The Urban Hierarchy in Africa: Competition and Complementarity*

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Abstract

In the urban hierarchy, what do different types, or tiers of human settlement do and what are their competitive versus complementary relationships to each other? We specify a hierarchy model of settlements and, in novel work, estimate the spatial relationships between them econometrically for sub-Saharan African countries. The paper uses satellite data to determine the number and extent of settlements (based on built area), from mega-cities down to hamlets. Settlements in different tiers of size generally specialise in different activities. We model this by supposing three settlement types: agricultural, agro-processing and traditional manufacturing, and higher order activities including business services and modern manufacturing. We ground-truth this production pattern by tier for 8 African countries for which data are available. Given many dispersed agricultural settlements, the model predicts regular spacing of agro-processing settlements, and of fewer and larger manufacturing/service settlements. This pattern is driven by a competitive relationship between settlements of the same type (competing for production inputs and in output markets) and a complementary relationship between settlements of different type (producing different goods in an input-output structure). We then turn to looking at city growth from 2000–2014 for 27 African countries, defining tiers empirically by what best explains patterns of growth under forces of competition and complementarity. In examining the relationships across cities in different tiers, we find a larger neighbour in the same tier impinges on own size, or cities are in a competitive relationship within their own tier. On the other hand, proximity to a larger settlement of a different tier than their own enhances size, revealing a complementary relationship across tiers.

Keywords: urban development, urban hierarchy, built settlement, Africa

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1 Introduction

Urbanization in sub-Saharan Africa is proceeding rapidly, yet little is known about the hierarchical structure of its urban systems. Existing empirical work in different contexts has focused largely on the role of large cities or on whether smaller cities suffer from being in the "shadow" of urban giants (e.g., Hornbeck et al. (2024) or Cuberes et al. (2021)). What is missing is a systematic understanding of how settlements of different sizes interact—whether they compete or complement each other within an urban hierarchy.

The paper studies the urban hierarchy for countries in sub-Saharan Africa. The region offers rapid urban growth, widespread small and informal settlements, and limited transport infrastructure. These make interactions across settlements in different tiers in a hierarchy within a country particularly important. [1] Analysis of Africa will provide methodological and conceptual insights relevant to other developing regions undergoing structural transformation. Also, for Africa and some other regions where there is non-detailed, scarce, or uneven population data, the study will highlight the value of satellite-based measures of the built environment.

We develop a theoretical model of an urban hierarchy and then estimate key relationships in the hierarchy. We have two principal interests. One is to identify a hierarchy for a large set of countries. Second is to show how interactions between settlements of different sizes and types, i.e., tiers in the hierarchy, are shaped by patterns of competition and complementarity. We find that settlements in the same tier are in competition, such that an increase in the size of one detracts from the sizes of neighbours of the same type. However, an increase in the size of a settlement benefits neighbours of other types, so settlements in different tiers complement each other. This is the first evidence of these competition versus complementarity effects and the first empirical estimation of an economic model of an urban hierarchy, that we know of.

We proceed in several stages. First, we describe the data and some of the technical issues involved in defining settlements as non-random clusters of built pixels. We briefly characterise the resulting size distribution of settlements. Akin to de Bellefon et al. (2020), who look at the built environment in France historically, we use satellite data on the built environment largely because of the low quality of sub-national population data for much of sub-Saharan Africa. Using the built environment data frees us to look not just at urban giants, but also at small and even tiny settlements of which there are thousands.

We then turn to conceptualising urban hierarchies. We were initially influenced by recent papers

[1] We use the term "settlement" to encompass built areas of all sizes.

on growth in the shadows of urban giants, such as Hornbeck et al. (2024), Cuberes et al. (2021), Beltràn Tapia et al. (2017), and Bosker and Buringh (2017). These papers explore whether smaller cities benefit or suffer from being near larger cities, given opposing competition and market potential effects, with Cuberes et al. (2021) arguing that which effect dominates the other changes over time in the USA. In exploring this notion for Africa in Henderson et al. (2022), while some of our empirical results suggest shadows may be an issue, we concluded that something more fundamental was at work, invoking notions of an urban hierarchy, as proposed in Lösch (1954) with modelling in Fujita et al. (1999) and Tabuchi and Thisse (2011), drawing on the new economic geography literature (Krugman, 1991).

In Section 3, we develop a theoretical model of an urban hierarchy in which each settlement can perform three possible functions. Some settlements are agricultural, using land and labour to produce output which is costly to transport. Some are "market/agro-processing" towns which use agricultural inputs and labour to produce consumption goods that have lower transport costs than unprocessed agricultural output. The final type are manufacturing/service cities which use labour to produce easy-to-ship final or intermediate goods. The ensuing structure of input-output and trade links between settlements creates patterns of complementarity and competition between places. Settlements can develop at any place on the geographical space and movement of labour generates a structure of settlements with many small agricultural settlements, a smaller number of larger and approximately equally spaced market/agro-processing towns; and a still smaller number of large, and approximately equally spaced, manufacturing/service cities. This spatial pattern emerges as settlements in the same tier are in a competitive relationship with each other whereby a shock to one reduces growth in near neighbours of the same type, while settlements in different tiers are in a complementary relationship whereby a shock in one increases growth in a near neighbour in a different tier.

Next is estimation based on the model. We derive the urban hierarchy for the 3-tier structure from the model for a set of 27 sub-Saharan countries. In determining the tier structure, we specify a city growth model, where growth of a city in a tier is driven by changes in its market access to cities in different tiers of the hierarchy and the relationships of complementarity and competition. In determining the cut-offs for a tier structure for cities ordered by size, we estimate individual country cut-offs between different tiers and choose the structure that maximises explanatory power. We ground-truth the structure of the hierarchy derived from the growth specification. For eight countries, we have data at the sub-national level on employment in three sectors which correspond to those in the model: agriculture, manufacturing and other secondary activity, and the tertiary sector. Although the production data are crude, we show that production patterns of sub-national areas across these three sectors line up pretty well with the urban hierarchy of tier 1, 2 and 3 cities.

Empirically, we think of tier-3 settlements as heavily involved in agricultural production and tier 1 as more involved in manufacturing and services, where business services are the fastest-growing sector in most countries in sub-Saharan Africa (Henderson and Kriticos, 2018).

For city growth equations, changes in market access come from both changes in neighbours' income and by changes in travel times between cities. We start with OLS results and also look at this decomposition between income and travel time effects. Then we turn to IV estimation. The IV estimation is challenged by the complexity of the model with a tier structure and the limited quality of the road travel time data in more recent times. Exogenous variation in market access comes from shocks to revenues of their nearby mines and to road improvements from roads that are further from the own settlement as in Jedwab and Storeygard (2021). Generally, OLS and first and second stage IV results are strong and plausible. As predicted by the model, settlement sizes in the data are negatively affected if settlements are close to larger neighbours in the same tier with which they compete. However, own sizes are generally positively affected if settlements are close to larger settlements in other tiers which are complementary.

The remainder of the paper is structured as follows. Section 2 introduces the settlement data. Section 3 develops the model of urban hierarchy. Section 4 presents the empirical strategy and OLS results, while Section 5 addresses identification. Section 6 reports on industrial composition of the hierarchy structure and reports the IV estimates. Section 7 concludes.

2 Data

Our primary data are based on the European Union's Global Human Settlements built cover data set, GHS-BUILT, that defines built surface derived from Landsat 30-meter resolution satellite data for different dates: 1975, 1990, 2000, and 2014. There is a companion data set on the spatial distribution of population from Gridded Population of the World [GPWv4], but we work with built cover in preference to population data for several reasons. First is accuracy. The GHS population data allocate administrative unit census population to the built cover data, smearing population into commercial or industrial buildings and roads (impermeable surface), as well as residential buildings. Smearing across areas of built cover is a crude procedure to determine where people actually live. Accuracy is particularly poor if administrative units for population are large, as is typically the case in Africa. Of the 12.9 million input population polygons worldwide in GPW, 10.5 million are in the United States, so accuracy for the USA is much higher than in much of the world. Equally compelling for some African countries, census population numbers are irregularly recorded and of questionable accuracy. While population numbers may be poorly and inconsistently measured across countries and time, built cover is more consistently measured. Thus, we use built cover rather than trying to ascertain where residential population lives.

In recording built cover, a 30×30 m pixel is built or not, and built area is simply the area covered by the built 30×30 m pixels. In working with 30×30 m resolution data, for computational purposes we aggregate to 210×210 m size super-pixels, summing from 30×30 m built pixels to get the built area of the super-pixel. The key decision, given all the built pixels in a country, concerns what comprises a settlement. Implicit is the idea that built pixels could be randomly located (rural) bits such as huts or hamlets within a country, but some subset are agglomerations or clusters that define a settlement. Settlements have high density values compared to a counterfactual: higher than the expected intensity of clustering, beyond what one would find on a "dartboard" (Ellison and Glaeser, 1999).

To proceed, we follow de Bellefon et al. (2020). As described in Appendix A, we use a smoothed surface to capture disconnected parts of built pixels within a settlement, so each super-pixel has a smoothed density from the surrounding area and itself. Super-pixels further from the own-pixel are discounted by distance up to a maximum of 2.3 km. Most super-pixels will have zero share of built area for themselves and surrounding pixels, meaning that the pixel is deemed not built. The normalised maximum is 1, in which case everything around the super-pixel and itself is built. Details are in Appendix A.

Next, we need a density cut-off or threshold to determine what is a significantly high degree of density. For this we must pose a counterfactual. In a similar vein to de Bellefon et al. (2020), we use a fixed large square area divided into pixels which we treat as a hypothetical country. We randomly allocate built pixels across this area. The number of allocated built pixels and counterfactual distribution varies by country, according to the share of actual built pixels within each country's total count in 2014.[2] Then for each counterfactual built-up density, we calculate its smoothed built-up density, as we did for the real spatial distribution. We bin the smoothed built-up in 10000 bins (many bins being 0). We repeat this process 500 times and sum up the counts in each bin to generate a stable distribution by leveraging the law of large numbers. The threshold we use for each country is the 95th percentile in the counterfactual built-up distribution. These cut-offs for each country are shown in Figure A2 in Appendix A. They range from a value close to 0 to about 0.006 for the smoothed share density threshold value. While that may seem small even at the upper end, in Appendix A we show that it makes a huge difference to what are defined as the extents of settlements, using Accra as one example.

[2]We did not use pixel-wise distribution to ease computational burdens, since we are dealing with a much larger area in Africa.

Finally, we need to define settlement areas. For each country, we take all contiguous super-pixels with smoothed density above its threshold and agglomerate them into a shell that defines the boundaries of the settlement. For coastal settlements, for example, there is some infill for non-built super-pixels on the coast surrounded by built surface. Then for this shell, the size of the settlement is the actual built area within the shell, based on the sum of all 30×30 m built pixels within the shell. Figures on numbers and size of settlements by country are given in Appendix Table A1. To give a sense of our settlements, in Appendix Figure A1 we depict the greater Accra area showing Accra distinguished from its satellite settlements.[3] In the hinterland, many built pixels are shown that are not urban and are masked out by the 95th percentile cutoff.

Table 1 depicts the summary of our 2014 data for Africa as a whole, covering 43 countries. Table A2 shows the corresponding data for 1975. Table 1 divides the data into 10 bins of (almost) equal share of total built area. Shares and total built area (in sq. km.) in each bin are given in columns 7 and 4 respectively. Because settlements are an integer count it is not possible, especially at the upper end with large cities, to get exactly 10% in each bin. Size categories and the minimum and maximum settlement sizes in each bin are given in columns 1-3. The largest city in the sample (1370 sq.km.) is about 52% of its bin total built area (2649 sq. km.).

There are two sets of notable facts in the table. First, smaller settlements can be as small as a single 30×30 m grid square of built area (size: 0.0009 sq. km.). In the first bin the maximum size is just 0.25 sq. km. of built area. Those small settlements account for 94.5% of the total 111469 settlements in the sample in 2014. Second, shell area, or the land area of settlements within their boundaries as defined in the algorithm used to characterise settlements is large, compared to the area of actual built pixels, especially for smaller settlements.

In the growth formulation we focus on growth from 2000 to 2014 for two reasons. First, the satellite imagery is more accurate and based on higher resolution information in the more recent time periods. Second, we want to control for historical own size, to help in identification. We restrict the sample to the 37007 settlements in 2014 that exist in 1975. There are 47519 settlements in 1975 from Table A2 but about 10500 merge into other (bigger) settlements. The 2014 sample in Table 1 consists of the 37007 plus 74462 births, or new cities since 1975. Of these births since 1975, in 2014, 99.4% remain in the bottom built-area decile in Table 1. Thus, our sample restriction to choose cities that survive since 1975 does eliminate many tiny settlements. These may be of less interest and should be of little consequence for market access measures for other cities. We did

[3]The more intense the colour, the greater is the built-up area in the figure. The greater Accra area and some satellite cities are outlined in blue. Also outlined within Accra are unoccupied areas such as forest preserves, salt ponds, or lakes.

check that if we use the sample of 2000 cities for growth from 2000 to 2014 (with then no control on lagged own sizes), results are similar for the two samples. The details of transition matrices and the evolution of built settlements over time, as well as other aspects such as Gibrat's Law and the rank size rule are in Henderson et al. (2022). They are not central to this paper.

We now turn to modelling an urban hierarchy, which will inform the empirical implementation.

3 The Geographical Pattern of Settlements: A Model of Urban Hierarchy

The central idea is that hierarchical patterns of settlements arise, with a particular geographical distribution, as a consequence of a pattern of competing and complementary interactions between settlements specialising in different sectors or functions. Competing, as places may supply similar outputs (goods that are close substitutes), and compete for similar primary inputs. Complementary, as places may produce quite different goods and services which are supplied to households in nearby locations, and are also used by firms as intermediate inputs. Demand from neighbours creates a demand or backwards linkage, and access to supply of intermediate inputs constitutes a cost or forwards linkage.

We capture this in a model with three different sectors which correspond broadly to activities in developing countries, in which primary sectors of production employ a large part of the labour force. Sector 3 is agriculture, using land and labour to produce goods that go both to final consumption and further processing, but are costly to ship (bulky or prone to rapid deterioration). Sector 2 is agro-processing, or more broadly manufacturing activities that support the agricultural sector; it uses sector 3 output as an input, and its output (such as processed food products) is less costly to ship. Sector 1 is modern manufacturing and services, outputs that are also relatively easy to ship between places.

A starting question is, where do these sectors locate? We suppose that there are many possible locations, each ex ante identical (endowed with the same amount of land and technology) and that labour is perfectly mobile between places and sectors. Starting from a position in which all places are identical we show how a pattern of settlement emerges, with settlements becoming of different types, i.e., specialising, at least partially, in different sectors. There is regularity in the spacing of settlements of different types, with types having different sizes and spatial frequencies. Along the path to this outcome settlements grow faster if they are near to settlements of different types and remote from settlements of the same type.

3.1 Model Structure:

We set up the model for a general input-output structure and geographical space. Results come from simulation and details of implementation and parameters are given in the following sub-section.

There are N points (or places) in a geographical space, labelled with subscripts i, j . The distance between two places is d_{ij}, this underpinning the costs of shipping goods and services around the space. Each place has a fixed endowment of land. There are three sectors of production, as outlined above, indexed by superscripts s, r = 1, 2, 3. There is place and firm specific product differentiation, represented by CES modelling of differentiation.

Sectoral demand: The price index for sector s products sold in place i is the usual CES aggregator, P_i^s,

$$P_i^s = [\sum_j n_j^s (t_{ji}^s p_j^s)^{(1-\sigma^s)}]^{1/(1-\sigma^s)}, \quad s = 1, 2, 3, \quad i = 1....N. \tag{1}$$

The price and number of varieties produced in place j are p_j^s and n_j^s , t_{ji}^s is the iceberg trade cost factor shipping from j to i, and σ^s is the elasticity of substitution between sector s varieties. All these variables and parameters are sector specific. The value of demand for sector s output in place j is E_j^s, so total demand (across all locations) for a sector s variety produced in place i is

$$x_i^s = (p_i^s)^{-\sigma^s} \sum_j E_j^s (P_j^s)^{(\sigma^s-1)} (t_{ij}^s)^{(1-\sigma^s)}, \quad s = 1, 2, 3, \quad i, j = 1....N. \tag{2}$$

Production: Production uses primary factors (labour and, in sector 3, also land) and intermediates with Cobb-Douglas technologies, so has unit cost functions (equal to price)[4]

$$p_i^s = (w_i^s)^{(1-a^{1s}-a^{2s}-a^{3s})} (P_i^1)^{a^{1s}} (P_i^2)^{a^{2s}} (P_i^3)^{a^{3s}}, \quad s = 1, 2, 3, \quad i = 1....N. \tag{3}$$

The exponents a^{rs} are the value share of sector r in production of sector s and w_i^s is the place i sector s price of primary factors. This allows for all sectors to be used as input to all other sectors, although we will set some of these input-output coefficients to zero in what follows. A key link is a^{32}, the input of primary in agro-processing, sector 3 to sector 2.

Sectors 1 and 2 (agro-processing, manufactures and services) are monopolistically competitive, with an endogenously determined number of firms each producing a distinct variety which breaks

[4]Eq. 3 is average cost at unit scale of production.

even when producing and selling one unit of output, so

$$x_i^s = (p_i^s)^{-\sigma^s} \sum_j E_j^s (P_j^s)^{(\sigma^s-1)} (t_{ij}^s)^{(1-\sigma^s)} = 1, \quad s = 1, 2, \quad i = 1....N. \tag{4}$$

Labour is the only primary factor used in these sectors, so Eqs. (3) and (4) can be thought of as defining a wage equation, i.e., giving the value of w_i^s at which firms break even, as a function of price indices, numbers of varieties, and expenditure levels throughout the economy.

Sector 3 is agriculture, and we give it a slightly different and simpler treatment. Each place is endowed with the same quantity of land and uses land and labour with fixed coefficients to produce a fixed quantity of a single place specific variety.[5] Sector 3 employment, L^3, is therefore the same everywhere and, in Eqs. (3) and (4) $n_i^3 = 1$, and x_i^3 takes fixed value, x^3. However, since demand may vary across places, so too does the market clearing price of each place's agricultural variety, p_i^3, and hence also w_i^3, the return to primary factors, labour and land. This return could be divided between a wage and a rent component but, since much African land is operated by family farms under traditional communal land tenure, we leave it as a combined return to labour and land. We assume that the return is large enough to retain L^3 units of labour in each place.

Income and expenditure: Wage bills in each sector and place are the share of labour in the value of output,

$$w_i^s L_i^s = (1 - a^{1s} - a^{2s} - a^{3s}) n_i^s p_i^s x_i^s, \quad s = 1, 2, 3, \quad i = 1....N. \tag{5}$$

where, as noted above, in sector 3 this takes the form $w_i^3 L^3 = (1 - a^{1s} - a^{2s} - a^{3s}) p_i^3 L^3$, with $w_i^3 L^3$, interpreted as a combined return to land and labour. Summing across sectors, total income in each place, Y_i, is given by

$$Y_i = w_i^1 L_i^1 + w_i^2 L_i^2 + w_i^3 L^3, \quad i = 1....N. \tag{6}$$

Expenditures in each place i on products of sector s come from final and derived demands and are

$$E_i^s = \mu^s Y_i + \sum_{r=1,2,3} a^{sr} n_i^r p_i^r x_i^r, \quad s = 1, 2, 3, \quad i = 1....N. \tag{7}$$

where consumer preferences are Cobb-Douglas, with sector shares μ^s. The consumer price index in each place, P_i, and per worker utility in each place-sector pair, u_i^s, are therefore

$$P_i = (P_i^1)^{\mu^1} (P_i^2)^{\mu^2} (P_i^3)^{\mu^3}, \qquad u_i^s = w_i^s / P_i, \quad s = 1, 2, 3, \quad i = 1....N. \tag{8}$$

The total labour force is fixed at L, of which NL^3 workers are engaged in agriculture, and the

[5]This is "Armington" product differentiation, in contrast to the firm-specific differentiation of sectors 1 and 2.

remaining $L - NL^3$ are perfectly mobile between sectors 1 and 2 and all places. It follows that all places that have employment in either sector 1 or 2 have equal values for u_i^s, $s = 1{,}2$, with utility less than or equal to this in places-sectors where there is no employment in these sectors.

Before moving to implementation of the model a few further comments are in order. First, all places – including large settlements with manufacturing or agro-processing – also have agriculture, sector 3. This is partly for simplicity, but also supported by evidence on widespread agricultural output produced in African urban areas Henderson and Kriticos (2018). Second, land is not explicitly modelled, except as an input to agriculture, where it is combined in fixed proportions with labour. Neither rent, nor amenity or congestion, enter consumer utility. This is for simplicity, although it also reflects the difficulty of modelling African land tenure across the range of settlements we study. Third, product differentiation and variety effects create agglomeration and spatial structure in this model, exactly as in the basic core-periphery model (Krugman 1991, and its extension to intermediate products in Fujita et al. 1999). The model is isomorphic to one in which the number of varieties is fixed and replaced by technological agglomeration externalities.

3.2 Implementation

We use numerical simulation to track the evolution of the system of settlements, focusing on several stylised cases. The simplest, and that which yields the greatest symmetry is to assume that places are located on the circumference of a circle – the racetrack economy – with radius of unity and distance between places measured around the circumference. For a richer picture we also show results for places on a hexagonal lattice set on a (near) circular disk. This has the advantage of being a two-dimensional space, but is complicated by having an edge (i.e., not being a featureless natural geography). Transport costs are assumed to be exponential in distance, $t_{ij}^s = exp(-t^s d_{ij})$, as in much of the theory (but not empirical) literature. For clarity, we present results only for the case in which just one of the input-output linkages is switched on, that of agricultural supply to agro-processing, so $a^{32} > 0$. Agricultural products from each place are assumed to be close substitutes ($\sigma^s = 20$) with high transport costs, such that shipping just 6 degrees around the circumference of the circle loses 50 percent of output. Elasticities of substitution and trade costs are lower in the other two sectors, and a full list of parameter values is given in Appendix C.

Our main experiment is to start this model from an equilibrium in which all places are identical, so employment in each sector is uniformly distributed across space. This is an equilibrium which is stable if trade costs are all very high, making each of the places autarkic. Spatial reorganisation is initiated by (a) reducing trade costs to a point at which this equilibrium is unstable, and (b) perturbing the equilibrium by a small random redistribution of the labour force, and having labour move in response to utility differences between sectors and places, u_i^s.

The ensuing long-run equilibrium is illustrated in Figure 1. The top panel is the racetrack economy, and has $N = 600$ places on the horizontal axis, the two ends connecting around the circle. Employment in sectors 1 plus 2 is on the vertical, (employment relative to mean employment in settlements and measured in log units, so 0 is the mean). Agricultural employment L^3, (tier-3 activity in the data) takes place everywhere and is not shown on the figure. Sectors 1 and 2 each concentrate in subsets of places, constituting tier-1 and tier-2 settlements, noting that tier-1 settlements contain both sector 1 and sector 2, while tier-2 settlements have only sector 2. Sector 1 operates in just four evenly spaced places and these are relatively large, the tall spikes in the figure. Sector 2 operates in these places and also in the 24 places indicated by the smaller spikes. The reason for concentration is the usual home-market effect, as consumers are attracted to places with a large supply of locally produced varieties, and firms are attracted to the large market created by these consumers. The relatively larger number of tier-2 places arises because sector 2 uses sector 3 output which is produced everywhere and is particularly costly to transport. Since it operates in more places, tier-2 settlements are (ceteris paribus) smaller than tier-1 settlements. In short, there are many "market towns" (tier-2 settlements) fairly evenly spread since they are supplied by dispersed agriculture, and fewer but larger manufacturing/service cities.

Figure 1 was generated by a small random perturbation of employment causing the system to evolve away from a uniform distribution of activity. Different simulations with the same parameters but different initial (small) perturbations all produce a very similar outcome for reasons first expounded (in a different context) by Turing (1952) and applied to the spatial context by Fujita et al. (1999).[6] The bottom panel of Figure 1 is a similar equilibrium, constructed with the same parameters but now with the geographical space being an entire disk, rather than just its circumference. The largest settlements (tier-1) are yellow shading to orange, smaller ones (tier-2) light-blue, and sector 3 (agriculture only) everywhere (dark-blue). A clear structure of settlements has emerged, with a central large tier-1 settlement, a further 8 such settlements further out with regular spacing (and rotational symmetry of order 4) and "market towns" (18 tier-2 settlements) interspersed between them.

Sensitivity of results with respect to key parameters is explored in Appendix C. Lower transport costs for primary output (sector 3) leads to fewer and larger tier-2 settlements as the benefits of locating agro-processing very close to agriculture are reduced. Lower transport costs for agro-processing

[6]Figure 1 displays an extreme degree of regularity that does not hold generally. Tier-1 and tier-2 settlements form at different frequencies, and the example in Figure 1 is constructed such that they mesh together in a regular way (i.e., 24 type-2 divided by 4 tier-1 is an integer).

(sector 2) increases the number of tier-2 settlements; proximity to consumers of output in tier-1 cities is less important than proximity to suppliers of inputs from tier-3 agricultural settlements. Lower transport costs for sector 1 reinforces agglomeration, increasing the size and reducing the number of tier-1 settlements. Similar experiments can be conducted with other parameters. The input-output linkage between sectors 2 and 3 is important, and reducing this below a critical point causes sectors 1 and 2 to co-locate, so there are no distinct tier-2 settlements.

Complementarity and competition between settlements is illustrated by perturbing one settlement and seeing its implications on neighbours. For example, raising productivity in a single tier-2 settlement, holding employment in all other places constant, has the effect of reducing utility in nearby tier-2 settlements, and raising it in nearby tier-1, the competing and complementary effects we expect. Letting employment in other places change in response to these utility differences creates spatial waves or ripples of activity. Nearby tier-2 places contract, their contraction causing places further away to expand, and so on. Since there is no sunk capital in the model, changes of this type may well cause settlements to move, i.e., some places empty out completely, and new settlements form.

For the following empirical analysis we need a quantitative measure of how the size of each settlement varies with proximity to other settlements in the same and in other tiers and we use the theory to suggest how to do this, working with place/sector employment in the theory, and with settlements' built area in the empirics. We measure place i's proximity to sector r employment in other places j as $\sum_{j \neq i} \theta_{ij} L_j^r$ assuming, in this section, $\theta_{ij} = exp(-Kd_{ij})$. Figure 2 (4 panels) uses repeated simulations to construct scatter plots of sector s employment in each place as a function of proximity to employment in the same and other sectors, r. The scatter plot in the upper-left panel has employment in sector $s = 1$ (L_i^1, in places where it is positive) on the vertical axis, and proximity to other places' sector $s = 1$ activity on the horizontal, while the lower left has L_i^1, against proximity to sector $s = 2$ employment. The plots combine 5 separate runs of the model, each with different random draws of productivity levels in each place, so the number of data points is the sum of all tier-1 settlements in the 5 runs, or 40 size and proximity pairs. The negative relationship in the upper panel illustrates the competing relationships that we expect between settlements of the same type, and the positive relationship in the lower panel illustrates the complementary relationship between different settlements of different types. The right hand column gives the relationships for sector 2 employment, L_i^2. In short, competing and complementary interactions show up with negative same-sector and positive cross-sector effects.

This suggests regressions of the form $L_i^s = \alpha^s + \beta^{ss} \sum_{j \neq i} \theta_{ij} L_j^s + \beta^{rs} \sum_{j \neq i} \theta_{ij} L_j^r + u_i^s, \quad r, s = 1, 2.$ Using the simulation output in the scatter plots gives significant negative own effects, β^{ss}, and significant positive cross effects, β^{rs}. The empirical work in the next section takes the African data to regressions adapted from this model.

4 Competition and Complementarity in the Urban Hierarchy: Correlations

In this section, we describe and report results from an empirical estimation of the model from Section 3. We work with three types of settlements, which represents the maximum differentiation we are comfortable with empirically given the data, and also aligns with the model. We first present the empirical specification and then the results. Description of the assignment of settlements into tiers is postponed until section 4.2.1.

4.1 Specification of the Basic Model

For each country, we categorise settlements by the size of their built area into three tiers, denoted as *G, H = 1,2,3*. For settlements of each type, we aim to determine the effect of proximity to other settlements of the same type (i.e., $G = H$), and to settlements in different tiers ($G \neq H$). The log of built area for settlement *j* in tier-*G* is lnV_j^G, and we define

$$MA_{it}^{GH} = \sum_{j \in G, i \neq j} \theta_{ijt} lnV_{jt}^G, \quad G, H = 1, 2, 3. \tag{9}$$

MA_{it}^{GH} captures the market access of settlement i in tier-H at time t to settlements in tier-G and is the weighted sum of the log built area of settlements *j* in tier-*G*, lnV_{jt}^G. Built area is a measure of scale, or economic mass of neighbours in tier-*G* to city i. These terms will be used to capture interactions between settlements in different tiers. For cities in the same tier where $G = H$, we exclude the own effect, so $i \notin G$. In this equation, θ_{ij} measures the proximity of settlement i to *j*, which we will define later as $\theta_{ij} = (1 + \tau_{ij})^{-\gamma}$ where τ_{ij} is travel time from i to j and γ is a parameter from the literature, capturing the rate at which interactions diminish with travel time.

The extension of the approach suggested by theory gives model equations for settlements *i* in each tier-*H*,

$$lnV_{it}^H = \alpha^H + \beta^{1H} MA_{it}^{1H} + \beta^{2H} MA_{it}^{2H} + \beta^{3H} MA_{it}^{3H} + \eta_i + \mu_t^H + X_{it} + \epsilon_{it}, \quad H = 1, 2, 3. \tag{10}$$

In (10), cities in tier-*H* experience market access effects separately from cities in each of the 3 tiers, where we expect these effects, the β's, to differ by tier. We will estimate this equation as a simple first difference between 2000 and 2014, which eliminates the area fixed effect η_i and the $\Delta\mu_t^H$ will be part of the constant term. Control variables X_{it} are discussed below. Thus, the OLS formulation becomes:

$$\Delta lnV_{it}^H = a^H + \beta^{1H}\Delta MA_{it}^{1H} + \beta^{2H}\Delta MA_{it}^{2H} + \beta^{3H}\Delta MA_{it}^{3H} + \Delta X_{it} + \epsilon_{it}, \quad H = 1, 2, 3. \tag{11}$$

We note that one can decompose the ΔMA_{it}^{GH} impact using a first order Taylor series expansion into a change in built mass (an "income" effect), $\sum_{j\in G}\theta_{ijt-1}[V_{jt}^G - V_{jt-1}^G]/V_{jt-1}^G$, and a change in travel time effect, $\sum_{j\in G} -\gamma[\tau_{ijt} - \tau_{ijt-1}](1+\tau_{ijt-1})^{-(1+\gamma)}lnV_{jt-1}^G$. Given the difficulties in measuring historical travel times across African countries in the final data set, this decomposition will be instructive.

The coefficients of interest are the nine β coefficients. The estimated coefficients β^{GH} capture the effect on built-up area of tier-H of market access to settlements in tier-G. From the model, we expect β^{11}, β^{22}, and β^{33} to be less than 0. This would be evidence of competition effects, or that settlements of the same type are in a competing relationship with each other. We expect $\beta^{GH} > 0$ for $H \neq G$, indicating that settlements of different types complement each other: a positive shock to a city in G generates greater demand for products of a settlement in tier-H, thus enhancing that tier-H city's size.

To obtain travel times, we utilised Michelin map data kindly shared by Jedwab and Storeygard (2021) covering 40 years. We assign a travel speed of 80 km/hr to highways, 60 km/hr to paved roads, 40 km/hr to improved roads, 12 km/hr to dirt roads, and 6km/hr when there are no roads and any remaining distance is straight line. We calculate the quickest route between all i and j within a country using the Dijkstra's algorithm. The discount factor, γ, is based on Donaldson (2018)'s basic elasticity of trade costs (represented by travel times) with respect to transport costs of trade, which is 0.169. We then need to multiply this by the elasticity of trade flows with respect to trade costs, which varies widely in the literature. Following Milsom (2023), we use the figure from Donaldson and Hornbeck (2016) (ftn, 55) of 3.8. The γ we use is 0.169*3.8, or 0.64. One remaining issue is units of travel time. Travel time is measured in minutes. In the results in the text, we divide by 900 or measure τ_{ij} in units of 15 hours. Given these assumptions, for a day's truck drive, say 12 hours, economic activity a day away is discounted by 31% and for 36 hours by 54%. In robustness checks, we will discuss results with overall sharper discounting and different patterns of discounting such as sharper at short distances and milder at longer ones.

The system above is described for any single country. In implementation we assume that spatial interactions occur only within country, so $\theta_{ij} = 0$ for i, j, based upon the very high border cost within Africa (e.g., Conte (2025)). We then estimate Eq. (11) separately for each country in our African sample, yielding different α, β coefficients for each country. We drop countries that have less than 200 settlements total and we lose more because of lack of data and drop the DRC because of very poor quality road data. In total we have 27 countries.

4.2 OLS Results

We start with OLS results. To do that we need to derive a tier structure. We describe the procedure as we do it for OLS; but, to avoid repetition, we delay a detailed description of the tier structure until we derive the one under IV estimation. They are similar.

4.2.1 Procedure for Deriving a Tier Structure

To derive a tier structure for each country we first rank all settlements by built-up in the initial period, 2000, from largest to smallest, then obtain the cumulative built-up. We define groups based on the cumulative share of built-up, using fractions k_1 and k_2. For the first group, k_1 sets the largest settlement in tier-1 to be the cut-off settlement such that the accumulated share of built-up for all tier-1 settlements is strictly equal or less than k_1. The second group includes the next-ranked settlements up to the point where the cumulative share of built-up reaches k_2; that cut-off defines tier-2 settlements (between k_1 and k_2). The last group includes the rest of the settlements. After some experimentation (noting how much of national built area the primate city takes up in each country), to choose the best k_1 and k_2 pair, we iterate k_1 from 0.75 to 0.95 with 0.01 as the interval and k_2 from 0.90 to 0.995 with 0.005 as the interval, thus defining 420 possible divisions.

For each k_1, k_2 cut, we estimate each of the 3 equations and calculate the sum of squared residuals (SSR) across all observations, picking the k_1, k_2 combination that minimizes the SSR. We constrain comparisons of the 420 possible divisions to those where the degrees of freedom are sufficient in terms of counts of cities to estimate all 3 equations for a country and we require that the number of tier-3 cities is greater than tier-2 which in turn is greater than tier-1.

In estimation of the model, we include 3-degree grid square fixed effects to control for unobservables as well as two sets of controls: the own city log of lagged areas from 1975 and from 1990 and the own city mining shocks discussed later.[7] The OLS results we present next are for the best k_1, k_2 pair for each country.

[7]We did experiment with a list of time invariant controls including measures of terrain ruggedness, distance to the nearest harbour, distance to large lakes, distance to rivers, elevation, distance to the coast, the Ramankutty land suitability index, temperature and precipitation as discussed in Henderson, et al. (2018). Results are similar.

4.2.2 OLS Results on Complementarity and Competition

The OLS results are in Figure 3. In that figure, as in the other figures to follow, the y-axis shows country coefficients. For OLS the x-axis apart from the country code shows the degrees of freedom in estimation. Points with green error bands show coefficients that are significant at the 10% level, but the error bands show 5% confidence intervals for robust standard errors. If the error bands would stretch the graph too far only the point is shown; and these points are mostly significant. All estimates and standard errors are in Appendix Table B2a. Orange triangles are positive and blue dots are negative coefficients. In the figure, "columns" from left to right relate in order to the tier-1, tier-2 and tier-3 samples and the three equations in estimation. The "rows" from top to bottom are for tier-1, tier-2 and tier-3 ΔMA effects on cities of each type. For example in column 1 row 2 for Angola, the tier-2 ΔMA effect on tier-1 cities shows a significant coefficient of about 0.10. The diagonal of sub-figures in Figure 3 shows the own MA type effect on the own type of tier, going from tier-1 effects on tier-1 cities at the top left corner to tier-3 effects on tier-3 cities at the bottom right corner.

There are three clear patterns of results in Figure 3. First, on the diagonal of the 81 possible coefficients across the 3 own-type effects, 65, or 80% are negative and at least significant at the 10% level, almost all at 5%. Only 2.5% are positive and significant at a 10% level. These results suggest competition effects among cities in the same tier. In terms of magnitude, under the specification in Eq. (10) it is nuanced. The elasticity for a tier-1 city of its scale with respect to the scale of a neighbouring tier-1 city is β^{11} times θ_{ij} . On the diagonal for tier 1 and 2 own effects, the β^{HH} coefficients tend to be about -0.4, so a strong effect but one which needs to be depreciated by pair travel-time. So at 36 hours travel-time distance, given θ_{ij}, this substitution effect is depreciated by just over 50%, so the elasticity is typically about -0.20. Tier-3 diagonal effects are weaker with elasticities like -0.20 before distance discounting.

Second, in terms of results, we have off-diagonal but adjacent tier effects which are the effect of tier-2 MA on tier-1 cities, the effects of tier-1 and tier-3 MA on tier-2 cities and the effects of tier-2 MA on tier-3 cities. Of the 108 possible coefficients, 71% are positive and significant at at least the 10% level, and only 3.7% are negative and significant at that level. This is suggestive of complementarity, where having cities in other tiers closer to a city is beneficial. In terms of magnitudes of these complementary effects, they differ by pair. For example, for the effect of tier-1 neighbours on tier-2 cities (middle column, top row), in some countries the elasticities before distance discounting are very large (1.0 or more) while in many others they are more like 0.25. This wide range seems to hold in most tier-pair comparisons, although for the effect of tier-3 neighbours on tier-2 cities (middle column, bottom row), the absolute range is smaller: roughly 0.03 to 0.45

for significant coefficients.

Finally, when looking at non-adjacent pairings – the effect of tier-3 MA on tier-1 cities or tier-1 MA on tier-3 cities– there is no clear pattern. Of these, some are positive and some are negative at the 10% level, with half being strongly insignificant. Complementarity does not seem to extend to tier-1 and tier-3 interactions.

4.3 Decomposition

In discussing Eq. (11), we did a decomposition of ΔMA into neighbours' change in "income" (built mass) and change in travel time components. Here we show the first part of the decomposition in Figure 4 and discuss issues with the second that will lead into a discussion of the IV approach. While results in Figures 3 and 4 are similar, Figure 4 for the income effect holding travel time constant shows much stronger patterns of complementarity and competition. These drive the results in Figures 3. [8] Our growth patterns are driven by changes in neighbour's mass or income.

What about changes in travel times and the second part of the decomposition? The problem is a data one: there is very little variation recorded in Michelin map road quality between 2000 and 2014 and we cannot reliably look at the OLS impact of pure travel time changes.[9] While Jedwab and Storeygard (2021) cite declining road investment as a source of decreasing variation, we know of countries like Uganda and Zambia where there is huge variation from 2000 to 2014 (see Peng and Wang (2024) and Bird and Venables (2020)), but none in the Michelin maps. The suspicion is that the quality of recording and updating for Michelin maps deteriorates over time, as people come to rely on GPS navigation systems and not paper maps. However, there is significant historical variation, which could be useful when instrumenting. For 2000-2014, for 7 countries, as shown in Appendix Table B3, there is absolutely no change in road quality in all the, typically thousands, of pairwise connections within a country. For 9 more countries, less than one third of pairwise connections within the country have any change, and, for many of that third, the fractions are tiny. So overall, about 60% of countries have less than a third of pairwise routes with any travel-time changes for 2000-2014. For 1990-2000 and 1975-1990 the 60% becomes respectively 33% and 4%, showing much more variation. Moreover, there is only one country with no changes for 1990-2000 and none for 1975-1990. Finally only Uganda shows tiny or no changes in all 3 time periods. In earlier years, many countries have high fractions of pairwise routes with road quality variation. In summary, the problem we face is that there is little (semi)-exogenous variation in road quality for 2000-2014, only historical. That leads into a discussion of identification issues.

[8] In this specification, replacement of base period travel time by travel distance gives almost the same strong results.

[9] Results for the 20 countries with any variation show essentially nothing. We think that occurs because of both the lack of variation, and, for countries with variation, very poor measurement in this time period.

5 Identification

Estimating Eq. (10) as a first difference in Eq. (11) in principle takes care of identification issues to do with time invariant unobservables. However, problems remain as usual. First, own growth is subject to time-varying omitted variables that may be correlated with contemporaneous parts of the ΔMA's. For example, settlements could be subject to regional time-varying productivity shocks which enhance their growth rates. If we expect β^{ii} coefficients to be negative common shocks could bias the coefficients upwards towards zero when shocks improve both the own and tier i neighbours' V. These same shocks could also affect decisions about local road investments. To try to deal with persistence over time from these shocks, in the estimation for growth from 2000 to 2014, one can insert variables for own 1975 and 1990 sizes, which help control for aspects of these influences (Duranton et al., 2014). But the problem of contemporaneous regional shocks affecting own and neighbours' growth remains. A classic way (Arellano and Bond, 1991) to deal with this is to instrument with lagged values, in this case 1975 and 1990 values of the neighbour-settlement type variables. While these are strong instruments, even the weak tests for exogeneity of such instruments cited in most empirical work completely fail in our context.

The second source of bias comes from the virtuous (or vicious) circle of NEG. A shock solely to the own city affects its neighbours through the own city demand for neighbour products and that neighbour effect in turn affects the own city, so effects are reinforcing. Negative effects potentially become more negative and positive ones more positive.

To deal with these sources of bias, we undertake instrumental variable estimation. We explore two types of instruments. One based on Jedwab and Storeygard (2021) treats changes in travel times beyond a certain perimeter as exogenous to the own locality. Given the extensive experimentation in Jedwab and Storeygard where results are fairly consistent across the many formulations to do with the perimeter and direction, we use their simple version with contemporaneous changes and historical ones. The first instrument associated with ΔMA_{it}^{GH} is $I\Delta MA_{it}^{GH}$ where

$$I\Delta MA_{it}^{GH} = \Big(\sum_{j \in G, i \neq j, d_{i,j} > r} \theta_{ijt} V_{jt-1}^{G} + \sum_{j \in G, i \neq j, d_{ij} \leq r} \theta_{ijt-1} V_{jt-1}^{G} \Big) - \sum_{j \in G, i \neq j} \theta_{ijt-1} V_{jt-1}^{G}. \tag{12}$$

We use this for the 2000 to 2014 time period with the perimeter set to a radius, r, of 55 km following the base specification in Jedwab and Storeygard (2021)[10], and check for robustness to

[10]The instrumental variable in Eq. (12) uses the change in market access due to road changes far away, while fixing built-up area of all cities at their initial levels. Eq. (12) is written in a compact form. Formally, the instrument is computed on a hybrid network in which roads inside the exclusion radius are fixed at their baseline ($t-1$) condition, while only roads outside the circle are updated to period t. The exclusion restriction is that road changes outside are exogenous. This approach effectively isolates variation from non-local road improvements while maintaining network

other distances. However, we know already there is little variation in this variable for 2000-2014. Thus we add lags for 1990 to 2000 and 1975 to 1990 where there is more recorded variation in road quality. Any power from the instrument must rely on correlation in road improvements over time and lagged effects from such improvements.

The second instrument is based on shocks to mining prices for nearby mines. First, we allocate revenue in time t for all operational mines, m_t, in a country to all towns, n, based on their distance to the mine. For neighbour city l, where d_{kj} is distance in 100's of kms from city k to mine j,

$$R_{lt} = \sum_{j=1}^{m_t} Q_j P_{jt} [d_{lj}^{-1/\rho} / \sum\nolimits_{k=1}^{n} d_{kj}^{-1/\rho}]. \tag{13}$$

In Eq. (13), Q_j will be a measure of capacity that is the same each time period in the data (see below). Price, P_{jt} is what varies over time. Then for city i in tier H, the mining revenue for cities in tier G which affect it is

$$MR_{it}^{GH} = \sum_{l \in G} lnR_{lt}^{GH} (1 + d_{il})^{-\gamma}. \tag{14}$$

The instrument for ΔMA_{it}^{GH} is the shock to city i in tier H from towns in tier G experiencing mine revenue shocks, that is

$$\Delta IMR_{it}^{GH} = MR_{i,t}^{GH} - MR_{i,t-1}^{GH}. \tag{15}$$

We use the instrument where shocks come from price changes and any changes in number of operating mines for 2000 to 2014 and the lagged version for those changes from 1990 to 2000. We note for mining instruments that price shocks may be more relevant in influencing tier 3 city sizes and those ΔMA measures, rather than larger cities as shocks may be very localised and relevant for smaller settlements, as indicated in Provenzano and Bull (2023) and Huang et al. (2024). In implementation in estimation of growth equations, we need to control for the own city mining shocks, which we do by controlling for own city mine revenue for 1990, 2000, and 2014. In the equations above, we use the same γ as in Eq. (9) and set ρ equal to 1.

In terms of data, some details are given in Table B1. Mine locations, primary mineral types, operational status, and primary mineral value are sourced from the African Deposit Database (ADD)[11]. International prices for each mine's primary ore or gem are obtained from the World Bank Commodity Price data and supplemented by the US Geological Survey (USGS) for 1960–2024. All nominal prices are adjusted for inflation using the World GDP deflator to ensure comparability over time. The ADD provides estimated primary mineral value, $V_{jt_{now}}$, during 2020-2023 for the

connectivity.

[11] The dataset is developed and licensed by MinEx Consulting.

relevant mineral for each mine. We recover $Q_j = \frac{V_{jtnow}}{P_{jtnow}}$ and treat Q_j as time-invariant.

6 Instrumental Variable Results

We break this discussion into two parts. The first concerns the tier structure, and the second presents our results on the forces of competition versus complementarity.

6.1 Characterisation of the Tier Structure

We now focus on the derivation of tier structure under instrumental variable estimation. As before we are looking over 420 possible k_1, k_2 pairs to find the best pair. In determining tier structure, because market access covariates are endogenous, we follow Hall et al. (2012) on multiple structural breaks with endogenous regressors. For each k_1, k_2 cut, we estimate each of the 3 equations by 2SLS. Then for that cut, we calculate the SSR across all observations based on estimated coefficients and using *predicted* values (from the first stage) for endogenous variables. We pick the k_1, k_2 combination that minimizes the SSR. As noted above we constrain comparisons to those where the degrees of freedom are sufficient in terms of counts of cities to estimate all 3 equations for the country and we require that the number of tier-3 cities is greater than tier-2 which in turn is greater than tier-1.

Results are in Table 2 listing the k_1, k_2 points and the number of cities in each country in each tier. Results in most cases seem appropriate with a limited number of tier-1, or top cities and numerous tier-3 settlements which are tiny ones at the bottom of the size distribution. There are 7 out of 54 cases cases where tier-1 city counts are upped to meet degrees of freedom needed for estimation. Clearly, the tier count restriction binds when counts of cities in tier-$(j + 1)$ and tier-j are almost equal. We relax this restriction in robustness checks.[12]

Theory suggests that this tier structure should be grounded in the production structure of places in each tier. We have data on the allocation of employment across the primary, secondary, and tertiary sectors by sub-national units for 8 countries (Benin, Cameroon, Ethiopia, Ghana, Mozambique, Tanzania, Uganda, and Zambia), circa 2000. These are second level sub-national units, creating a crude spatial cut, not at the settlement level, but rather at a very aggregated level as we will see from sample sizes. For each sub-national unit j in country c, we calculate the share of sector s in unit j's employment, $ShareInd^s_{j,c}$. For the three industries, we then have a share equation for each industry across the sub-national units of a country. As explanatory variables, we use the share in

[12]Also, in 14 of the 54 cases we are at a corner, revealing issues with finding interior cut-offs.

unit j of tier-1, -2, and -3 settlements in total urban built area within the unit, $Sharebuilt^s_{j,c}$. [13] Thus, we have 3 equations, each with 2 explanatory variables: the share of tier-2 and -3 cities in the total built-up area of the sub-national unit. Note that, with a constant term, since shares add to one, we only have two free tier share variables. In summary we estimate

$$ShareInd^s_{j,c} = \gamma^s + \gamma^{2s} Sharebuilt^2_{j,c} + \gamma^{3s} Sharebuilt^3_{j,c} + \nu_c + \epsilon^s_{j,c}, \quad s = 1, 2, 3. \tag{16}$$

We focus on the pooled results for the 8 countries with country fixed effects ν_c and common γ coefficients. We estimate the system of equations by MLE [14]. We also report individual country results.

Results are in Table 3. The main pattern is clear. For the pooled and individual results, tier-2 and -3 cities have significantly more agriculture, significantly less manufacturing and even less service shares than tier-1, in line with theory structure. The problem lies in distinguishing activities of tier-2 versus tier-3 cities. We know from Henderson and Kriticos (2018) that below the very largest cities in a country, in census data, 40-50% of the population living in towns report their primary occupation as farming, making it difficult to distinguish their other daily work activities. The lack of city level data obviously doesn't help the situation. In the individual country results in Table 3, when there is a clearer tier-2 and-3 separation in the 8 countries in Table 2, there seems to be less manufacturing in tier-2 compared to tier-3 (which could be focused on agro-processing). For the clearest hierarchy of these 8 countries from Table 2, Ghana, there is a clear distinction with tier-3 compared to tier-2 being more manufacturing oriented and less service oriented.

6.2 Results on Competition and Complementarity

We now turn to the IV results on patterns of competition versus complementarity. As noted above, in estimation, our instruments are the $I\Delta MA^{GH}_{it}$ terms in Eq. (12) for 2000-2014, 1990-2000, and 1975-1990 and the ΔIMR^{GH}_i term in Eq. (15) for 2000-2014 and for 1990-2000. IV results are in Figure 5, following the same format as in Figure 3. Now on the x-axis, however, what is reported are 1st stage Sanderson-Windmeijer F's. [15]

In general, results are supportive of the qualitative OLS results, despite the demands on the data from the tier structure and poor quality road data in the contemporaneous period. Exact coefficients

[13] When settlements span unit borders, we allocate built for that city in that tier in each sub-national unit according to each unit's share of built area of the city.

[14] We use iterated seemingly unrelated regressions.

[15] The Sanderson-Windmeijer F-statistic builds upon the conditional first-stage F-statistic proposed by Angrist and Pischke (2009) and allows the econometrician to bound the bias induced by weak instruments in linear IV models with multiple endogenous variables.

and standard errors are given in Appendix Table B2b. The IV results mimic the OLS in patterns of complementarity and competition, with similar magnitudes for significant coefficients. It may be that, overall, IV coefficients are arguably modestly smaller in absolute magnitude, for example with tier-2 own effects in some cases. If smaller, that would indicate the bias in estimation under OLS may come more from the NEG virtuous or vicious reinforcing circle, rather than common shocks. But again overall, it seems the two sources of bias may typically approximately cancel out. However, in the results, now there are also more "incorrect" signs. On the diagonal under OLS, for coefficients significant at the 10% level, while 80% were negative and 2.5% positive, under IV the percentages are respectively 52% and 15%. Similarly, on the off-diagonal but adjacent in tier structure numbers, again at the 10% level, while under OLS, 71% were positive and 3.7% negative, under IV the respective percentages are 42% and 14%. That said, this is very challenging estimation with a tier structure to MA effects and within that opposing forces of competition and complementarity where separation of the observations into tiers is itself estimated with imperfect instruments. Some F-stats on the horizontal axis in Figure 5 are weak, especially for countries where there is little recent recorded variation in road quality. Hansen-J stats for the estimation are reasonable under the circumstances. For the 27 x 3 equations as reported in Appendix Table B4, of the 27 countries, for tier-1, 59% pass the Hansen-J test at the 5% level; for tier-2 it is 48% and for tier-3 70%. We interpret the IV evidence as supportive of the forces of competition and complementarity that we found under OLS.

Robustness We conducted many robustness checks concerning the number of instruments, lists of control variables, spatial rate of discount, and constraints on the tier structure.[16] For all of these, results are similar. For example we can shorten the instrument list by dropping either the lagged mining instrument or the 1975-1990 ΔIMA instrument, or add geo-controls (but that heightens degrees of freedom problems in tier-1). Similarly, we avoid imposing in the tier structure that tier-3 counts > tier-2 > tier-1. Results are robust across these items.[17]

The one we report on in the Appendix concerns the nature of spatial decay, always a source of contention. We tried several experiments with similar outcomes. For one, rather than measuring τ_{ij} in units of 15 hours, we measure it in units of 5 hours and we change γ from 0.64 to 0.33 (the number in Milsom (2023)). Relative to the base, that gives a somewhat sharper discount at low travel times but a somewhat milder one at high travel times. Results for this are given in Appendix Figures B1a and B1b and are similar to those in Figures 3 and 5. For example in Figures 3 and 5 on

[16]Additional robustness check results are available at this link.

[17]For example, for no restriction on counts of cities by tier in the IV estimated tier structure, we get on the diagonal for OLS and IV respectively, 81% and 46% of negative coefficients significant at the 10% level. These are very close to what we have in the main results.

the diagonal under OLS and IV respectively, we had 80% and 52% of coefficients are negative and significant at the 10% level. In Appendix Figures B1a and B1b these percents are 81% and 47%. [18]

7 Conclusion

Sub-Saharan Africa has experienced enormous urban growth since the end of the colonial era. What has emerged is a hierarchy of settlements that is likely to shape future development for decades—if not centuries—to come. This paper describes this process and provides insights into some of the factors shaping this emerging hierarchy. We develop a method for characterising the hierarchy based on explanatory power of the model and ground-truthed by production patterns at different tiers of the hierarchy. We show that the relative performance of settlements is strongly dependent on their relationship to neighbouring settlements. Settlements are negatively affected if they are close to larger settlements of the same type, but are positively affected if close to larger settlements in different tiers. We rationalise this in terms of a theoretical model in which settlements perform different functions—primary and agriculture, primary-processing and traditional manufacturing, and higher-tech and services. Patterns of complementarity and competition between these functions generate the performance and emergent urban hierarchy that we see in the data.

[18] We also tried just τ in units of 5 hours and γ=0.64 which is very sharp discounting. That gives on the diagonal, 69% negative and significant at the 10% level for OLS and 35% for IV.

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Tables

Table 1: The data in the 2014 cross-section

	(1) Size category	(2) Min size	(3) Max size	(4) Total built	(5) Shell area	(6) Count	(7) Share built
1	[0.0009,0.251]	0.0009	0.2511	2608	447165	105366	0.1000
2	(0.251,1.44]	0.2520	1.4445	2607	112957	4716	0.1000
3	(1.44,5.85]	1.4454	5.8536	2606	62547	954	0.0999
4	(5.85,18.2]	5.8554	18.1845	2595	41014	261	0.0995
5	(18.2,43.6]	18.3942	43.6311	2586	26117	91	0.0991
6	(43.6,95.5]	43.6869	95.4792	2645	34056	41	0.1014
7	(95.5,173]	96.8661	173.4880	2494	25710	20	0.0956
8	(173,313]	173.6270	313.4980	2486	17023	10	0.0953
9	(313,544]	347.6650	543.6480	2804	20616	7	0.1075
10	(544,1.37e+03]	634.6690	1370.4000	2649	12997	3	0.1016

Note: The table depicts a summary of our 2014 data for Africa as a whole. It divides the data into 10 bins of (almost) equal share of total built area. Shares and total built area (in sq. km.) in each bin are given in columns 7 and 4 respectively.

Table 2: City counts by country in each tier and optimal cut-offs

				Number of settlements		
Isocode	Country name	k1	k2	tier-1	tier-2	tier-3
AGO	Angola	95	99.5	124	627	640
BEN	Benin	95	98	81	84	182
BFA	Burkina Faso	93	98	35	87	313
BWA	Botswana	94	98	36	43	232
CAF	Central Afr. Rep.	95	99	222	271	302
CIV	Cote d'Ivoire	91	98	862	947	951
CMR	Cameroon	87	99	56	454	492
ETH	Ethiopia	94	99	253	263	366
GHA	Ghana	87	95	81	229	844
GIN	Guinea	88	92.5	145	158	1141
KEN	Kenya	95	98.5	74	106	282
LBR	Liberia	85	97	31	315	365
MLI	Mali	93	99	226	686	690
MOZ	Mozambique	93	99.5	67	410	418
MWI	Malawi	88	97.5	32	182	324
NAM	Namibia	93	99	55	175	264
NER	Niger	86	98	122	522	627
NGA	Nigeria	95	99	789	1220	1303
SDN	Sudan	95	99.5	56	196	370
SEN	Senegal	92	98.5	64	196	251
SLE	Sierra Leone	94	97.5	201	207	346
TCD	Chad	94	99.5	46	209	251
TGO	Togo	94	98.5	38	84	122
TZA	Tanzania	95	99	240	473	648
UGA	Uganda	94	98.5	69	142	252
ZMB	Zambia	95	99.5	40	287	400
ZWE	Zimbabwe	95	99	96	319	476

Note: Cut-off numbers give the fraction of national urban built area accumulated by tier 1 and tier 2 cut-offs (k1 and k2). Corners occur if cut-offs are at 75 or 95 (tier 1) and 90 and 99.5 (tier 2). While we the pick value that minimizes SSR as described in the text based on 2SLS and predicted values of variables, among all k1 and k2 pairs, pairs considered are constrained to values so there are sufficient degrees of freedom to conduct reduced form estimation and to ensure the count of tier-1 cities< tier-2< tier-3.

Table 3: Industrial composition by tier

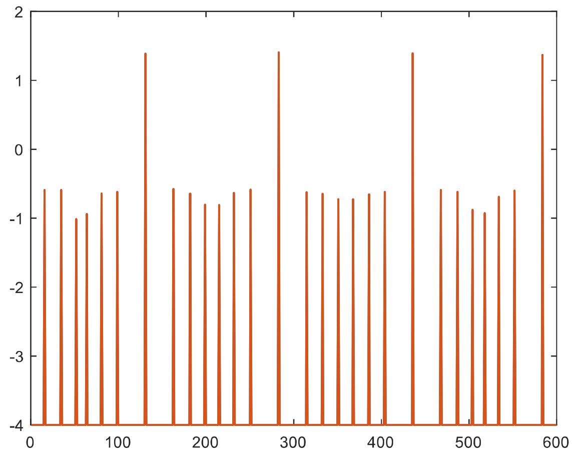
Country name	Variables	Share primary	Share manu	Share tertiary
	Share tier-2	0.302***	−0.069***	−0.233***
		(0.023)	(0.005)	(0.019)
Pooled	Share tier-3	0.275***	−0.065***	−0.210***
		(0.031)	(0.008)	(0.025)
	N		811	
	Share tier-2	0.578***	−0.188***	−0.390***
		(0.130)	(0.042)	(0.102)
Benin	Share tier-3	0.243	−0.102***	−0.141
		(0.159)	(0.024)	(0.140)
	N		75	
	Share tier-2	0.376***	−0.108***	−0.268***
		(0.094)	(0.025)	(0.077)
Cameroon	Share tier-3	0.378	0.150	0.228
		(0.433)	(0.120)	(0.373)
	N		58	
	Share tier-2	0.368***	−0.108**	−0.260***
		(0.111)	(0.037)	(0.079)
Ethiopia	Share tier-3	0.263***	−0.070***	−0.193***
		(0.058)	(0.020)	(0.042)
	N		68	
	Share tier-2	0.298***	−0.079***	−0.220***
		(0.049)	(0.022)	(0.034)
Ghana	Share tier-3	0.401***	−0.107***	−0.294***
		(0.059)	(0.024)	(0.042)
	N		110	
	Share tier-2	0.304***	−0.066***	−0.239***
		(0.042)	(0.008)	(0.036)
Mozambique	Share tier-3	0.363***	−0.083***	−0.280***
		(0.045)	(0.009)	(0.037)
	N		141	
	Share tier-2	0.216***	−0.043***	−0.173***
		(0.058)	(0.013)	(0.046)
Tanzania	Share tier-3	0.186**	−0.046***	−0.140**
		(0.077)	(0.012)	(0.068)
	N		127	
	Share tier-2	0.301***	−0.060***	−0.241***
		(0.055)	(0.011)	(0.046)
Uganda	Share tier-3	0.236***	−0.039***	−0.197***
		(0.050)	(0.013)	(0.039)
	N		160	
	Share tier-2	0.277***	−0.048***	−0.229***
		(0.066)	(0.014)	(0.052)
Zambia	Share tier-3	0.271***	−0.049***	−0.223***
		(0.057)	(0.017)	(0.044)
	N		72	

Note: These regressions are estimated using maximum likelihood estimation (MLE). We use iterated seemingly unrelated regressions. Note that since tier shares add to 1, there are only two free share-tier variables. In share primary, mining employment is excluded. In the pooled results, we control for the country fixed effects. Robust standard errors are in parentheses. ***, **, * denote statistical significance at the 1%, 5%, 10% levels, respectively.

Figures

Figure 1: Model simulation: employment

Employment around a circle (600 locations)



Employment on a disk (hexagonal lattice, 1147 locations)

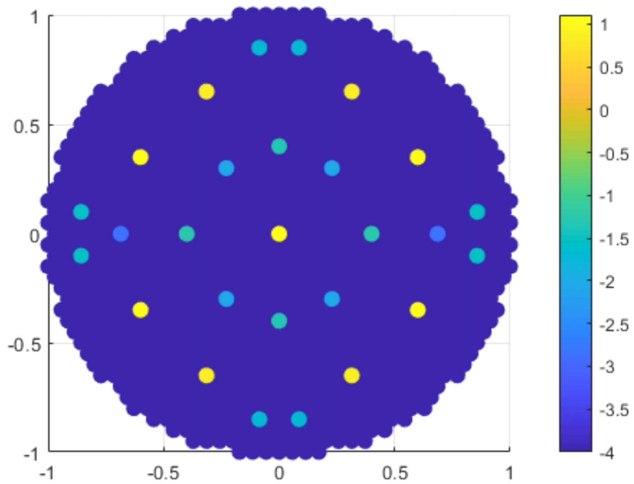


Figure 2: Employment and own- and cross-tier effects

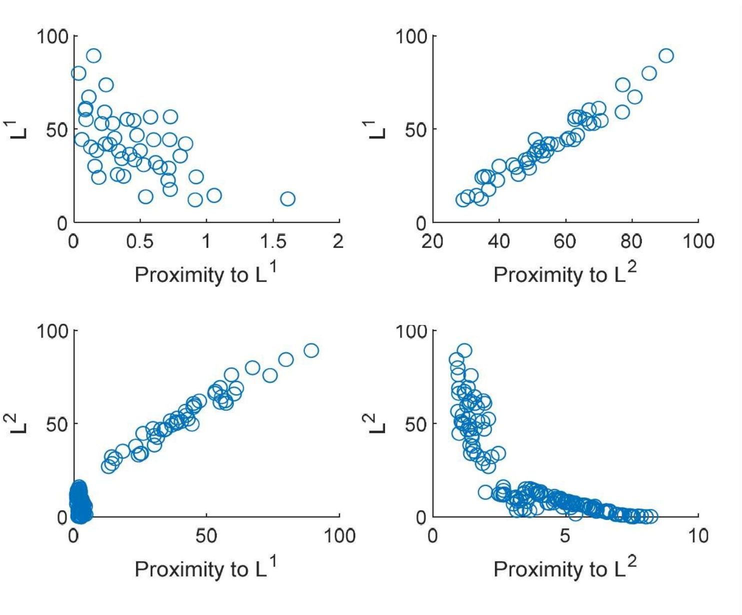
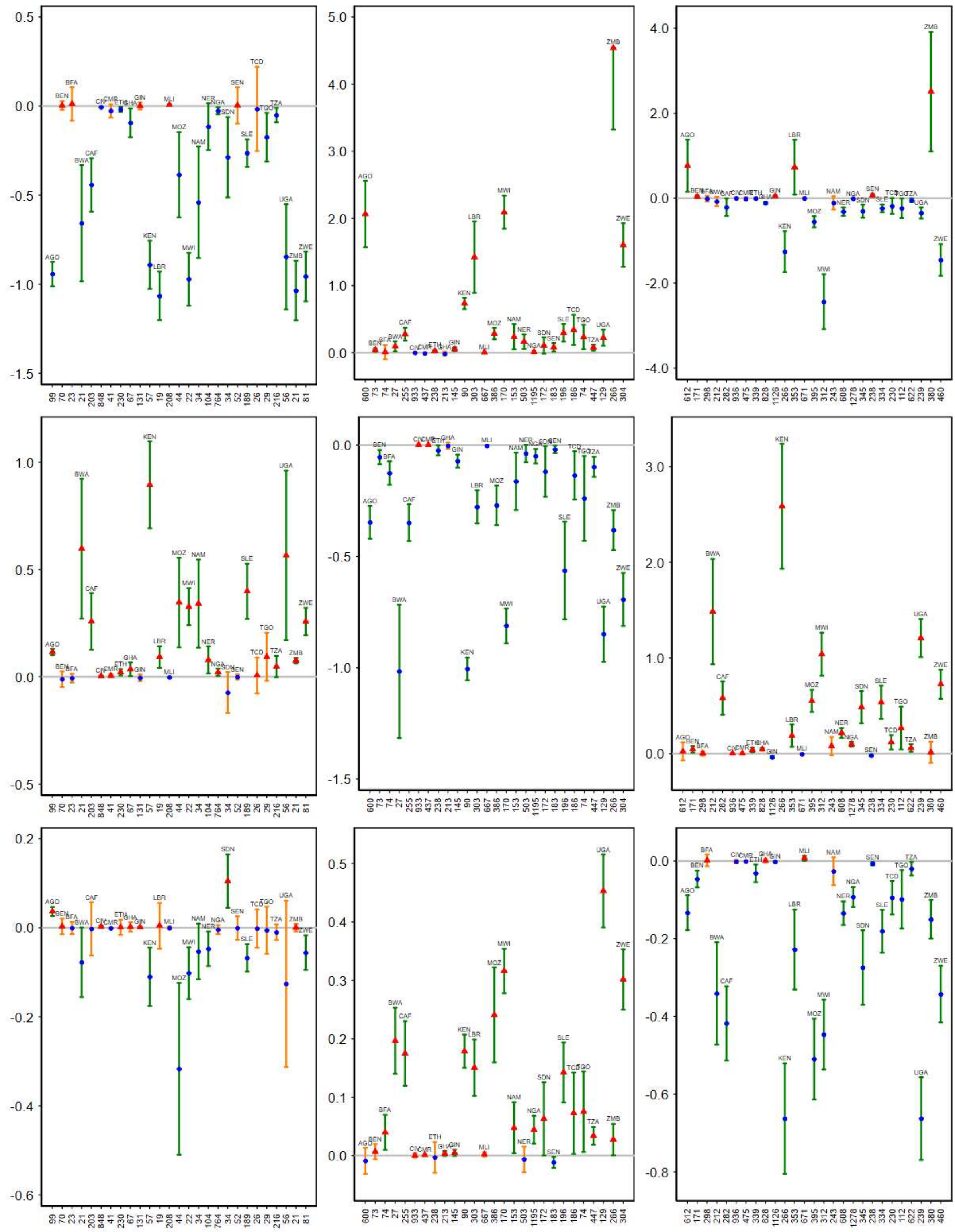
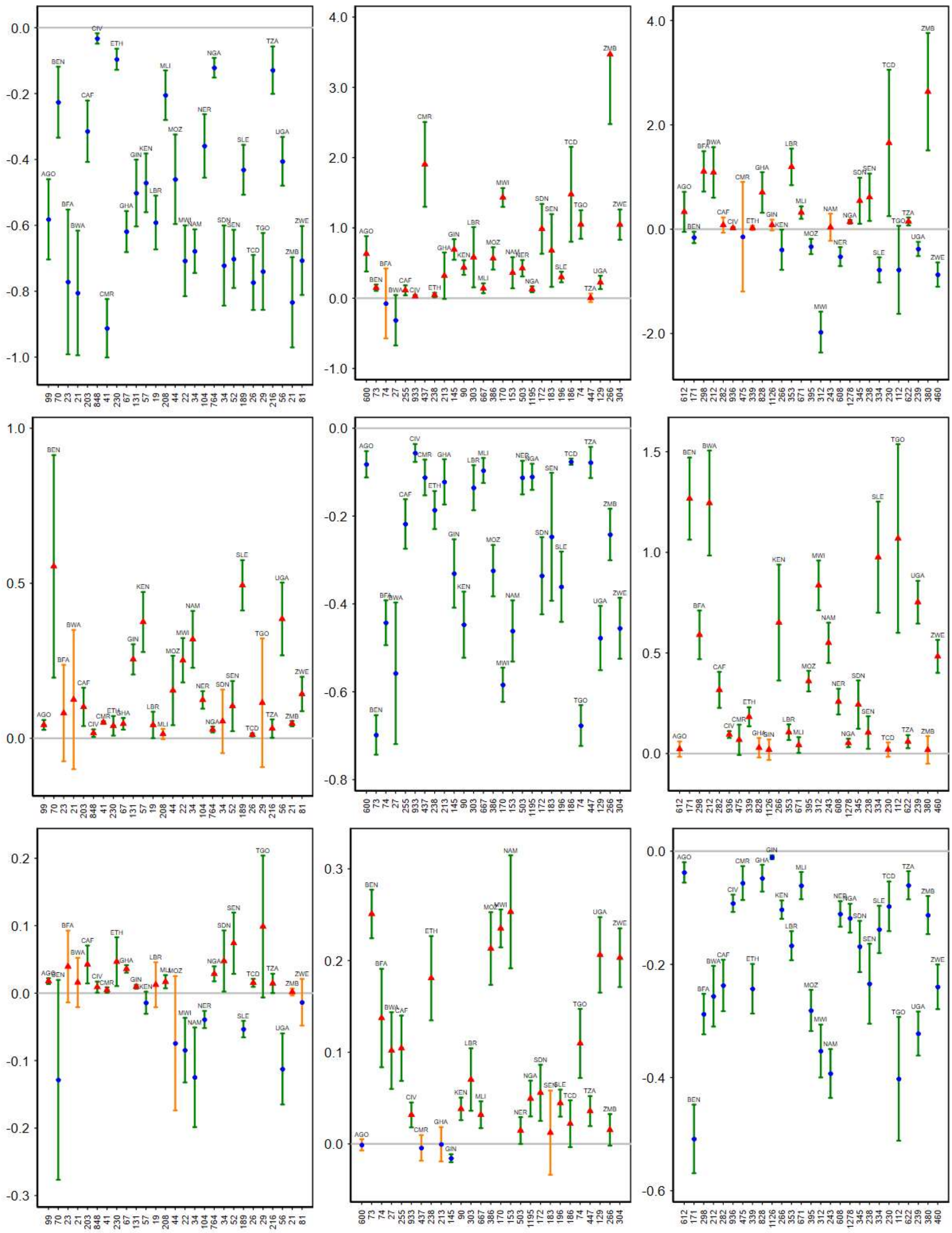


Figure 3: OLS coefficients by country code



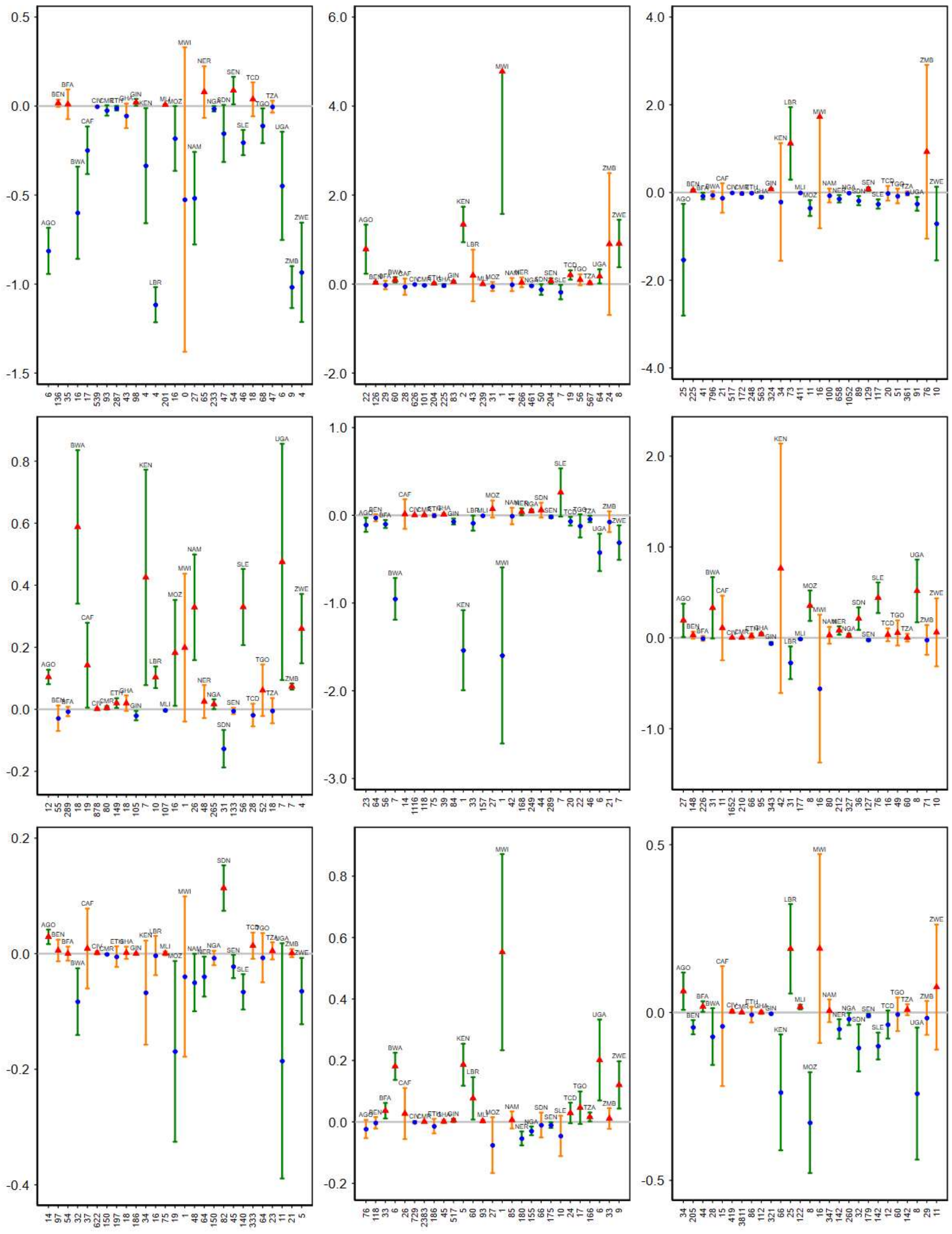
Note: Columns show coefficients for cities in tiers 1 to 3 from left to right. Rows are for tier 1, 2 and 3 (top to bottom) ΔMA effects on cities of each type. Points with green error bands show points that are significant at the 10% level, but error bands show 5% confidence intervals. Blue [orange] points are negative [positive]. Numbers on horizontal axis are degrees of freedom in estimation.

Figure 4: Decomposition coefficients by country code: Income effects



Note: Columns show coefficients for cities in tiers 1 to 3 from left to right. Rows are for tier 1, 2 and 3 (top to bottom) ΔMA effects on cities of each type. Points with green error bands show points that are significant at the 10% level, but error bands show 5% confidence intervals. Blue [orange] points are negative [positive]. Numbers on horizontal axis are degrees of freedom in estimation.

Figure 5: IV coefficients by country code



Note: Columns show coefficients for cities in tiers 1 to 3 from left to right. Rows are for tier 1, 2 and 3 (top to bottom) ΔMA effects on cities of each type. Points with green error bands show points that are significant at the 10% level, but error bands show 5% confidence intervals. Blue [orange] points are negative [positive]. Numbers on horizontal axis show 1st stage partial Sanderson-Windmeijer F-stats.

Appendix

A Data

A.1 The Method to Define Urban Area

We first upsample (aggregate smaller pixels to bigger pixels by taking the mean) built-up in 30×30 pixels to 210×210 pixels, which we call super-pixles. This step is simply to reduce the computational burden, since we are targeting the whole SSA. We then generate a smoothed built-up surface by smoothing over using a 11×11 kernel. This is to capture continuous built-up area by filling potentially disconnected parts in cities. The width and height of the kernel is thus 2.3km ($\approx 210m \times 11$). Weight is a decreasing function of distance as in de Bellefon et al. (2020), that is, weight $K_h(d_{ij}) = [1 - (\frac{d_{ij}}{h})^2]^2 1\{d_{ij} < h\}$, where d_{ij} is the distance of a pixel in coordinates (x_i, y_i) to the center pixel in coordinates (x_j, y_j) in the kernel $d_{ij} = \sqrt{(x_j - x_i)^2 + (y_j - y_i)^2}$, h is the bandwidth of ($\approx 210m \times 11/2$). Smoothed density $\hat{z_j}$ in pixel (x_j, y_j) is $\frac{1}{\sum_i K_h(d_ij)} \sum_i K_h(d_{ij}) z_i$, where z_i is the built-up density in pixel i. The aggregation includes the own pixels in both the smoothed actual built-up and the counterfactual built-up.

The built-up surface is continuous between 0 and 1. To decide which area is urban, we need a threshold. This threshold is obtained based on a counterfactual smoothed built-up density where built-up are randomly allocated.

Counterfactual distribution of random built-up We take the following steps to generate a counterfactual distribution of random built-up:

1. Generate a matrix of 7000×7000 with 0 and 1, with the mean of actual country-specific share of built-up in the year 2014 based on the 30m $\times$ 30m pixels. Using the mean built-up in earlier years, e.g. 1990, gives less rigorous results for year 2014 as measurement is better in 2014. Varying years is also not desirable as this makes comparing built-up over time problematic. This corresponds to the original 30m data.

2. Downsample to 1000×1000 by taking average over 7×7 patches, which corresponds to the 210m data.

3. Generate smoothed built-up surface using the 11×11 kernel as we did for the raw built-up.

4. Bin the smoothed share of built-up into 100000 groups, and take the count of observations in each bin. Bins are evenly distributed between 0 and 1[19]. The size of each bin is $\frac{1}{100000}$.

5. Repeat steps 1-4 500 times and sum up the counts of obs by bins in each iteration.

[19]As the weight in the kernel are normalised, the max of smoothed built-up is still 1.

We choose the 95th percentile of the distribution in each country as the threshold; these are shown in Figure A2.

Identified urban area

As in de Bellefon et al. (2020), continuous pixels with smoothed built-up density above the threshold are defined as the smoothed urban boundary, which we call the shell. Within the shell, we have the actual built-up (not smoothed) from the GHSL data in the resolution of 30 m by 30 m.

Smoothed shells

Settlements that are defined in this way have a generous shell around the actual built-up. This is not obvious for large cities, e.g., Accra and Nairobi, as shown in Figure A1(a) and (c)), but quite significant for small towns, as shown in Figure A1(d), in which Nyeri is a small town to the north of Nairobi. There are occasionally holes within the boundaries that were created in this approach. As a remedy, these enclosed areas are filled using the Aggregate polygon tool in ArcGIS.

Note, using the 95th percentiles as the cut-off is important to isolate cities, especially in dense areas. If we don't cut the distribution, although we have the entire built-up, we have a much smaller count of settlements. This occurs because we have huge agglomerations of cities that are unreasonable. For example, as shown in Figure A1(b), Accra cannot be isolated from the second largest city Kumasi if no cut-off is applied. On the other hand, if we cut the distribution at a higher threshold, we capture less built-up and risk missing out some important towns.

Table A1 shows the built-up by countries using the methodology defined above in 2014.

Table A1: Built by countries 2014

Isocode	Country Name	Numbers of Settlements	Total Shell (km^2)	Built-up area: Total (km^2)	Mean (km^2)	Min (km^2)	Max (km^2)	Share (%)
COD	DR Congo	19498	120336.80	2048.09	0.11	0.0009	163.48	7.85
NGA	Nigeria	10221	97178.38	7370.73	0.72	0.0009	1370.40	28.26
MLI	Mali	6142	36976.31	435.62	0.07	0.0009	188.15	1.67
AGO	Angola	5977	33587.40	1199.91	0.20	0.0009	543.65	4.60
CIV	Cote d'Ivoire	5369	31568.46	1172.27	0.22	0.0009	252.83	4.49
NER	Niger	4657	52041.15	400.70	0.09	0.0009	60.48	1.54
ETH	Ethiopia	4162	26189.77	506.41	0.12	0.0009	136.58	1.94
TZA	Tanzania	4087	30131.74	870.39	0.21	0.0009	311.89	3.34
ZMB	Zambia	3648	20705.72	578.58	0.16	0.0009	163.21	2.22
MOZ	Mozambique	3363	31042.95	978.79	0.29	0.0009	357.85	3.75
GIN	Guinea	3285	18326.49	510.91	0.16	0.0009	186.73	1.96
ZWE	Zimbabwe	3069	25198.89	524.29	0.17	0.0009	304.98	2.01
SDN	Sudan	2982	25877.56	840.06	0.28	0.0018	368.81	3.22
CMR	Cameroon	2980	22154.09	703.53	0.24	0.0009	173.63	2.70
MDG	Madagascar	2733	12921.70	184.82	0.07	0.0009	74.82	0.71
GHA	Ghana	2489	24045.29	2063.33	0.83	0.0009	634.67	7.91
UGA	Uganda	2489	14524.96	427.30	0.17	0.0009	249.92	1.64
BFA	Burkina Faso	2078	11140.58	359.06	0.17	0.0009	171.35	1.38
KEN	Kenya	2023	16338.74	288.30	0.14	0.0009	108.49	1.11
SLE	Sierra Leone	1836	9896.72	238.55	0.13	0.0009	68.47	0.91
CAF	Central Afr. Rep.	1644	11275.89	147.76	0.09	0.0009	64.84	0.57
LBR	Liberia	1634	9628.08	233.42	0.14	0.0009	109.05	0.90
TCD	Chad	1536	11425.47	185.68	0.12	0.0009	84.15	0.71
SEN	Senegal	1524	14165.55	661.50	0.43	0.0018	347.67	2.54
BWA	Botswana	1288	11332.85	302.26	0.23	0.0018	113.68	1.16
COG	Republic of the Congo	1189	9164.72	214.87	0.18	0.0009	128.01	0.82
MWI	Malawi	1167	7279.15	164.84	0.14	0.0009	61.30	0.63
NAM	Namibia	1079	7818.23	110.69	0.10	0.0009	24.66	0.42
BEN	Benin	1073	11136.86	597.71	0.56	0.0009	307.60	2.29
SOM	Somalia	995	10179.89	585.61	0.59	0.0009	120.02	2.25
SSD	South Sudan	860	6048.82	100.75	0.12	0.0009	42.03	0.39
GAB	Gabon	694	3609.37	86.61	0.12	0.0009	46.77	0.33
TGO	Togo	610	4338.59	257.66	0.42	0.0009	173.49	0.99
GNB	Guinea-Bissau	582	3377.96	68.20	0.12	0.0009	29.50	0.26
RWA	Rwanda	499	3624.15	154.92	0.31	0.0009	95.48	0.59
BDI	Burundi	389	1961.55	72.78	0.19	0.0009	41.22	0.28
MRT	Mauritania	384	3049.38	126.70	0.33	0.0009	99.68	0.49
SWZ	Eswatini	344	3485.37	56.60	0.16	0.0018	29.68	0.22
LSO	Lesotho	229	2738.02	71.76	0.31	0.0018	52.71	0.28
GNQ	Equatorial Guinea	227	1159.11	35.18	0.16	0.0009	19.95	0.13
ERI	Eritrea	224	1881.98	9.31	0.04	0.0009	4.39	0.04
GMB	Gambia	202	1310.90	132.55	0.66	0.0027	98.14	0.51
STP	Sao Tome and Principe	8	27.66	0.35	0.04	0.0036	0.31	0.00

Note: We drop countries that have less than 200 settlements existing from 1975 to 2014 in total and we lose more because of lack of data and drop the DRC because of very poor quality road data. In total we have 27 countries for our analysis. The "Share" column indicates the proportion of an individual country's built-up area relative to the sum of built-up areas across all sample countries.

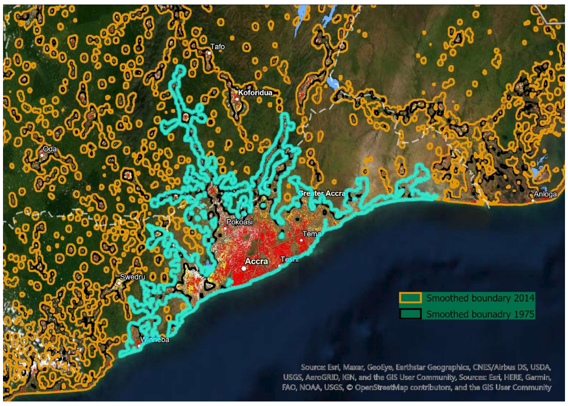
Table A2: The data in the 1975 cross-section

	(1) Size category	(2) Min size	(3) Max size	(4) Total built	(5) Shell area	(6) Count	(7) Share built
1	[0.0009,0.222]	0.0009	0.2223	1071	171039	44790	0.1001
2	(0.222,1.35]	0.2232	1.3464	1068	37138	2068	0.0998
3	(1.35,5.37]	1.3572	5.3730	1070	20892	424	0.1000
4	(5.37,13.5]	5.4747	13.4703	1060	12627	123	0.0991
5	(13.5,26.9]	13.5765	26.8965	1063	11355	56	0.0993
6	(26.9,56.9]	27.0990	56.9205	1046	6482	27	0.0977
7	(56.9,95.6]	61.4259	95.6313	1075	8200	14	0.1005
8	(95.6,146]	102.7250	146.0940	1077	7779	9	0.1006
9	(146,213]	182.7150	212.9180	1000	7137	5	0.0935
10	(213,472]	328.6430	472.2970	1169	4383	3	0.1093

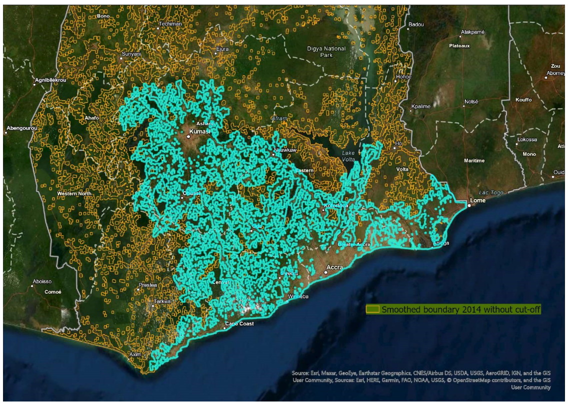
Note: The table depicts a summary of our 1975 data for Africa as a whole. It divides the data into 10 bins of (almost) equal share of total built area. Shares and total built area (in sq. km.) in each bin are given in columns 7 and 4 respectively.

Figure A1: Accra, Nairobi, Small towns

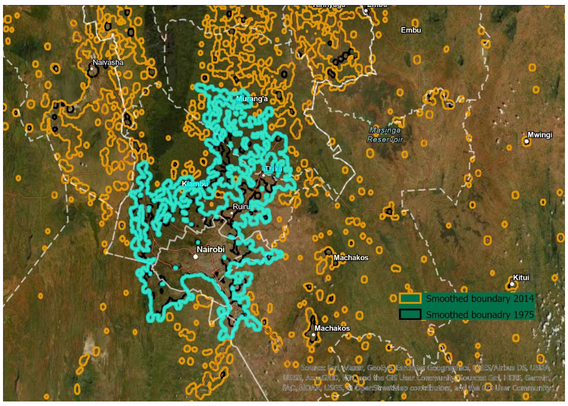
(a) Accra



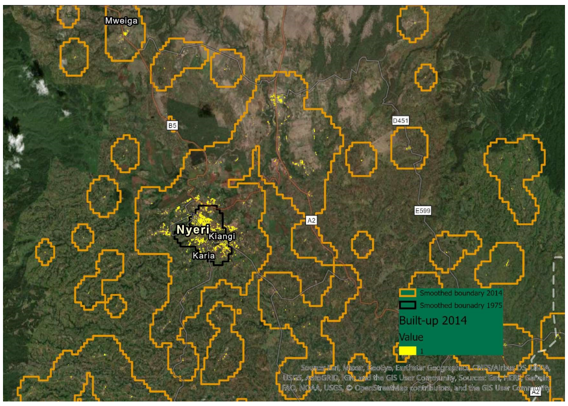
(b) Accra(No cut-off)



(c) Nairobi

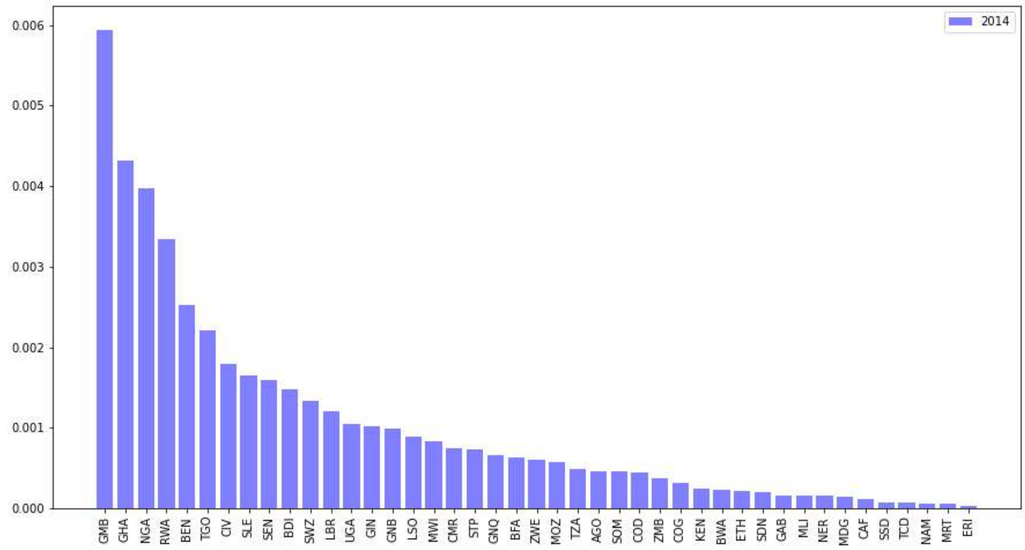


(d) Nyeri



Note: The Figure shows the boundaries of four sample cities. Panel (a), (c), (d) show the boundaries generated using the 95% cut-off in year 1975 and 2014. Panel (b) shows the boundaries generated if using zero cut-off for Accra.

Figure A2: Smoothed density cut-off



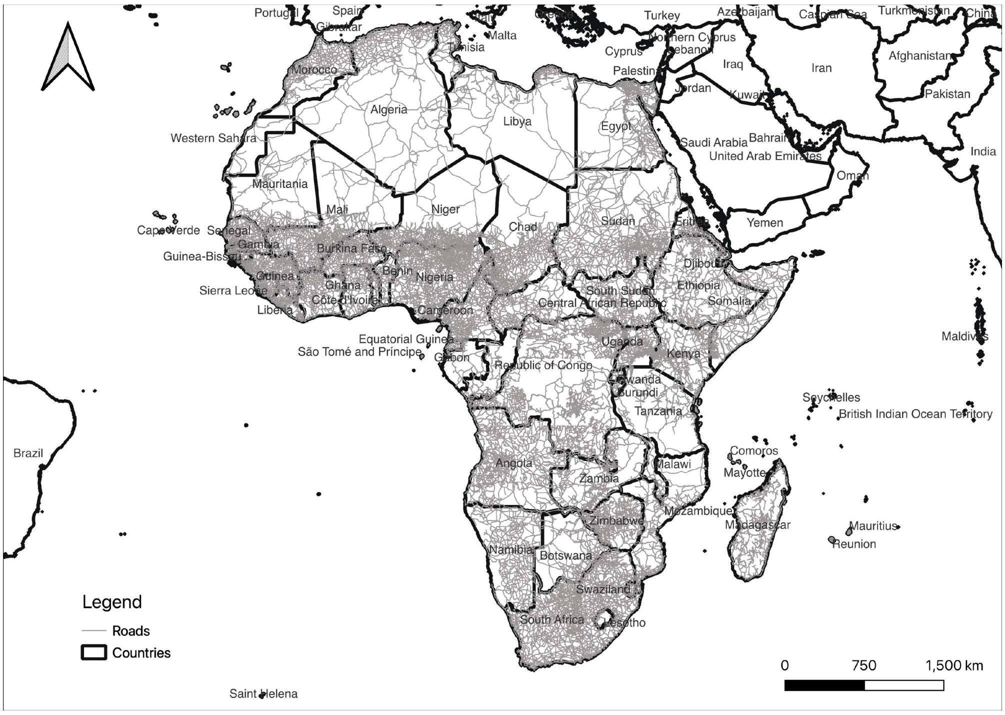
Note: Y axis shows the smoothed built-up density cut-off by 210×210.

A.2 Travel Time Calculation

This section outlines the methodology used to compute the matrix of bilateral travel times along the African road network shared by Jedwab and Storeygard (2021) between all settlements in our sample. For each country, we conduct the following steps:

1. Prepare road data: Check the topological consistency of the road network data and fix disconnected segments. Figure A3 shows the road data.
2. Build road network: Construct a graph representation by decomposing each road segment into its constituent coordinate points. Each coordinate point becomes a node in the graph, with edges created between consecutive coordinates along the same road segment. This approach preserves the exact geometry of the road network.
3. Assign speed: To convert distance to time, we assign appropriate travel speeds based on road classification: 80 km/h for highways, 60 km/h for paved roads, 40 km/h for improved roads, and 12 km/h for dirt roads. Areas without roads are assigned a very slow speed of 6 km/h.
4. Calculate travel time: Find the projected points of each settlement on the nearest road, and record the off-road travel distance. The total travel time includes the off-road travel time on both ends and the travel time through the road network. The network travel time is calculated using the Dijkstra's algorithm. We also calculate the straight-line travel time between an origin and destination pair assuming a travel speed of 6 km/h. We take the minimum travel time of the straight-line–based travel time and the network-based travel time. This avoids travel between close neighbors being routed through the road network unnecessarily.

Figure A3: Road data in Africa



Note: The data were kindly shared by the authors of Jedwab and Storeygard (2021).

B Appendix Tables and Figures

Table B1: Data source of price series and number of mining sites in different time period by mineral

	Price series range		Number of operating mines			
Commodity	First year	Last year	1990	2000	2014	Source
Asbestos	1960	2022	3	3	0	USGS
Bauxite	1960	2021	7	5	5	USGS
Chromium	1960	2022	3	3	3	USGS
Coal	1984	2024	12	13	18	World Bank
Cobalt	1960	2021	3	4	6	USGS
Copper	1960	2024	41	40	62	World Bank
Diamonds	1960	2021	59	71	92	USGS
Gold	1960	2024	214	236	423	World Bank
Graphite	1960	2022	1	1	1	USGS
Iron Ore	1960	2024	6	4	12	World Bank
Lead	1960	2024	2	2	3	World Bank
Manganese	1960	2022	6	4	8	USGS
Nickel	1960	2024	9	7	5	World Bank
PGE	1960	2022	1	3	4	USGS
Phosphate	1960	2022	6	6	7	USGS
Platinum	1960	2024	1	1	1	World Bank
Soda Ash	1960	2022	1	1	1	USGS
Sulphur	1960	2022	1	1	1	USGS
Tantalum	1974	2022	2	3	4	USGS
Tin	1960	2024	9	7	7	World Bank
Tungsten	1960	2019	5	5	5	USGS
Zinc	1960	2024	1	1	3	World Bank
Zircon	1960	2021	0	0	1	USGS

Note: All nominal prices are converted to constant 1990 prices using the World GDP deflator to ensure comparability over time. For each point in time, the mineral price is measured as the three-year average centered around that year.

Table B2a: Market potential coefficients, OLS

Isocode	Tier 1			Tier 2			Tier 3		
	X1	X2	X3	X1	X2	X3	X1	X2	X3
AGO	-0.942***	0.116***	0.037***	2.066***	-0.347***	-0.009	0.764**	0.023	-0.133***
	(0.034)	(0.007)	(0.005)	(0.252)	(0.038)	(0.011)	(0.314)	(0.048)	(0.023)
BEN	0.004	-0.011	0.003	0.039***	-0.054***	0.007	0.039***	0.045**	-0.046***
	(0.012)	(0.018)	(0.009)	(0.014)	(0.016)	(0.007)	(0.013)	(0.018)	(0.011)
BFA	0.012	-0.006	-0.001	0.007	-0.125***	0.040***	-0.009	0.002	0.002
	(0.045)	(0.010)	(0.007)	(0.053)	(0.027)	(0.015)	(0.033)	(0.012)	(0.008)
BWA	-0.657***	0.598***	-0.078*	0.092**	-1.016***	0.197***	-0.075	1.485***	-0.341***
	(0.157)	(0.156)	(0.038)	(0.036)	(0.146)	(0.028)	(0.055)	(0.279)	(0.067)
CAF	-0.442***	0.258***	-0.003	0.276***	-0.349***	0.175***	-0.212**	0.581***	-0.418***
	(0.076)	(0.067)	(0.030)	(0.048)	(0.042)	(0.028)	(0.104)	(0.088)	(0.048)
CIV	-0.006***	0.004***	0.003*	-0.002	0.002	0.000	-0.001	0.002	-0.001
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
CMR	-0.026	0.005	-0.001	-0.011	0.001	0.001**	-0.014	0.003	-0.000
	(0.018)	(0.004)	(0.001)	(0.007)	(0.001)	(0.001)	(0.015)	(0.003)	(0.001)
ETH	-0.018***	0.021***	0.001	0.024***	-0.024**	-0.003	-0.004	0.038***	-0.032***
	(0.007)	(0.007)	(0.009)	(0.009)	(0.011)	(0.013)	(0.008)	(0.012)	(0.012)
GHA	-0.094**	0.035**	0.002	-0.016	-0.003	0.004*	-0.108***	0.044***	0.001
	(0.040)	(0.016)	(0.005)	(0.015)	(0.007)	(0.002)	(0.014)	(0.007)	(0.002)
GIN	0.001	-0.005	0.001*	0.052***	-0.072***	0.005*	0.049***	-0.038***	-0.002***
	(0.010)	(0.008)	(0.001)	(0.014)	(0.015)	(0.003)	(0.008)	(0.006)	(0.000)
KEN	-0.891***	0.895***	-0.110***	0.733***	-1.005***	0.179***	-1.257***	2.585***	-0.663***
	(0.067)	(0.101)	(0.033)	(0.042)	(0.026)	(0.014)	(0.245)	(0.332)	(0.072)
LBR	-1.065***	0.092***	0.004	1.424***	-0.278***	0.151***	0.731**	0.188***	-0.228***
	(0.065)	(0.024)	(0.025)	(0.271)	(0.038)	(0.024)	(0.328)	(0.060)	(0.052)
MLI	0.007**	-0.002*	-0.000	0.004	-0.003**	0.002	-0.002	-0.005	0.007**
	(0.003)	(0.001)	(0.002)	(0.003)	(0.001)	(0.002)	(0.007)	(0.004)	(0.003)
MOZ	-0.385***	0.347***	-0.317***	0.284***	-0.271***	0.241***	-0.553***	0.551***	-0.510***
	(0.118)	(0.104)	(0.096)	(0.043)	(0.045)	(0.041)	(0.067)	(0.059)	(0.053)
MWI	-0.971***	0.327***	-0.102***	2.091***	-0.812***	0.316***	-2.436***	1.040***	-0.447***
	(0.071)	(0.041)	(0.028)	(0.125)	(0.040)	(0.019)	(0.329)	(0.114)	(0.046)
NAM	-0.540***	0.342***	-0.053*	0.237**	-0.163**	0.048**	-0.108	0.079	-0.026
	(0.154)	(0.101)	(0.031)	(0.095)	(0.065)	(0.022)	(0.078)	(0.048)	(0.018)
NER	-0.115*	0.079**	-0.047**	0.164***	-0.038*	-0.006	-0.314***	0.216***	-0.134***
	(0.066)	(0.032)	(0.020)	(0.056)	(0.020)	(0.011)	(0.050)	(0.026)	(0.015)
NGA	-0.026***	0.021**	-0.004	0.010	-0.049***	0.045***	-0.010**	0.099***	-0.093***
	(0.010)	(0.009)	(0.005)	(0.010)	(0.016)	(0.012)	(0.005)	(0.013)	(0.013)
SDN	-0.286**	-0.073	0.105***	0.105*	-0.119**	0.063**	-0.304***	0.484***	-0.274***
	(0.111)	(0.047)	(0.029)	(0.061)	(0.058)	(0.032)	(0.078)	(0.086)	(0.049)
SEN	0.004	-0.001	-0.001	0.079**	-0.020**	-0.011**	0.065***	-0.019***	-0.007***
	(0.050)	(0.006)	(0.013)	(0.032)	(0.008)	(0.005)	(0.017)	(0.005)	(0.002)
SLE	-0.264***	0.399***	-0.068***	0.296***	-0.564***	0.143***	-0.238***	0.537***	-0.181***
	(0.039)	(0.065)	(0.016)	(0.066)	(0.111)	(0.026)	(0.046)	(0.088)	(0.028)
TCD	-0.016	0.006	-0.002	0.338***	-0.136**	0.073**	-0.184*	0.119***	-0.095***
	(0.115)	(0.041)	(0.021)	(0.113)	(0.055)	(0.035)	(0.094)	(0.038)	(0.022)
TGO	-0.174**	0.093	-0.006	0.232**	-0.239**	0.075**	-0.237**	0.268**	-0.099**
	(0.067)	(0.055)	(0.026)	(0.091)	(0.096)	(0.035)	(0.116)	(0.113)	(0.038)
TZA	-0.050**	0.048*	-0.010	0.076***	-0.098***	0.034***	-0.048**	0.059***	-0.020**
	(0.020)	(0.025)	(0.009)	(0.022)	(0.023)	(0.008)	(0.023)	(0.020)	(0.009)
UGA	-0.845***	0.566***	-0.126	0.222***	-0.849***	0.453***	-0.347***	1.208***	-0.663***
	(0.147)	(0.197)	(0.093)	(0.061)	(0.063)	(0.031)	(0.068)	(0.101)	(0.054)
ZMB	-1.035***	0.076***	0.000	4.540***	-0.382***	0.027**	2.508***	0.013	-0.150***
	(0.081)	(0.006)	(0.004)	(0.617)	(0.046)	(0.014)	(0.715)	(0.057)	(0.025)
ZWE	-0.956***	0.258***	-0.056***	1.604***	-0.693***	0.302***	-1.453***	0.725***	-0.343***
	(0.070)	(0.032)	(0.020)	(0.165)	(0.061)	(0.026)	(0.191)	(0.077)	(0.037)

Note: The table reports coefficients and standard errors for Figure 3. There are three sets of columns from left to right for the samples of tier-1, tier-2 and tier-3 cities. $X1$, $X2$ and $X3$ refer to the ΔMA access variables from tier-1, -2 and -3 cities as they affect cities in the three tiers. Our control variables include the log of each city's lagged area (1975 and 1990) and its mining revenue (1990, 2000 and 2014). Robust standard errors are in parentheses. ***, **, * denote statistical significance at the 1%, 5%, 10% levels, respectively.

Table B2b: Market potential coefficients, IV

Isocode	Tier 1			Tier 2			Tier 3		
	X1	X2	X3	X1	X2	X3	X1	X2	X3
AGO	-0.813***	0.104***	0.029***	0.784***	-0.108***	-0.023	-1.533**	0.192**	0.063**
	(0.066)	(0.012)	(0.006)	(0.281)	(0.041)	(0.015)	(0.649)	(0.093)	(0.028)
BEN	0.016	-0.029	0.006	0.032**	-0.027	-0.003	0.048***	0.030	-0.044***
	(0.010)	(0.021)	(0.010)	(0.013)	(0.020)	(0.010)	(0.013)	(0.020)	(0.011)
BFA	0.010	-0.007	0.000	-0.020	-0.099***	0.036***	-0.081**	-0.006	0.018**
	(0.043)	(0.008)	(0.006)	(0.048)	(0.023)	(0.013)	(0.038)	(0.013)	(0.008)
BWA	-0.599***	0.588***	-0.083***	0.096***	-0.952***	0.181***	-0.060	0.331*	-0.072*
	(0.132)	(0.126)	(0.029)	(0.030)	(0.121)	(0.023)	(0.045)	(0.172)	(0.043)
CAF	-0.248***	0.142**	0.009	-0.058	0.014	0.027	-0.126	0.108	-0.041
	(0.068)	(0.070)	(0.035)	(0.093)	(0.086)	(0.042)	(0.171)	(0.181)	(0.091)
CIV	-0.003	0.002	0.001	-0.003	0.003*	-0.001	-0.004	0.001	0.003
	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)
CMR	-0.025*	0.005*	-0.001*	-0.025***	0.004**	0.001	-0.020	0.003	0.000
	(0.015)	(0.003)	(0.000)	(0.008)	(0.002)	(0.001)	(0.016)	(0.003)	(0.001)
ETH	-0.012*	0.020**	-0.005	0.015*	-0.002	-0.014	-0.010	0.020	-0.006
	(0.007)	(0.008)	(0.009)	(0.009)	(0.010)	(0.012)	(0.007)	(0.014)	(0.012)
GHA	-0.055	0.020	0.002	-0.030*	0.010	0.001	-0.102***	0.042***	0.001
	(0.035)	(0.013)	(0.005)	(0.016)	(0.007)	(0.003)	(0.014)	(0.007)	(0.002)
GIN	0.021**	-0.020***	0.000	0.050***	-0.071***	0.005*	0.077***	-0.060***	-0.003***
	(0.010)	(0.008)	(0.000)	(0.013)	(0.017)	(0.003)	(0.010)	(0.007)	(0.001)
KEN	-0.335**	0.425**	-0.067	1.340***	-1.538***	0.186***	-0.214	0.765	-0.238***
	(0.165)	(0.177)	(0.046)	(0.203)	(0.233)	(0.035)	(0.685)	(0.701)	(0.088)
LBR	-1.116***	0.104***	-0.003	0.194	-0.089**	0.077**	1.120***	-0.274***	0.190***
	(0.050)	(0.018)	(0.017)	(0.296)	(0.044)	(0.035)	(0.421)	(0.092)	(0.068)
MLI	0.006***	-0.003**	0.001	0.003	-0.003**	0.003	-0.005	-0.012***	0.016***
	(0.002)	(0.001)	(0.002)	(0.003)	(0.001)	(0.002)	(0.007)	(0.004)	(0.004)
MOZ	-0.182**	0.182**	-0.169**	-0.052	0.071	-0.076	-0.354***	0.354***	-0.328***
	(0.093)	(0.087)	(0.080)	(0.052)	(0.050)	(0.046)	(0.092)	(0.086)	(0.077)
MWI	-0.525	0.199	-0.040	4.776***	-1.597***	0.552***	1.727	-0.559	0.191
	(0.436)	(0.122)	(0.071)	(1.632)	(0.512)	(0.163)	(1.296)	(0.415)	(0.144)
NAM	-0.517***	0.329***	-0.050**	-0.011	-0.008	0.006	-0.068	0.028	0.005
	(0.133)	(0.087)	(0.025)	(0.075)	(0.048)	(0.014)	(0.081)	(0.047)	(0.017)
NER	0.079	0.025	-0.040**	0.038	0.040**	-0.054***	-0.143***	0.081***	-0.049***
	(0.074)	(0.027)	(0.018)	(0.056)	(0.020)	(0.012)	(0.043)	(0.023)	(0.015)
NGA	-0.015*	0.016**	-0.007	-0.035***	0.050***	-0.029***	-0.009	0.026***	-0.019**
	(0.008)	(0.008)	(0.006)	(0.008)	(0.009)	(0.007)	(0.006)	(0.009)	(0.009)
SDN	-0.154*	-0.127***	0.114***	-0.122**	0.059	-0.010	-0.186***	0.212***	-0.105***
	(0.082)	(0.031)	(0.020)	(0.061)	(0.043)	(0.021)	(0.054)	(0.063)	(0.036)
SEN	0.087**	-0.005	-0.022**	0.070**	-0.017**	-0.010**	0.078***	-0.022***	-0.009***
	(0.039)	(0.005)	(0.010)	(0.031)	(0.008)	(0.005)	(0.020)	(0.006)	(0.003)
SLE	-0.205***	0.330***	-0.066***	-0.180**	0.260*	-0.045	-0.263***	0.441***	-0.100***
	(0.036)	(0.063)	(0.016)	(0.083)	(0.140)	(0.033)	(0.054)	(0.086)	(0.020)
TCD	0.038	-0.018	0.014	0.204***	-0.068***	0.029*	-0.018	0.034	-0.036*
	(0.049)	(0.019)	(0.012)	(0.053)	(0.026)	(0.017)	(0.086)	(0.036)	(0.021)
TGO	-0.111**	0.061	-0.007	0.097	-0.121*	0.046*	-0.080	0.054	-0.005
	(0.050)	(0.042)	(0.022)	(0.063)	(0.067)	(0.027)	(0.085)	(0.071)	(0.026)
TZA	-0.004	-0.004	0.005	0.026	-0.042**	0.016**	-0.021	0.002	0.008
	(0.017)	(0.021)	(0.008)	(0.018)	(0.019)	(0.007)	(0.024)	(0.022)	(0.008)
UGA	-0.448***	0.475**	-0.186*	0.174**	-0.423***	0.201***	-0.258***	0.516***	-0.241**
	(0.155)	(0.194)	(0.104)	(0.080)	(0.109)	(0.067)	(0.080)	(0.176)	(0.100)
ZMB	-1.017***	0.074***	0.001	0.900	-0.073	0.011	0.928	-0.023	-0.016
	(0.060)	(0.005)	(0.004)	(0.813)	(0.060)	(0.017)	(1.011)	(0.084)	(0.026)
ZWE	-0.934***	0.260***	-0.065**	0.912***	-0.311***	0.120***	-0.709*	0.060	0.076
	(0.142)	(0.057)	(0.029)	(0.272)	(0.100)	(0.039)	(0.428)	(0.191)	(0.095)

Note: The table reports coefficients and standard errors for Figure 5. There are three sets of columns from left to right for the samples of tier-1, tier-2 and tier-3 cities. $X1$, $X2$ and $X3$ refer to the ΔMA access variables from tier-1, -2 and -3 cities as they affect cities in the three tiers. Our control variables include the log of each city's lagged area (1975 and 1990) and its mining revenue (1990, 2000 and 2014). Robust standard errors are in parentheses. ***, **, * denote statistical significance at the 1%, 5%, 10% levels, respectively.

Table B3: Pairwise road change over time

Isocode	Country name	2000-2014	1990-2000	1975-1990
AGO	Angola	0.00%	47.35%	73.39%
BEN	Benin	65.37%	38.20%	82.91%
BFA	Burkina Faso	46.10%	33.65%	93.00%
BWA	Botswana	9.05%	64.54%	95.39%
CAF	Central Afr. Rep.	0.00%	28.98%	80.81%
CIV	Cote d'Ivoire	47.79%	32.15%	96.99%
CMR	Cameroon	75.03%	59.80%	91.04%
ETH	Ethiopia	50.14%	69.00%	91.31%
GHA	Ghana	62.24%	21.82%	82.47%
GIN	Guinea	23.74%	79.67%	64.04%
KEN	Kenya	0.00%	0.80%	94.59%
LBR	Liberia	0.00%	0.00%	93.79%
MLI	Mali	68.95%	51.53%	77.57%
MOZ	Mozambique	50.44%	48.22%	86.09%
MWI	Malawi	0.00%	0.37%	77.29%
NAM	Namibia	12.00%	60.94%	88.67%
NER	Niger	5.85%	37.10%	96.99%
NGA	Nigeria	1.17%	52.64%	95.62%
SDN	Sudan	9.57%	65.43%	89.26%
SEN	Senegal	26.64%	38.25%	89.05%
SLE	Sierra Leone	42.83%	43.27%	91.30%
TCD	Chad	57.80%	13.80%	77.24%
TGO	Togo	69.18%	42.62%	68.82%
TZA	Tanzania	0.67%	29.91%	80.44%
UGA	Uganda	2.29%	15.67%	8.31%
ZMB	Zambia	0.00%	51.85%	90.54%
ZWE	Zimbabwe	0.00%	48.31%	81.51%

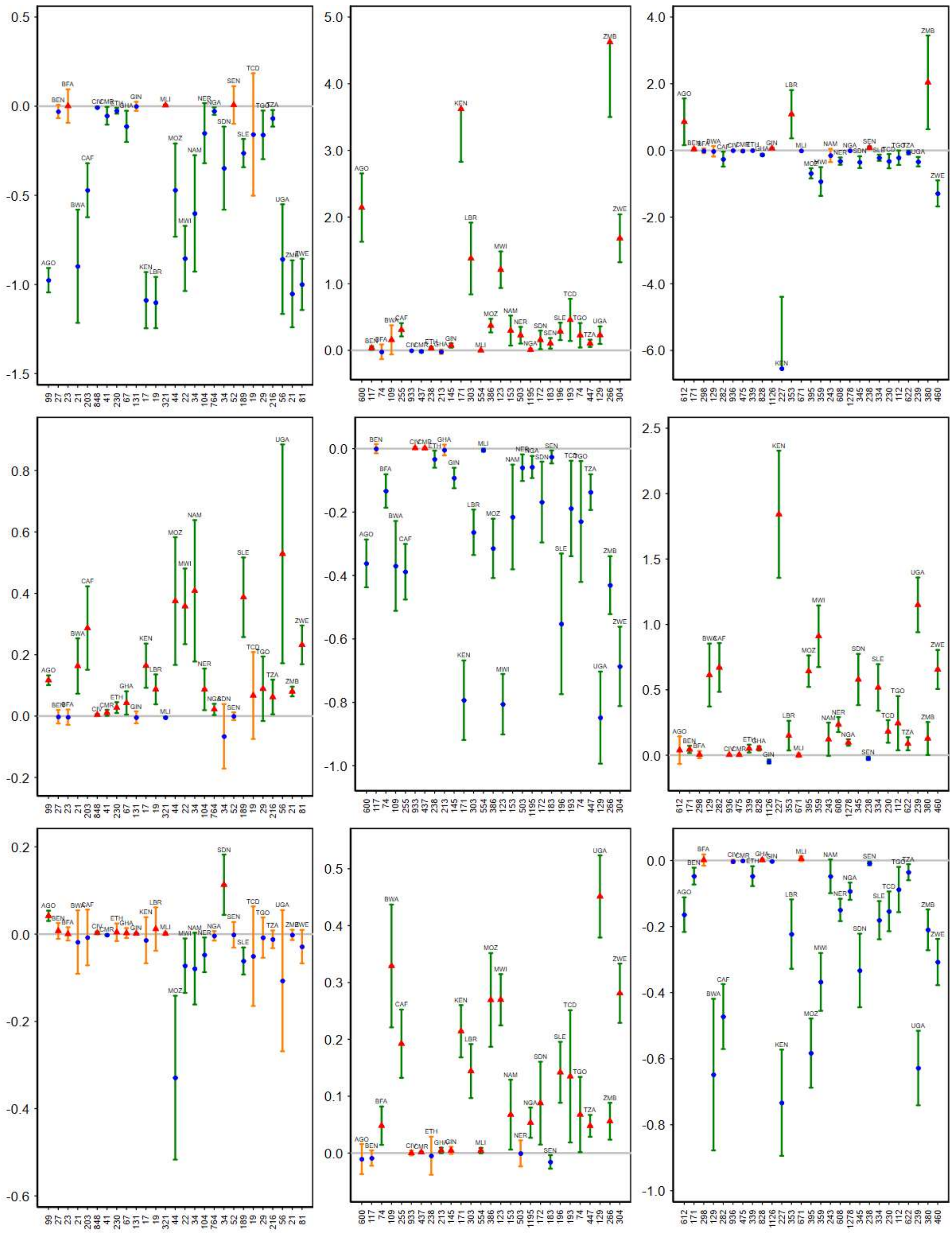
Note: The table reports the share of a travel route that was changed (e.g., paved or new road) during each specified time period. These shares are averaged across all pairwise routes (i,j) connecting the settlements included in the sample for each country.

Table B4: Hansen-J stats on main IV results

		Tier-1		Tier-2		Tier-3	
Isocode	Country name	Hansen-J	pvalue	Hansen-J	pvalue	Hansen-J	pvalue
AGO	Angola	32.746	0.000	22.327	0.008	21.539	0.010
BEN	Benin	16.149	0.185	17.473	0.133	15.831	0.199
BFA	Burkina Faso	10.931	0.535	17.863	0.120	11.361	0.498
BWA	Botswana	20.090	0.065	15.488	0.216	17.293	0.139
CAF	Central Afr. Rep.	15.228	0.085	15.221	0.085	9.947	0.355
CIV	Cote d'Ivoire	49.415	1.77e-06	60.616	1.74e-08	26.860	0.008
CMR	Cameroon	17.961	0.117	41.779	0.000	11.430	0.492
ETH	Ethiopia	12.816	0.383	26.890	0.008	26.902	0.008
GHA	Ghana	10.198	0.599	20.491	0.058	58.419	4.38e-08
GIN	Guinea	20.877	0.052	23.879	0.021	54.642	2.10e-07
KEN	Kenya	3.453	0.750	3.730	0.713	16.153	0.064
LBR	Liberia	10.804	0.095	24.666	0.000	11.759	0.068
MLI	Mali	24.382	0.018	36.947	0.000	20.128	0.065
MOZ	Mozambique	12.587	0.400	19.410	0.079	29.750	0.003
MWI	Malawi	8.131	0.043	2.590	0.459	3.516	0.475
NAM	Namibia	20.856	0.053	23.886	0.021	13.900	0.307
NER	Niger	25.456	0.013	32.761	0.001	20.726	0.055
NGA	Nigeria	29.839	0.003	22.618	0.031	59.999	2.26e-08
SDN	Sudan	12.669	0.394	15.586	0.211	15.272	0.227
SEN	Senegal	21.054	0.050	22.661	0.031	20.902	0.052
SLE	Sierra Leone	21.724	0.041	18.216	0.109	20.582	0.057
TCD	Chad	17.223	0.141	11.336	0.500	18.748	0.095
TGO	Togo	18.086	0.113	10.948	0.533	14.243	0.285
TZA	Tanzania	24.255	0.019	26.003	0.011	17.105	0.146
UGA	Uganda	23.023	0.018	26.697	0.009	14.754	0.255
ZMB	Zambia	15.929	0.068	4.246	0.895	8.553	0.480
ZWE	Zimbabwe	18.726	0.028	22.973	0.006	20.187	0.017

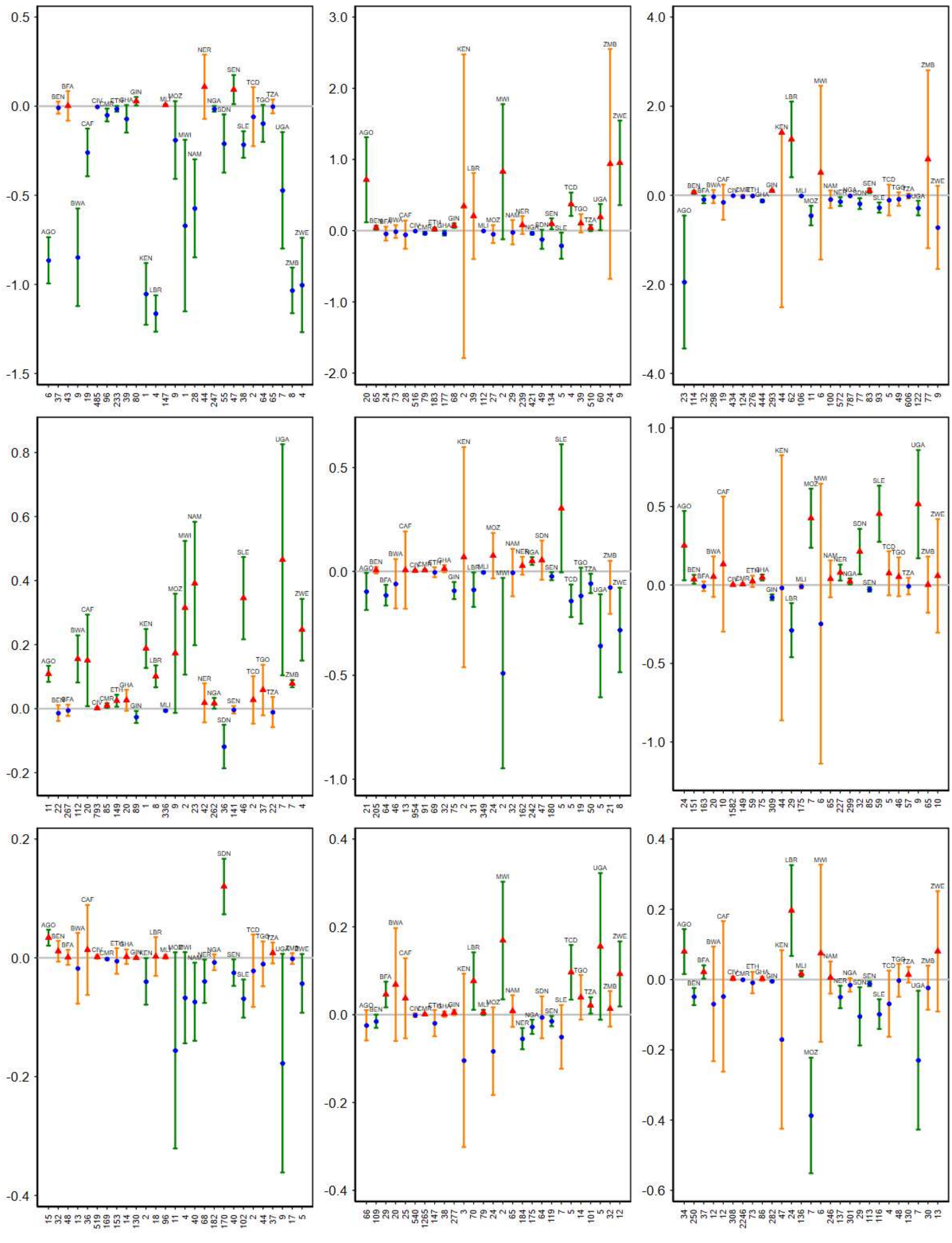
Note: These correspond to the estimates in Figure 5 and Table B2b.

Figure B1a: Results with sharper travel time discount-OLS



Note: Columns show coefficients for cities in tiers 1 to 3 from left to right. Rows are for tier 1, 2 and 3 (top to bottom) ΔMA effects on cities of each type. Points with green error bands show points that are significant at the 10% level, but error bands show 5% confidence intervals. Blue [orange] points are negative [positive]. Numbers on horizontal axis are degrees of freedom in estimation.

Figure B1b: Results with sharper travel time discount-IV



Note: Columns show coefficients for cities in tiers 1 to 3 from left to right. Rows are for tier 1, 2 and 3 (top to bottom) ΔMA effects on cities of each type. Points with green error bands show points that are significant at the 10% level, but error bands show 5% confidence intervals. Blue [orange] points are negative [positive]. Numbers on horizontal axis show 1st stage partial Sanderson-Windmeijer F-stats.

C Parameters Used in Simulation

Racetrack: Maximum distance = 1; $(radius = 1/\pi)$
Demand shares: $\mu^3 = 0.1; \mu^2 = 0.7; \mu^1 = 1 - \mu^3 - \mu^2;$
Cost shares:
$a^{31} = 0.0; a^{21} = 0.0; a^{11} = 0.0; \quad b^1 = 1 - a^{31} - a^{21} - a^{11};$
$a^{32} = 0.5; a^{22} = 0.0; a^{12} = 0.0; \quad b^2 = 1 - a^{32} - a^{22} - a^{12};$
$a^{33} = 0.0; a^{23} = 0.0; a^{13} = 0.0;$
Elasticities of substitution: $s^3 = 10; \quad s^2 = 7; \quad s^1 = 7;$
Trade costs: $t^3 = 20; \quad t^2 = 2.5; \quad t^1 = 2.5;$

Disk: Max distance = 2; 1147 cells
Parameters as above, except: Trade costs: $t^3 = 20; \quad t^2 = 6; \quad t^1 = 4;$

Sensitivity: n^1, n^2 denote the number of type-1, type-2 settlements in the racetrack economy.
Base simulation: $n^1 = 4; n^2 = n^1 \times 6 = 24$

Cut t^3 by 20 percent: $n^1 = 4; n^2 = n^1 \times 4 or 5 = 18$
Cut t^2 by 20 percent: $n^1 = 4; n^2 = n^1 \times 8 or 9 = 34$
Cut t^1 by 20 percent: $n^1 = 3; n^2 = n^1 \times 8 = 24$
Cut all t by 20 percent: $n^1 = 3; n^2 = n^1 \times 10 = 30$

Cut all σ by 20 percent: $n^1 = 4; n^2 = n^1 \times 4 = 16$

Reducing a^{32} below the critical value causes the number of pure type-2 settlements to fall to zero as all sector 2 and sector 3 activities colocate.

Figure C1 illustrates an equilibrium with randomly and independently different place-sector productivity differentials in sectors 1 and 2. It is conceptually similar to the bottom panel of Figure 1, but the rotational tidiness of Figure 1 is disturbed. Crucially, it retains a pattern of few (8) well-spaced tier-1 settlements interspersed with tier-2 (of which there are 22).

Figure C1: Employment on a disk with productivity variation