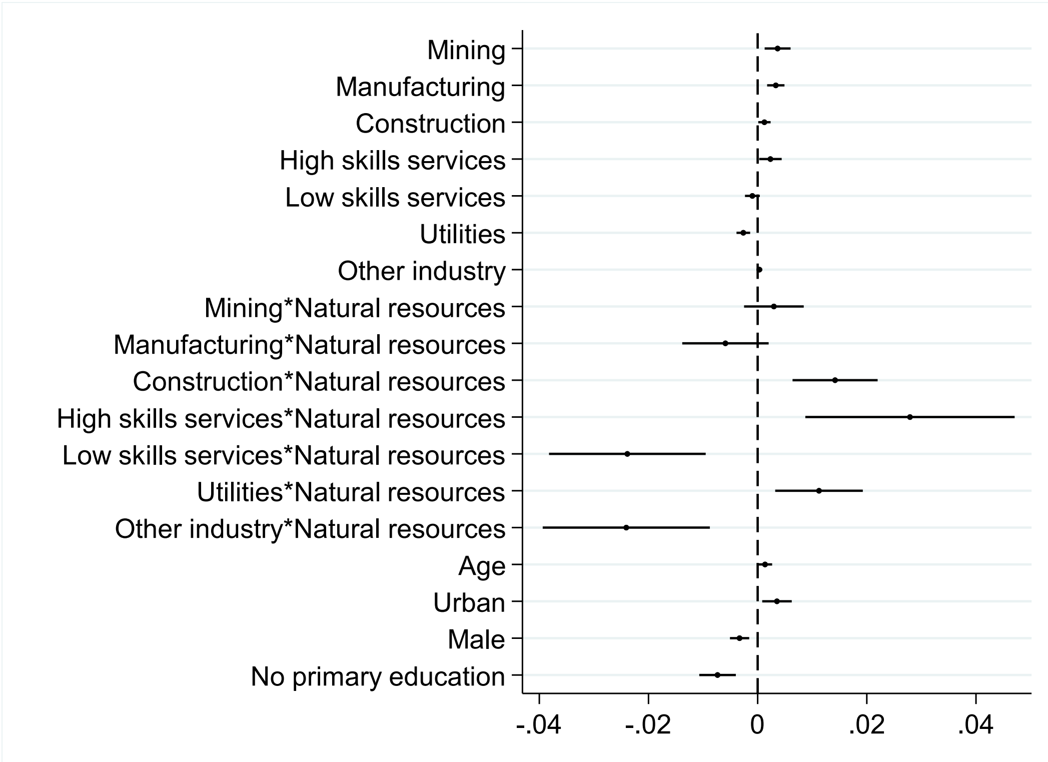
Note: OLS regression weighted by population with standard errors clustered by ADMIN units. The outcome variable is nightlight *per capita*. The model includes ADIMN and wave fixed effects. The number of observations is 2,909 and the R^2 is 0.967. 90% C.I.

Figure B5 High skills services and growth: The mediating effect of the incidence of malaria



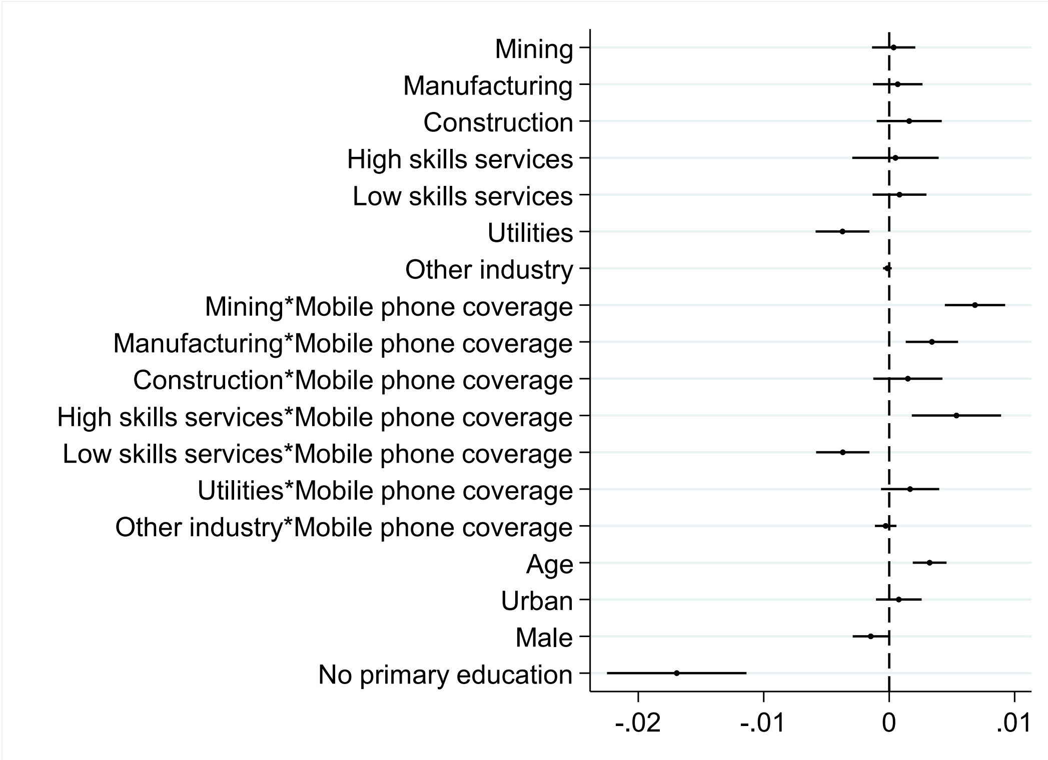
Note: OLS regression weighted by population with standard errors clustered by ADMIN units. The outcome variable is nightlight *per capita*. The model includes ADIMN and wave fixed effects. The number of observations is 2,829 and the R^2 is 0.970. 90% C.I.

Figure B6 High skills services and growth: The mediating effect of natural resources



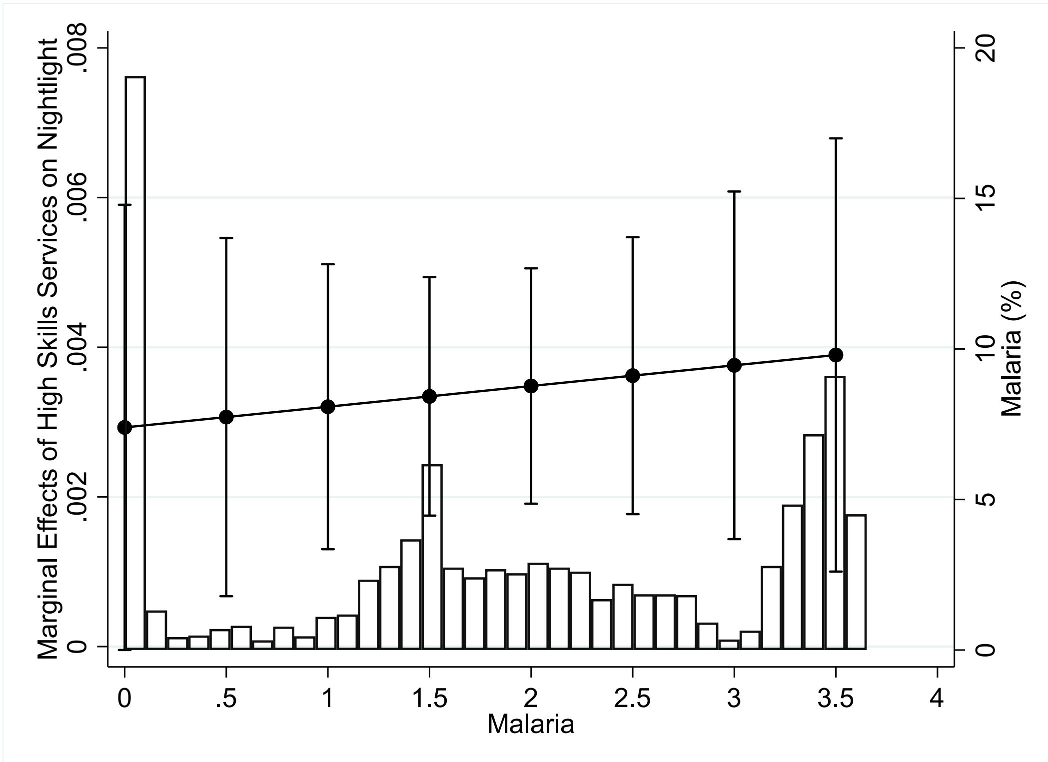
Note: OLS regression weighted by population with standard errors clustered by ADMIN units. The outcome variable is nightlight *per capita*. The model includes ADIMN and wave fixed effects. The number of observations is 2,811 and the R^2 is 0.966. 90% C.I.

Figure B7 High skills services and growth: The mediating effect of technology



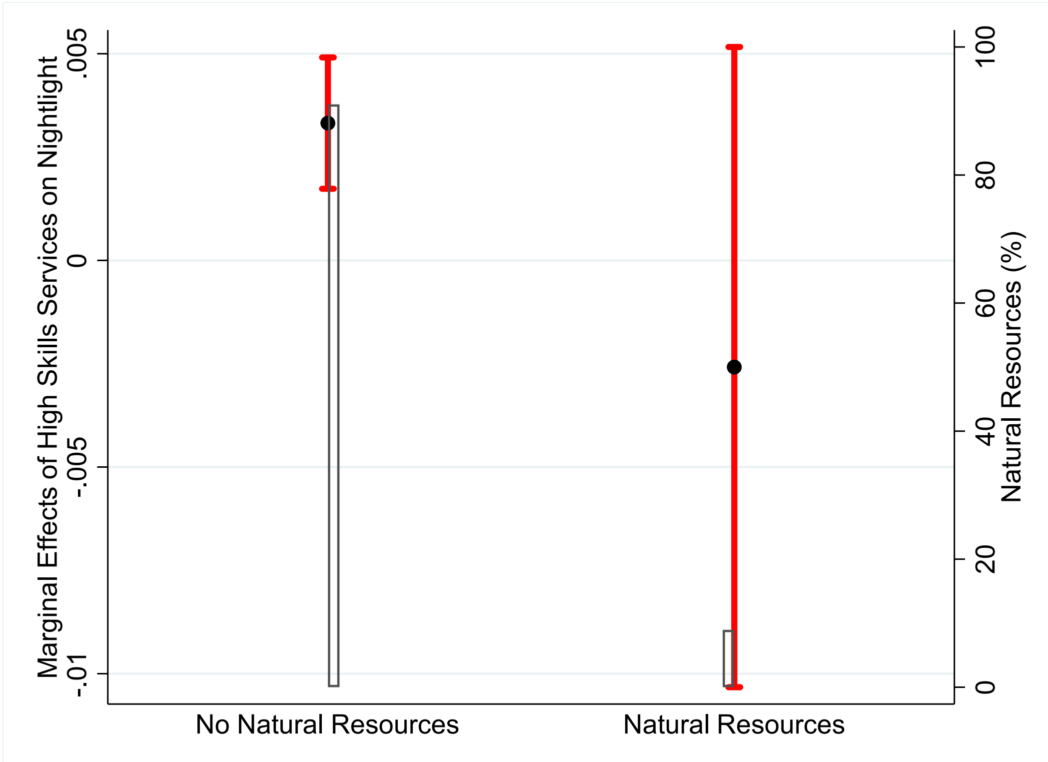
Note: OLS regression weighted by population with standard errors clustered by ADMIN units. The outcome variable is nightlight *per capita*. The model includes ADIMN and wave fixed effects. The number of observations is 1,958 and the R^2 is 0.975. 90% C.I.

Figure B8 Manufacturing and growth: The mediating effect of malaria



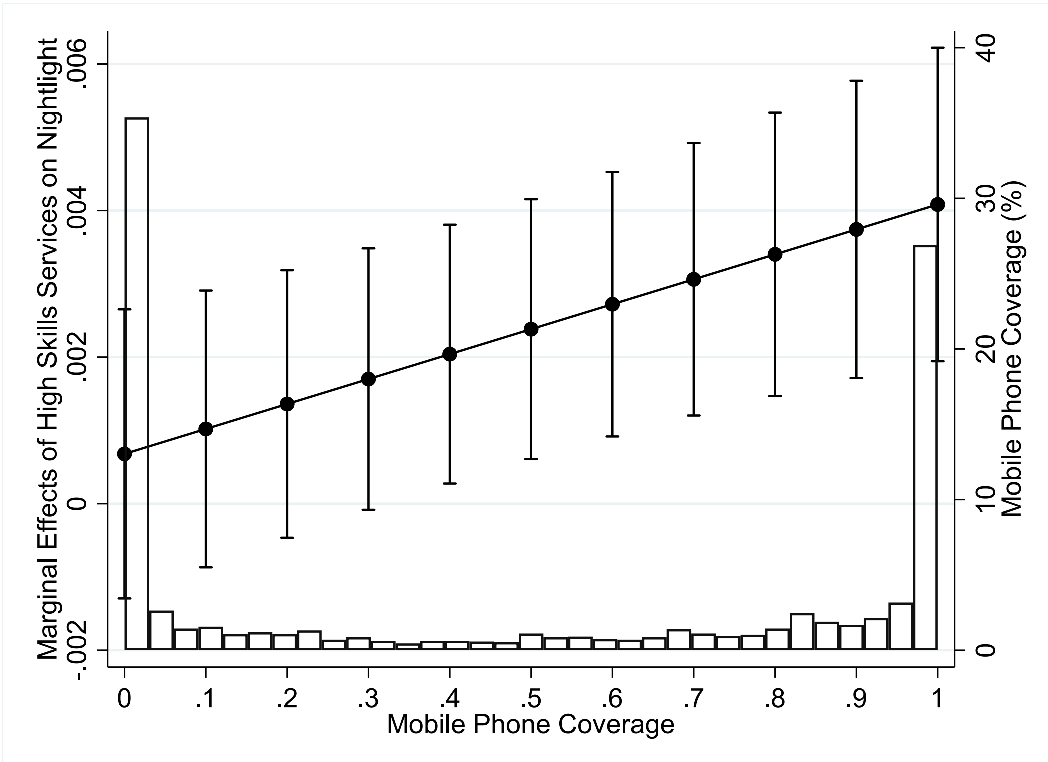
Note: OLS regression weighted by population with standard errors clustered by ADMIN units. The outcome variable is nightlight *per capita*. The model includes ADIMN and wave fixed effects. The number of observations is 2,829 and the R^2 is 0.970. 90% C.I.

Figure B9 Manufacturing and growth: The mediating effect of natural resources



Note: OLS regression weighted by population with standard errors clustered by ADMIN units. The outcome variable is nightlight *per capita*. The model includes ADIMN and wave fixed effects. The number of observations is 2,811 and the R^2 is 0.966. 90% C.I.

Figure B10 Manufacturing and growth: The mediating effect of technology



Note: OLS regression weighted by population with standard errors clustered by ADMIN units. The outcome variable is nightlight *per capita*. The model includes ADIMN and wave fixed effects. The number of observations is 1,958 and the R^2 is 0.975. 90% C.I.

Table B1 Main analysis

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS					
	Nightlight *per capita*					
Secondary sector	-0.000	0.006***	0.005***	-0.002	0.006***	0.006***
	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Tertiary sector	0.010***	0.003**	-0.000	0.012***	-0.001	-0.001
	(0.002)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Constant	0.018***	0.019***	0.020***	0.017***	0.020***	0.019***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)
Admin FE	No	Yes	Yes	No	Yes	Yes
Wave FE	No	No	Yes	No	No	Yes
Controls	No	No	No	Yes	Yes	Yes
Observations	3,214	3,213	3,213	2,982	2,909	2,909
R-squared	0.075	0.962	0.963	0.188	0.965	0.965

Note: OLS regression weighted by population with standard errors clustered by ADMIN units. The outcome variable is nightlight *per capita*. The model includes ADIMN and wave fixed effects. *** p<0.01, ** p<0.05, * p<0.1

Table B2 Macro service clusters

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS					
	Nightlight *per capita*					
Mining	0.009***	0.004***	0.004***	-0.119***	0.005***	0.005***
	(0.001)	(0.001)	(0.001)	(0.027)	(0.002)	(0.002)
Manufacturing	-0.001	0.004***	0.003***	0.010	0.003*	0.003**
	(0.002)	(0.001)	(0.001)	(0.066)	(0.001)	(0.001)
Construction	0.003***	0.004***	0.003*	0.113*	0.003*	0.003*
	(0.001)	(0.001)	(0.001)	(0.059)	(0.001)	(0.001)
Utilities	0.003	-0.000	-0.001	0.063	-0.001	-0.001
	(0.002)	(0.001)	(0.001)	(0.059)	(0.001)	(0.001)
Other industry	-0.000	0.000	-0.000	0.041	-0.009	-0.009
	(0.001)	(0.000)	(0.000)	(0.215)	(0.010)	(0.010)
High-skill services	0.011***	0.008***	0.007***	0.353***	0.005**	0.005**
	(0.002)	(0.003)	(0.003)	(0.072)	(0.002)	(0.002)
Low-skill services	-0.002	-0.002	-0.003	-0.090	-0.004**	-0.004**
	(0.001)	(0.002)	(0.002)	(0.061)	(0.002)	(0.002)
Constant	0.017***	0.018***	0.019***	0.519***	0.017***	0.015***
	(0.001)	(0.001)	(0.001)	(0.045)	(0.002)	(0.003)
Admin FE	No	Yes	Yes	No	Yes	Yes
Wave FE	No	No	Yes	No	No	Yes
Controls	No	No	No	Yes	Yes	Yes
Observations	3,214	3,213	3,213	2,982	2,909	2,909
R-squared	0.175	0.964	0.964	0.172	0.968	0.968

Note: OLS regression weighted by population with standard errors clustered by ADMIN units. The outcome variable is nightlight *per capita*. The model includes ADIMN and wave fixed effects. *** p<0.01, ** p<0.05, * p<0.1

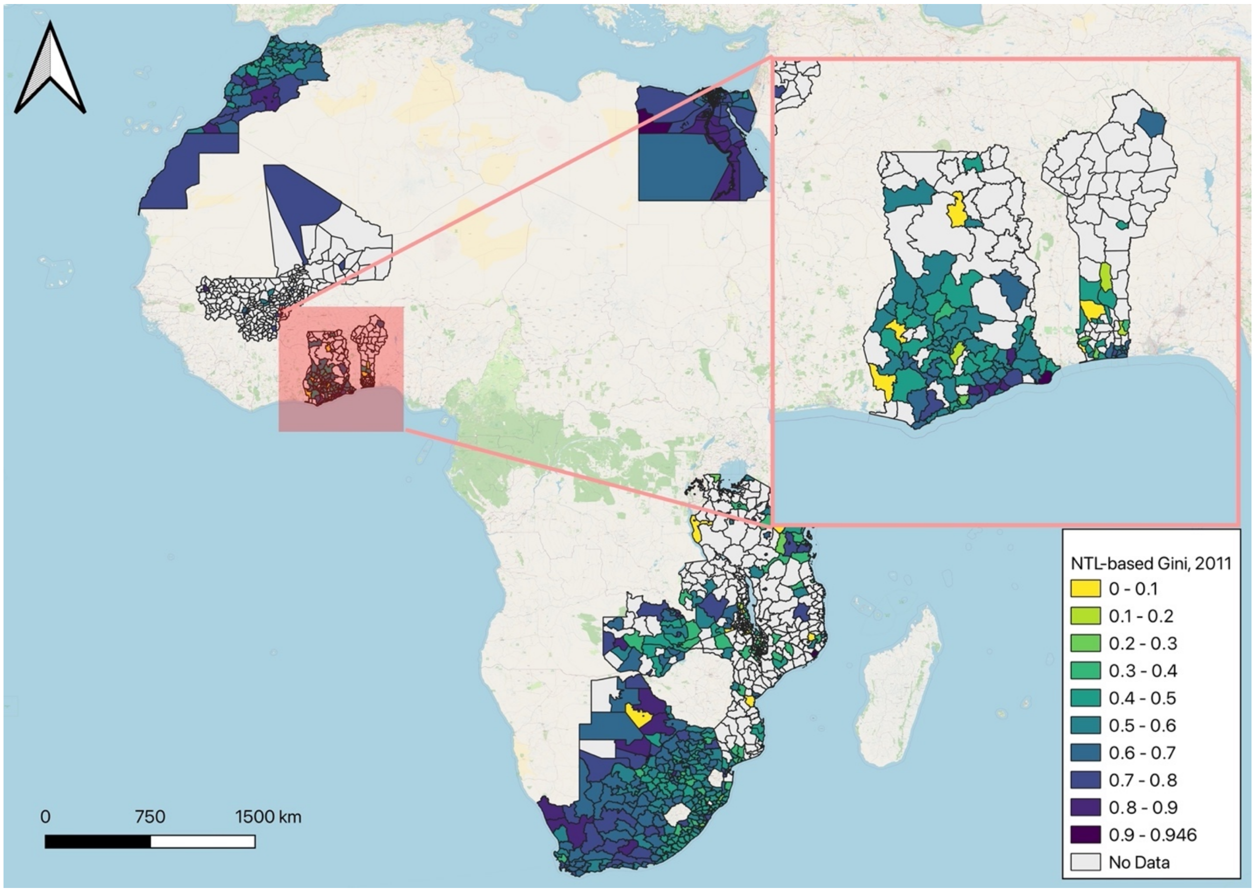
Table B3 Individual service industries

	(1)	(2)	(3)	(4)	(5)	(6)
	OLS					
	Nightlight *per capita*					
Mining	0.008***	0.004**	0.003**	-0.096***	0.004**	0.004**
	(0.001)	(0.001)	(0.001)	(0.021)	(0.002)	(0.002)
Manufacturing	-0.003*	0.003***	0.003***	0.047	0.003**	0.003**
	(0.002)	(0.001)	(0.001)	(0.058)	(0.001)	(0.001)
Construction	0.002	0.003***	0.003***	0.116**	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.058)	(0.001)	(0.001)
Utilities	0.003*	-0.000	-0.001	0.013	-0.001	-0.001
	(0.002)	(0.001)	(0.001)	(0.058)	(0.001)	(0.001)
Other industry	-0.001	-0.001	-0.001	0.053	-0.005	-0.005
	(0.001)	(0.000)	(0.000)	(0.188)	(0.008)	(0.008)
Accommodation	0.001	0.002***	0.002***	0.095**	0.001**	0.001**
	(0.001)	(0.001)	(0.001)	(0.039)	(0.000)	(0.001)
Private household	0.004***	-0.002***	-0.002***	-0.243***	-0.003***	-0.003***
	(0.001)	(0.001)	(0.001)	(0.038)	(0.001)	(0.001)
Transport	0.009***	-0.009*	-0.010**	-0.164***	-0.011**	-0.011**
	(0.003)	(0.005)	(0.005)	(0.060)	(0.005)	(0.005)
Trade	-0.011***	0.002**	-0.000	0.187***	-0.001	-0.001
	(0.002)	(0.001)	(0.001)	(0.066)	(0.001)	(0.001)
Business	0.005***	0.003**	0.002**	-0.026	0.001	0.001
	(0.001)	(0.001)	(0.001)	(0.051)	(0.001)	(0.001)
Education	-0.003*	0.002	0.001	0.251***	0.001	0.002
	(0.002)	(0.001)	(0.001)	(0.066)	(0.001)	(0.001)
Finance	-0.006***	0.001	0.001	-0.010	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.060)	(0.001)	(0.001)
Health	0.004***	0.004***	0.003***	0.102	0.003***	0.003***
	(0.001)	(0.001)	(0.001)	(0.063)	(0.001)	(0.001)
Other services	0.005***	0.002***	0.001	-0.151**	0.000	0.000
	(0.001)	(0.001)	(0.001)	(0.061)	(0.001)	(0.001)
Public	0.005***	0.002**	0.003***	0.191*	0.002**	0.002**
	(0.002)	(0.001)	(0.001)	(0.105)	(0.001)	(0.001)
Unspecified services	0.001***	0.001***	0.000*	-0.023	0.000*	0.000
	(0.000)	(0.000)	(0.000)	(0.019)	(0.000)	(0.000)
Constant	0.018***	0.019***	0.021***	0.513***	0.018***	0.016***
	(0.001)	(0.001)	(0.001)	(0.037)	(0.002)	(0.002)
Admin FE	No	Yes	Yes	No	Yes	Yes
Wave FE	No	No	Yes	No	No	Yes
Controls	No	No	No	Yes	Yes	Yes
Observations	3,214	3,213	3,213	2,982	2,909	2,909
R-squared	0.256	0.968	0.969	0.230	0.972	0.972

Note: OLS regression weighted by population with standard errors clustered by ADMIN units. The outcome variable is nightlight *per capita*. The model includes ADIMN and wave fixed effects. *** p<0.01, ** p<0.05, * p<0.1.

Appendix C

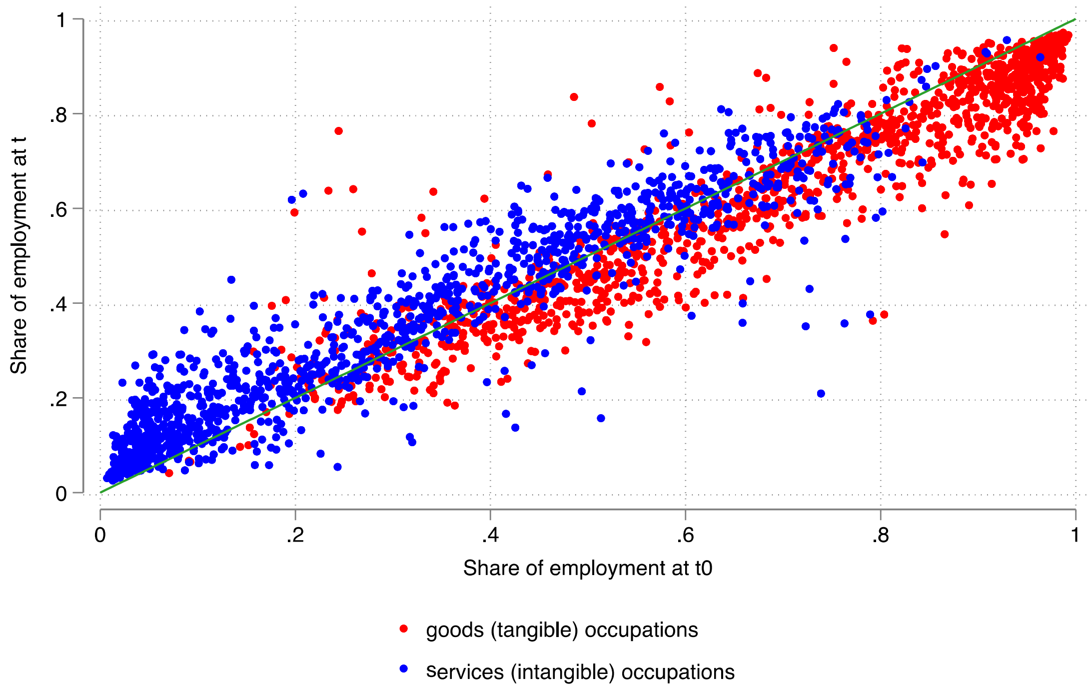
Figure C1. Spatial Gini indicator (based on Mirza et al. (2021))



Source: Author's elaboration on Li et al. (2020), LandScan and GPW v3

Figure C2. Structural transformation at the sub-national level: Agriculture, manufacturing and services

Figure C3. Changes in type of occupations within the Manufacturing sector



Notes: Goods and Services occupations are constructed on the basis of the classification of Duernecker & Herrendorf (2020) and relative to those employed in the manufacturing sector only.
Source: Author's elaboration on IPUMS.

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