Perpetual Motion: Human Mobility and Spatial Frictions in Three African Countries*

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Abstract

Frictions affecting human mobility have been identified as important potential sources of the spatial gaps in wages and living standards that characterize many low-income countries. However, little direct data has been available to characterize high-frequency mobility. We use a novel data source that provides highly detailed location data on more than one million devices across three large African countries for an entire year. This allows us to examine high-frequency mobility patterns for a subset of high-quality observations for whom we can determine home locations confidently. We link our users with spatial data on population density and nationally representative micro-survey data to characterize this non-random sample. We then propose a number of metrics to measure characterize mobility related to frequency, spatial extent and densities visited. We find that users are remarkably mobile in terms of the fraction of days seen at least 10km away from their home location, and the average distance for non-home location pings. Individuals residing in low-density locations are well linked to high-density locations and a significant fraction of visitors to the largest cities comes from non-urban areas. Finally, the observed mobility patterns suggest large agglomeration effects: a doubling of population is associated with a doubling of city fixed effects. Our estimates are in line with previous gravity estimates in the literature across a wide range of spatial and temporal scales.

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1. Introduction

In most developing countries, there are large gaps in nominal wages and productivity across sectors (Gollin, Lagakos, and Waugh, 2014). There are similarly large gaps in living standards across space, with people in sparsely populated rural locations consistently worse off than those in dense urban settlements (Gollin, Kirchberger, and Lagakos, 2020). The persistence of these gaps raises the possibility that significant frictions and market imperfections limit the movements of people and information, leading to spatial and sectoral misallocation.

This paper aims to advance our understanding of sectoral and spatial gaps by documenting and analyzing high-frequency mobility patterns within three low-income African economies. By examining the frequency with which individuals move across space – from rural areas to towns and villages, or from cities to rural areas – we can assess the salience of some key frictions. For instance, a world in which rural people travel frequently to distant towns and cities is not one in which narrowly defined costs of mobility can plausibly explain sectoral or spatial gaps.

Understanding high-frequency mobility has previously been limited by the lack of data. Census data or standard household surveys (e.g., those carried out in collaboration with the World Bank's program of Living Standards Measurement Surveys) typically measure longer-term migration flows but lack data on day-to-day mobility over a given time period. Surveys providing detailed commuting data available in high-income countries, such as the American Community Survey, provide information on commutes but miss non-work related trips. Such surveys are not available for most low-income countries.

In this paper, we measure mobility using newly available, fine-grained, but anonymized, data on smartphone locations. Unique to our study is the scale at which we can study the phenomenon of short- and long-term population movements. Our data covers more than one million smartphone devices over an entire year across three large African countries: Nigeria, Kenya, and Tanzania.[1] We are therefore able to present data on mobility that is both fine-grained and large-scale.

Each observation in our data reflects an instance when a user's phone connects to the internet to use a certain app. For each such use, we observe the GPS location and the precise time. This type of data has been used, for example, to study the length of time that individuals spend with their families for Thanksgiving in the US (Chen and Rohla, 2018), to construct a measure of experienced segregation (Athey, Ferguson, Gentzkow, and Schmidt, 2020), to study the effect of chance meetings on knowledge spillovers in the Silicon Val-

[1] In the remainder of the paper we will refer to a device as a user. We recognize that this is an inexact equivalence: some users possess more than one device, and some devices are shared by multiple users. We address these issues in detail in Section 3.

ley (Atkin, Chen, and Popov, 2020), or to measure the effectiveness of social distancing (Mongey, Pilossoph, and Weinberg, 2020). We add to this literature by focusing on three countries in sub-Saharan Africa and by looking at patterns of mobility.

We propose to use the fact that devices are seen at different locations within countries to characterize movements of users across space, and particularly between rural and urban areas. We use the data to map and categorize the movements of people and the connectedness of locations. For instance, we can ask how frequently a given rural location is visited by individuals from a nearby town or city; we can also ask how frequently residents of that rural location pass through a given city or market centre; or, how the composition of visitors to the capital differs from visitors to secondary cities.

The paper makes three main contributions. First, we construct a novel set of metrics for characterizing mobility across space related to frequency, spatial extent, densities and places visited. Second, we analyze these measures to provide insights into the patterns of human mobility within the three countries where our data originate. Third, we use findings of recent quantitative spatial models to study returns to mobility across space. Our data allows us to examine the sensitivity to distance of our measures of mobility and connectedness at different spatial and temporal scales; it also allows us to compare our findings to those of previous studies, such as those that have used gravity models to consider within-country migration.

We find striking evidence of a high degree of mobility within these three African countries. Although the population we study is undoubtedly atypical for Kenya, Nigeria, and Tanzania, we find evidence that a substantial fraction of the people in these countries is highly mobile. Users are seen more than 10km away from home on about one-sixth of the days on which they are observed. Residents from more sparsely populated areas are more frequently away from home than city center residents and they venture far when they do. Spatial transition matrices show that towns and many villages in these countries appear to receive visits from urban dwellers, and in turn these villages seem to generate travellers who go to larger towns and cities. The networks of connectivity between different geographies are strong. This challenges, for instance, the notion that villages and towns in relatively remote areas are isolated – and therefore ignorant of what goes on in the big cities. The data also cast doubt on the notion that the monetary and non-monetary costs of mobility are simply prohibitive. Beyond these qualitative findings, we show that large cities exert a disproportionate influence: Nairobi, Lagos, and Dar es Salaam are powerful magnetic forces that pull in visitors from every corner of their countries while secondary cities appear to be substitutes for each other. This too is important for our understanding of spatial frictions. One could imagine that rural people seldom venture beyond their nearest towns or cities. But the data show persuasively that people from these remote villages and towns do indeed travel to capital cities. These findings can help inform our understanding of spatial frictions in developing countries. In particular, they can discipline models that incorporate spatial and sectoral frictions. Finally, we find large agglomeration effects: a doubling of city size is associated with a doubling of the estimated city fixed effect. Our estimates for the elasticity of mobility with respect to travel are robust to different spatial and temporal scales, such as estimating mobility between virtual regions and at a quarterly level, showing that movement costs are significant in these contexts.

Our analysis requires some serious discussion of the representativeness – or lack thereof – of the population from which our data are drawn. While smartphone users might arguably, in 2020, be representative of the wider population in rich countries, it would be unreasonable to assume that the same holds in low-income countries. We do not have personal information on the users of our devices, and for ethical and privacy reasons, we have not attempted to exploit the data for the purpose of extracting identifying information.[2] The one personal characteristic that we construct for each device is its "home location". We define this as the modal 0.01-degree cell ($\approx 1.1km$ at the equator) at which we observe the user between 7pm and 7am.[3] We then select a subset of “high-confidence” users that we observe at least 10 nights and who spend at least half of these in the home location.

We characterize our users in three steps. First, we compare the distribution of population density at our users’ home locations with that of the overall population. Second, we propose a new method to characterize the places our users reside by linking user’s home locations with widely available micro-survey data. While we do not have characteristics of users such as age, education or gender, this allows us to gauge how representative our users’ home locations are compared to locations where no users reside. Third, we use additional nationally representative micro-data to compare basic characteristics such as income, age and education of individuals across ownership of different types of phone devices, from basic phones to smartphones. We argue that these steps are crucial in order to understand the characteristics of our users, given that our data are generated from a population that does not represent a statistical sample, selected with the benefit of defined sampling frames and protocols. A rough summary of our efforts to characterize the sample is that we find our sample to be, unsurprisingly, more urban than the population as a whole, and also younger and better off. However, our best assessment is that our population is not extraordinarily atypical in any of these dimensions. Our users’ home locations seem generally unremarkable. The urban users seem to live in "relatively normal" urban areas (in a sense that we will characterize below), and our rural users live in similarly normal rural areas. Third, we use micro-data to compare basic characteristics of individuals owning a smartphone to

[2]It might be possible, for instance, to use the location information from individual users to identify or infer their religious observance, gender, and other attributes. In this paper, we do not attempt to use the data for these purposes, in recognition of the obvious privacy concerns.

[3]In practice, we define the modal 2-decimal rounded location at night as the home location, so our 0.01-degree grid cells have 2-decimal rounded coordinates as centroids.

those owning a different type of phone or no phone. As smartphones have diffused through sub-Saharan Africa in recent years, smartphone users have come to look more and more like the rest of the population. In the sections that follow, we address these nature of our sample in greater detail.

This research builds on a growing literature in economics that seeks to understand the salience of spatial frictions for development and growth. Spatial frictions limit the mobility of goods, information, and people within economies. In contexts where spatial frictions are high, the allocation of factors across firms will tend to result in gaps in marginal products. Similarly, spatial frictions may lead to allocations such that marginal utilities are not equalized across consumers, and utility may not be equalized across people living in different locations. These static effects may also lead to dynamic impacts, as frictions move the economy away from a theoretically efficient benchmark.[4]

The importance of within-country spatial frictions in the movement of goods has been documented in recent work (e.g., Arkolakis, Costinot, and Rodríguez-Clare (2012); Costinot and Donaldson (2016); Atkin and Donaldson (2015); Donaldson and Hornbeck (2016); Donaldson (2018); Allen and Arkolakis (2014)). This emerging literature has pointed out that spatial frictions have implications for patterns of specialization and exchange. An additional literature has documented the importance of spatial frictions as they relate to the flow of information. In particular, a number of papers (e.g., Aker (2010); Jensen (2007)) have shown the impact of mobile phones on the dispersion of prices across space. Allen (2014) suggests that information frictions can compound spatial frictions.

Both these literatures have used new data sources to understand spatial frictions at a highly localized level. For movement of goods, many frictions occur in the proverbial "last mile", making it important to consider spatially disaggregated data. Similarly, for information frictions, studies have often looked at price dispersion across nearby markets. For movement of people, however, the literature has largely focused on crudely defined measures of migration or broad-brush comparisons of rural-urban gaps in living standards (Young (2013); Hamory Hicks, Kleemans, Li, and Miguel (2017); Bryan, Chowdhury, and Mobarak (2014); Akram, Chowdhury, and Mobarak (2017)). Our paper builds on the work of Blumenstock (2012) and Lu, Wrathall, Sundsøy, Nadiruzzaman, Wetter, Iqbal, Qureshi, Tatem, Canright, Engø-Monsen et al. (2016) in using more spatially detailed data on human mobility.

This paper is structured as follows. Section 2 discusses the smartphone app data we use and how we define home locations. Section 3 shows our methodology to understand sample selection and characterize the sample. Section 4 presents our mobility indicators. Section

[4] It is not entirely clear whether one should view real frictions – such as transport costs – as a source of inefficiency, in the way that a tariff would be viewed as inefficient. The social planner cannot wish away distance or mountain ranges; real resources would be required to reduce or eliminate these frictions. To avoid this largely semantic issue, we prefer in this paper to use the term "friction" rather than "barrier" or "distortion," and we have sought to avoid language that would imply "inefficiency."

5 estimates the returns to mobility. Section 6 concludes.

2. Smartphone app data

This paper draws primarily on smartphone app location data for three African countries: Kenya, Nigeria and Tanzania. We selected these countries based on data availability and a sufficiently high number of users in the sample. We discuss our main choices of how we process the raw data here and refer the interested reader to Appendix A.

Each observation in our data set (referred to hereafter as a "ping") represents an instance where a smartphone accesses the internet via a set of apps. Pings are sourced from thousands of apps that need to access location data.[5] These apps include standard social, navigation, information and other apps, but we do not know precisely which apps, and we cannot associate specific pings with specific apps.

Each ping comes from a device – i.e., a particular smartphone. For each ping we know the device identifier (i.e., a particular phone, rather than a SIM card), a timestamp and longitude/latitude coordinates of the current position, measured to an accuracy of approximately 10 meters. Each country dataset covers a period of one year.[6]

In the remainder of the paper we refer to a device as a user, subject to the caveats already mentioned in footnote 1 and discussed in further detail below. In this section we start by discussing how we assign home locations to users and outline how we identify and deal with irregularities in the data.

We use two criteria to define home locations. First, we identify the modal 0.01-degree cell ($\approx 1.1km$ at the equator) in which the user is seen at night (between 7pm and 7am, local time).[7] Second, we consider two additional restrictions: (a) that a user is observed for a minimum of 10 nights; and (b) that the user is at the inferred home location for at least 50% of the total nights when that user is observed anywhere. These two restrictions eliminate cases where the user is seen infrequently at night, or is seen frequently but at multiple locations.

Given the central role home location plays in our analysis, we define our core sample – which we call the "high-confidence" sample – as users that satisfy both criteria. Unless specified otherwise, we use our high-confidence users for our analysis. This is a sample of

[5]We only observe a "ping" when a phone is connected to the internet. We are therefore not able to draw conclusions about areas without internet coverage.

[6]The time frame is 2016-12-01 to 2017-12-01 in Kenya and 2017-04-01 to 2018-04-01 in Nigeria and Tanzania.

[7]The accuracy of GPS data would theoretically allow us to infer home locations at higher resolutions. We choose to settle for a relatively coarser resolution to reduce computational time and because we deem it preferable for the analyses we conduct throughout the paper. In particular, for our purposes, we would like to consider pings from a few hundred meters apart as belonging to the same home location, rather than defining the home location as a particular house or plot of land.

just under 120,000 devices across the three countries, with an average of over 2,000 pings observed per user, as show in Table 1.[8]

We then examine the spatial distribution of home locations and identify users with apparent mislabelled locations by tabulating home locations and displaying them visually. This reveals what we call "irregularities" such as data sinks (e.g. a large fraction of users inexplicably assigned by the data-generating software to a spurious location, such as a country centroid) and other apparent errors in the data, e.g. users with equal latitude and longitude coordinates in locations where no people reside (visible on the 45 degree line on a map). For example, 372,661 users in Tanzania seem to have been assigned to an arbitrary spot in the middle of Dodoma. Examining data for outliers is important when working with any data set. Data input errors may seem more likely in micro-surveys where misinterpretation of questions or data entry errors are known sources of measurement error. Established procedures such as piloting of questionnaires, extensive interviewer training, and background checks help minimize these errors. Big data such as automatically recorded smartphone app location data - recorded without human interaction - might seem less prone to measurement error. However, we find that working with data of this nature opens new sources of error and misclassification; unless consistency of the data is examined with a similar attention to detail than the micro data, it is not reasonable to expect meaningful results. Appendix A provides further information on this quantitative extent of misclassification and our procedure to remove observations affected by apparent irregularities.

Table 1 shows the number of users and pings per user for our base sample of users.

Table 1: Sample and pings per user

	All		**High confidence**	
	Users (1)	Pings ratio (2)	Users (3)	Pings ratio (4)
Kenya	195,630	593	18,535	4,867
Nigeria	659,407	304	78,694	1,722
Tanzania	234,213	457	22,728	2,123
TOTAL	1,089,250	389	119,957	2,284

Note: Columns (1) and (2) show the total number of users per country and average pings per user. Columns (3) and (4) only use high-confidence users (users who are observed for a minimum of 10 nights and who are at the inferred home location for at least 50% of the total observed nights.)

Columns (1) and (2) show the number of users and average pings per user over the entire year who are observed at least once at night, where the average is computed by summing over all pings and dividing by the number of users; for this sample we have on average

[8]We also build other subsets based on alternative values for the minimum number of nights observed: (i) the "medium confidence set" includes users with at least 8 nights observed and (ii) the "low confidence set" with users seen at least 5 nights in total. Our results are generally robust to using these alternative subsets.

slightly more than one ping per day per user. Columns (3) and (4) apply the second restriction to obtain our high-confidence sample by imposing that we see a user for at least 10 nights and she is at the inferred home location in at least half of these nights. This drastically reduces our sample size and increases the ratio of pings per user to 2,284. Users in the high-confidence dataset are therefore seen on average 6 times per day, compared to users in the complete dataset who are seen on average slightly more than once per day. As is common with these types of data, there is a large variation in the number of pings across users, with about 59% of users having at most 20 pings in the initial sample. Our two conditions defining high-confidence users reduce the fraction of users with at most 20 pings to 0.3%.

Table 2 summarizes user-level temporal statistics for our high-confidence users.

Table 2: User-level temporal statistics by country

	Variable	**Mean**	**Median**	**Min**	**Max**
Kenya	Length of obs. (in days)	102.1	74.4	8.7	365.0
	Days seen	39.2	30.0	8.0	352.0
	Mean pings per day	98.2	8.9	1.0	20,665.4
Nigeria	Length of obs. (in days)	100.9	81.9	8.6	365.0
	Days seen	40.4	29.0	8.0	346.0
	Mean pings per day	40.1	12.8	1.0	9,585.8
Tanzania	Length of obs. (in days)	95.1	70.6	8.6	364.9
	Days seen	38.8	28.0	7.0	349.0
	Mean pings per day	51.4	10.6	1.0	14,765.6
TOTAL	Length of obs. (in days)	99.0	78.1	8.6	365.0
	Days seen	39.8	29.0	7.0	349.0
	Mean pings per day	42.1	11.9	1.0	14,765.6

Note: This table shows the duration over which we observe a user, the number of distinct days we observe a user, and mean pings per day, defined as the ratio of the total number of pings for a user divided by the number of distinct days she is seen.

It considers three different measures. The first is the duration over which we observe a particular user in the dataset, defined as the number of days between the first and the last observation of that user. The second is the number of distinct days on which we see a particular user. The third statistic is the mean number of pings per day per user. The mean number of pings per day is defined as the ratio of the total number of pings for a user, divided by the number of distinct days she is seen.[9] These statistics are roughly similar for the three countries. We see users on average over a span of about 100 days, on about 40 distinct days, and they have between 40 and 100 pings per day on average.[10]

[9]This differs from the pings ratio in Table 1 which simply summed over all pings in the data across all users and divided by the number of users.

[10]The minimum number of days is less than 10 as some users are seen on 10 nights but have pings on fewer

Figure C.1 shows the distribution of users and pings per user over time. The graphs show that there is an upward trend in the number of users over the period in which we observe the sample, likely due to a combination of factors. One is the steady and secular increase in the rate of smartphone ownership and usage. Another possible reason is the introduction of new apps in the sourcing of data during this period. The number of pings per user shows discontinuities, possibly due to further apps being added (or removed) and users switching between apps. This could bias our estimates of mobility if different types of users are added on to the sample later in the year. For example, assume that at the start only higher-income individuals living in dense areas have access to phones, and assume that they make one trip every three months to the largest nearby city. Later in the year, some lower-income individuals from lower densities might be able to afford a smartphone, but their mobility is far below the spatial mobility of higher-income individuals, so that they make one trip every six months. The fact that they enter the sample later, means that we might not observe them sufficiently long to observe one of their trips they make every six months and would thereby underestimate their mobility. We do not have access to income data for our users, but we can test whether individuals coming into the sample in later months reside in different densities. We find that the R-squared between the date of entering our data and population density at home location ranges from 0.0006 to 0.001 in our three countries. Most of our metrics are aggregated over the entire year, and thus they should not be sensitive to these particular discontinuities.

3. Characteristics of users

The key selection concern when using smartphone app location data is that we only capture individuals who own a smartphone. A further restriction affecting selection into our sample is that individuals require data credit on their phones, similar to requiring phone credit to make calls or send texts. On the other hand, as app usage is increasing through the use of messaging services (e.g., Facebook Messenger or Whatsapp), replacing "traditional" calling and texting, we are more likely to capture locations of individuals engaging in this kind of activity. Further, we are more likely to capture passive use of a mobile phone if a device connects to an app without the deliberate action of the holder of the device. This would make location detection more representative, in some sense, than relying on call and text events only. In terms of characteristics of the selected sample, we expect this to bias our sample towards richer, more educated and younger individuals.

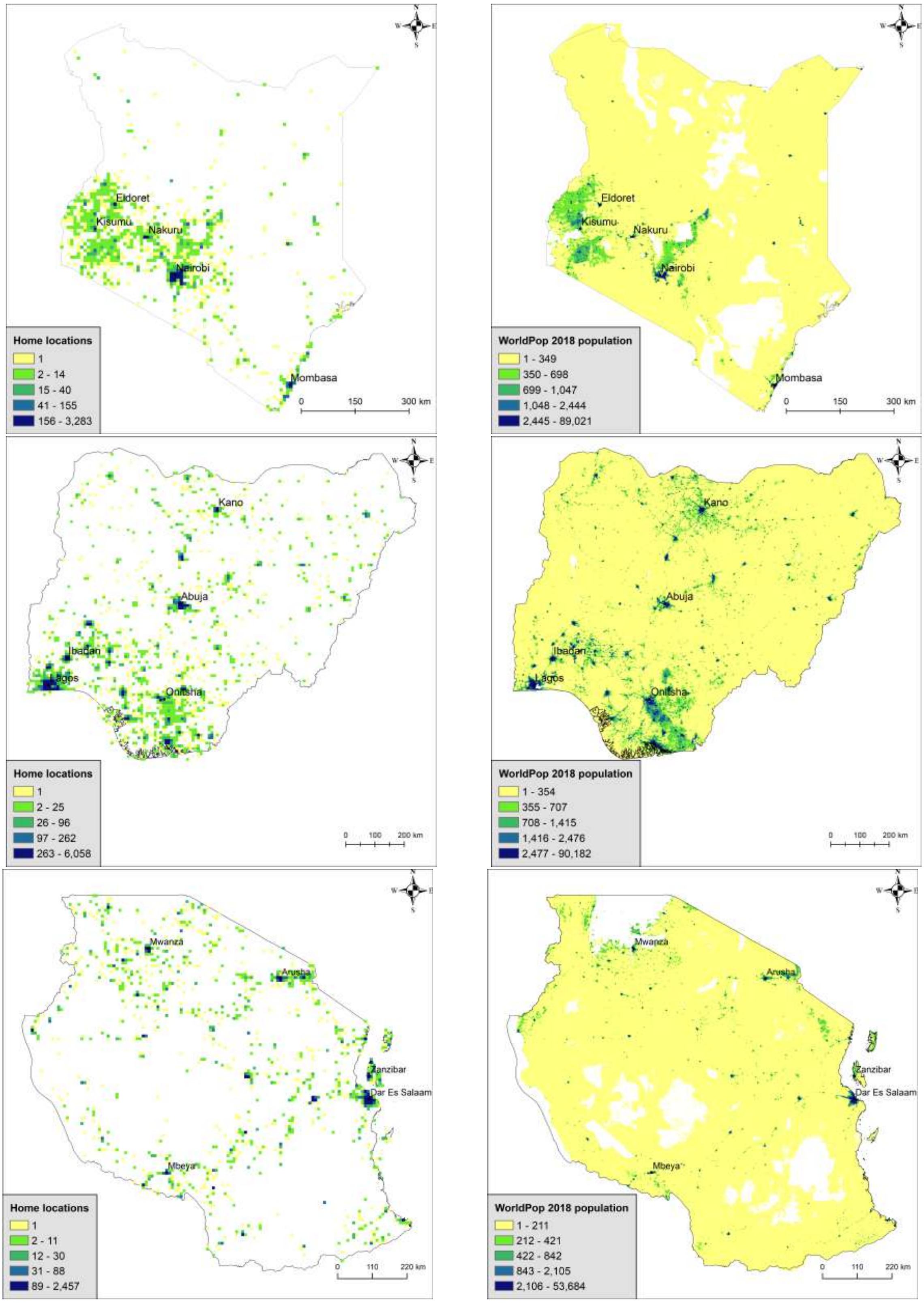
Given these general concerns about selection, we seek to understand how our population of users compares to the broader populations of these three countries. We proceed in three steps. First, we link users' locations with geo-coded population density data from WorldPop to understand how representative users are for different levels of population densities.

than 10 days.

Second, to measure how representative our users are, in terms of their home locations, we develop a methodology to match home locations with nationally representative micro-data from the Demographic and Health Surveys (DHS). This allows us to say something about whether the locations where our users live are typical or atypical. Third, we draw on data from other nationally representative surveys – specifically, the ICT Access and Usage Surveys – to examine differences between individuals who own a smartphone and those who do not. To the extent that our population of smartphone app users is typical of all smartphone owners, these survey data will tell us something about how our users compare to the broader national populations of their countries.

Figure 1 shows the distribution of home locations in the left panel and compares it with the population distribution in the right panel.

Figure 1: Distribution of home locations and population.

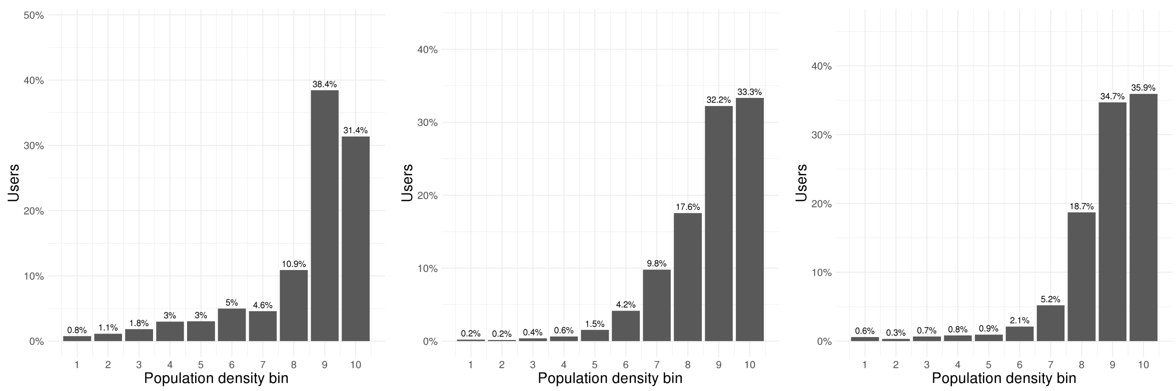


Note: This figure shows the distribution of home locations of users (on the left) and the distribution of the population (on the right).

Darker values indicate a higher number of users. Unsurprisingly, we observe a higher number of users in the main cities. However, the figure shows that coverage of users is broadly national, with users residing in fairly distant places as well as in the densest cities. In fact, we have users in all but three of the 115 regional capitals in the three countries we study.[11] Maps in Figures C.2 and C.3 in the appendix show these comparisons for the three capitals as well as Mombasa, Lagos and Dar es Salaam.

To examine how representative home locations of our users are for different levels of population density, we extract the population density values at users' home locations using WorldPop population grids and we then infer the distribution of users across population density bins. The distribution of users is largely skewed to the right with around 70 percent of users falling in the two densest bins (see Figure 2).[12] We also used other population density products such as Landscan in Figure C.4. Using these products our users are more represented in the lower quintiles. We therefore view these results as the most conservative population density distributions.

Figure 2: Users by population density decile.



(a) Kenya (b) Nigeria (c) Tanzania

Note: This figure shows the distribution of users across population density deciles based on national population data so that each decile contains one tenth of the population (rather than one thenth of grid-cells).

We compute three further metrics to measure the representativeness of our users across

[11] Regional capitals are broadly understood as capital cities for subdivisions of the first administrative level. More specifically, Kenya has 47 counties, Nigeria has 36 states and a Federal Capital Territory and there are 31 regions (or *mikoa*) in Tanzania. Cities' boundaries are defined according to GRUMP 3km-buffered polygons. For the 19 regional capitals that have no boundaries defined in the GRUMP product, we overlay the ArcGIS labelled World Imagery basemap with our users' home location rasters and evaluate qualitatively whether some users are found within the built-up areas of the cities considered.

[12] To be specific, we divide each country into gridcells and assign each gridcell an absolute population density based on WorldPop or other data. Using the national population data, we can divide the entire population into equal-sized bins based on the population density in which they live. This gives rise to a set of gridcells associated with each density decile. We can then identify each of our users with the population density and/or the density bin of their home location; e.g., we can speak of a user whose home location is in the third density decile. Note that our users are not evenly allocated across the density decile. As shown in Figure 2, our users are skewed towards the more densely populated bins.

different levels of population density: first, we take all 10-km pixels in a country and regress the number of users in a pixel on population of the corresponding pixel. We find that the R-squared ranges between 0.36 in Kenya to 0.81 in Tanzania, depending on the source of the population density estimates.[13] Second, we compare the rank in terms of the total number of users at the first administrative level in our three countries with the rank of the population. The bivariate correlation coefficients range between 0.29 in Nigeria and 0.7 in Tanzania.[14]

Next, we compare the fraction of users located in cities of at least 200,000 people with the corresponding fraction of the population living in those.[15] In Nigeria, 86.1% of our users are found in cities of 200,000 whereas these are host to only 20.5% of the population. Similar results are observed in Kenya and Tanzania where we find 75.9% and 68% of users in major cities that host 15.9% and 16.7% of the population respectively, which is indicative of an urban selection pattern.

The urban tilt of our sample is unsurprising; we expect that smartphone users will be concentrated in cities. In all of our analysis, we account for this aspect of the data. The more interesting question is how our urban users compare with other urban dwellers, and how rural users compare with other rural residents. For this, we can turn to other data sources.

To characterize the home locations of our users, we draw on recently available DHS data. The key challenges are how to link a relatively small number of DHS survey clusters (the total number of clusters ranges from 608 in Tanzania to 1,594 in Kenya) to a large number of home locations for our users, spread across the entire geography of our three countries. Adding to the challenge is that the published locations for the DHS clusters are randomly displaced (between 0 and 10 kilometers) in an effort to ensure data confidentiality.[16] For our analysis, we seek a DHS cluster that might be considered comparable to each user's home location. We outline our main methodology here and provide further details in Appendix B.

We start by classifying our users into urban and rural areas. For each user, we select the set of DHS clusters located within a given distance d from her home location. We set $d = 10$km for rural users and $d = 5$km for urban users. This yields a set of DHS clusters that are com-

[13] We find a significantly higher correlation when using Landscan data than other sources.

[14] See Appendix Figure C.7.

[15] We use city polygons from the Global Rural-Urban Mapping Project (GRUMP) to which we apply a 3km buffer in order to better capture commuting zones. We overlay 2018 WorldPop population grids with GRUMP city polygons to obtain city-level population estimates and, for the sake of consistency, total population counts are also based on 2018 population grids. Cities which have boundaries less than 3km apart are merged. As a result, we find that there are 6, 39, and 10 cities of at least 200,000 in Kenya, Nigeria and Tanzania respectively.

[16] To be precise, the published geo-referenced locations for the DHS clusters are displaced by selecting a random compass direction and then a random distance. Urban DHS clusters are randomly displaced by 0-2km, and rural clusters are randomly displaced by 0-5km, with 1 percent of clusters randomly selected to be displaced by 10km (Perez-Heydrich, Warren, Burgert, and Emch, 2013).

parable, in some sense, to the home location of our user. The number of these comparison clusters will be either zero or a strictly positive number of clusters. Not all these nearby clusters will offer valid comparisons, however. For example, a user at the outskirts of Dar Es Salaam might be associated with a nearby rural cluster as well as a number of urban clusters. To ensure that we do not falsely assign an urban cluster as a comparison location for a rural user (or vice-versa), we add the restriction that the cluster's average population density (calculated over a 5km buffer) must be within 25% of the average population density that we have computed for the user's home location. If this does not hold, we drop the DHS comparison cluster.

Following this methodology, we pair 70% of our users in the high-confidence sample with at least one DHS cluster.[17] We call the subset of respondents within paired clusters the "matched DHS" sample.[18] Unsurprisingly, unmatched users are found in low density areas where the probability of selection in the DHS is lower by design - the average density for unmatched users is estimated at 2,496 people/km^2 against 8,835 people/km^2 for users with at least one paired cluster.

This matching exercise allows us to see whether the home locations of our users are atypical, relative to the nationally representative sampling frames that have yielded the DHS clusters. In other words, if we look at the set of DHS clusters where we find our users, we can ask whether this matched DHS sample looks statistically similar to the overall ("raw") set of DHS clusters. We carry out this analysis by conducting t-tests for equality of means between the raw DHS and matched DHS samples on a range of directly quantifiable household characteristics, such as whether the household has a constructed floor, walls, roof, overcrowding and access to public services such as electricity and tap piped water. Moreover, we produce results for rural and urban sub-samples separately to account for both the prevalence of urban users in our sample and the lower matching rate in low density areas, which together may lead to results being mainly driven by the urban component of the sample. We produce t-tests comparing our two weighted data sets, with bootstrapped standard errors robust to heteroskedasticity. The survey weights are used for the reference DHS sample, while those of the matched DHS sample correspond to the number of users each cluster is paired with. Definitions for all variables used are given in Table B.1.

Tables 3-5 show differences between clusters that are associated with the home locations of our device users (matched clusters) compared to the full set of raw DHS clusters representative of the whole population.

[17] The country-specific matching rates are 90% in Kenya, 66% in Nigeria, 72% in Tanzania.

[18] Some clusters are paired to more than one user so the matched DHS sample contains a number of duplicates. In practice, we construct a weighted subset of unique respondents within paired clusters, with weights being equal to the number of users each corresponding cluster is matched to.

Table 3: T-tests for equality of means between matched DHS and DHS samples, Kenya.

	Difference in characteristics of home locations		
Variable	**All**	**Urban**	**Rural**
Household size	-0.91***	-0.26***	-0.19***
Age of HH head	-5.6***	-1.8***	0.45***
Education of HH head	2.3***	0.56***	0.99***
Access to electricity	0.43***	0.15***	0.081***
Radio	0.062***	0.0023	0.071***
Television	0.29***	0.091***	0.067***
Rooms per adult	0.0023	-0.019***	0.028***
Access to piped water	0.35***	0.11***	0.011
Constructed floor	0.37***	0.1***	0.068***
Constructed walls	0.28***	0.075***	0.0011
Constructed roof	0.097***	0.014***	0.11***

Note: This table shows differences in characteristics between households in all DHS clusters compared to DHS clusters we could match with home locations of users, by rural and urban classification.

Table 4: T-tests for equality of means between matched DHS and DHS samples, Nigeria.

	Difference in characteristics of home locations		
Variable	**All**	**Urban**	**Rural**
Household size	-0.86***	-0.61***	-0.93***
Age of HH head	-0.12	-0.023	-0.57***
Education of HH head	4.1***	1.9***	4.2***
Access to electricity	0.39***	0.11***	0.42***
Radio	0.24***	0.13***	0.14***
Television	0.41***	0.18***	0.43***
Rooms per adult	-0.087***	-0.077***	0.0056
Access to piped water	0.026***	-0.0075	0.049***
Constructed floor	0.23***	0.076***	0.32***
Constructed walls	0.16***	0.044***	0.21***
Constructed roof	0.11***	0.018***	0.16***

Note: This table shows differences in characteristics between households in all DHS clusters compared to DHS clusters we could match with home locations of users, by rural and urban classification.

Tables C.1-C.3 show the levels for these variables in addition to the differences. Perhaps unsurprisingly, we find statistically significant differences between the matched clusters and the raw DHS clusters. Our users live in locations that are not nationally representative. In particular, the DHS data show that individuals residing in matched clusters have smaller household size than that found in the nationally representative DHS sample. The matched clusters also have younger household heads with higher education, and better access to services and housing characteristics.

Most of the differences are statistically significant. What is perhaps more striking, however, is that the absolute levels are relatively closely comparable; the differences between matched clusters and the raw DHS data are quantitatively small, especially *within* the rural and the urban samples. For example, individuals in urban matched clusters in Kenya live typically in households with a size of 3.02 people and a household head with 10.46 years of education. Residents in urban clusters that we were not able to match live in households with a size of 3.28 people and the household heads have an average of 9.9 years of education. The magnitude of these averages for matched and unmatched clusters, within urban and rural areas, are therefore roughly similar. This is true for housing characteristics, access to public services and measures of asset ownership. In almost two-thirds of rural and urban comparisons for these three categories of variables, the differences between the matched and unmatched clusters are less than 10 percent. In short, users live in locations that are not fully representative of the national population – but at the same time, these locations are not wildly atypical or weirdly distorted. We are not seeing only a small population of people living in gated communities or in rural holiday spots. The locations where our users live look fairly similar to a nationally representative sample of locations where people live.

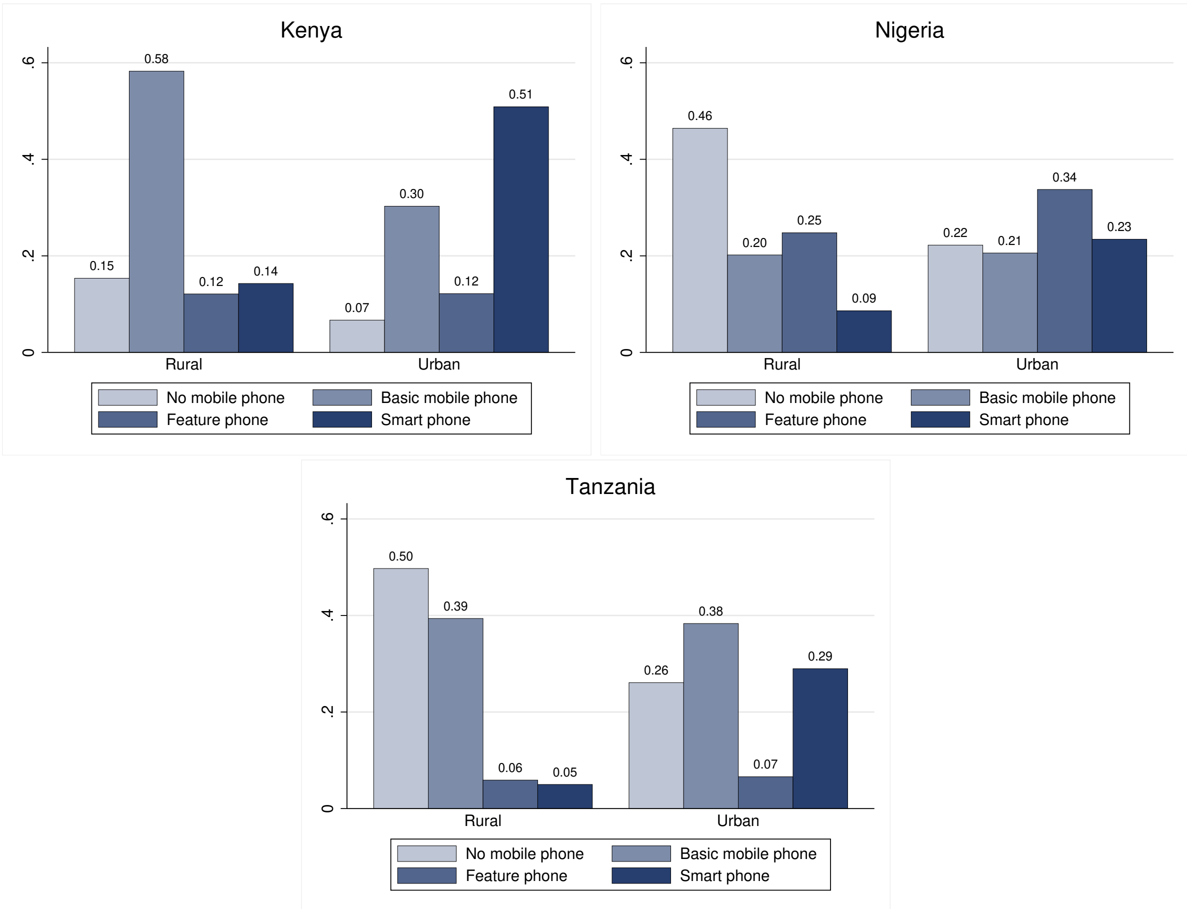
Table 5: T-tests for equality of means between matched DHS and DHS samples, Tanzania.

	Difference in characteristics of home locations		
Variable	**All**	**Urban**	**Rural**
Household size	-0.7***	-0.24***	-0.16***
Age of HH head	-3.8***	-0.67*	-2.2***
Education of HH head	2.4***	0.39***	1.1***
Access to electricity	0.55***	0.17***	0.23***
Radio	0.14***	0.012	0.12***
Television	0.44***	0.14***	0.2***
Rooms per adult	-0.017***	-0.03***	0.025***
Access to piped water	0.29***	0.00094	0.27***
Constructed floor	0.51***	0.093***	0.37***
Constructed walls	0.18***	0.028***	0.12***
Constructed roof	0.24***	0.023***	0.22***

Note: This table shows differences in characteristics between households in all DHS clusters compared to DHS clusters we could match with home locations of users, by rural and urban classification.

This comparison of locations does not, of course, preclude the possibility that our users are very different from other *people*. Smartphone users almost certainly are atypical, compared to the general population. How different are they? To address this question, we use data from the ICT Access and Usage Survey 2017-2018 for Nigeria, Kenya and Tanzania. These surveys are nationally representative and have detailed questions on mobile phone ownership and usage, as well as individual and household characteristics. Overall, between 19 and 43 percent of the population have either a feature phone or a smartphone in our three countries.[19] Figure 3 shows ownership rates for different types of mobile phones, comparing rural and urban locations.

Figure 3: Device ownership by location.



Note: These figures show device ownership rates for rural and urban respondents. All figures use the sample weights provided.

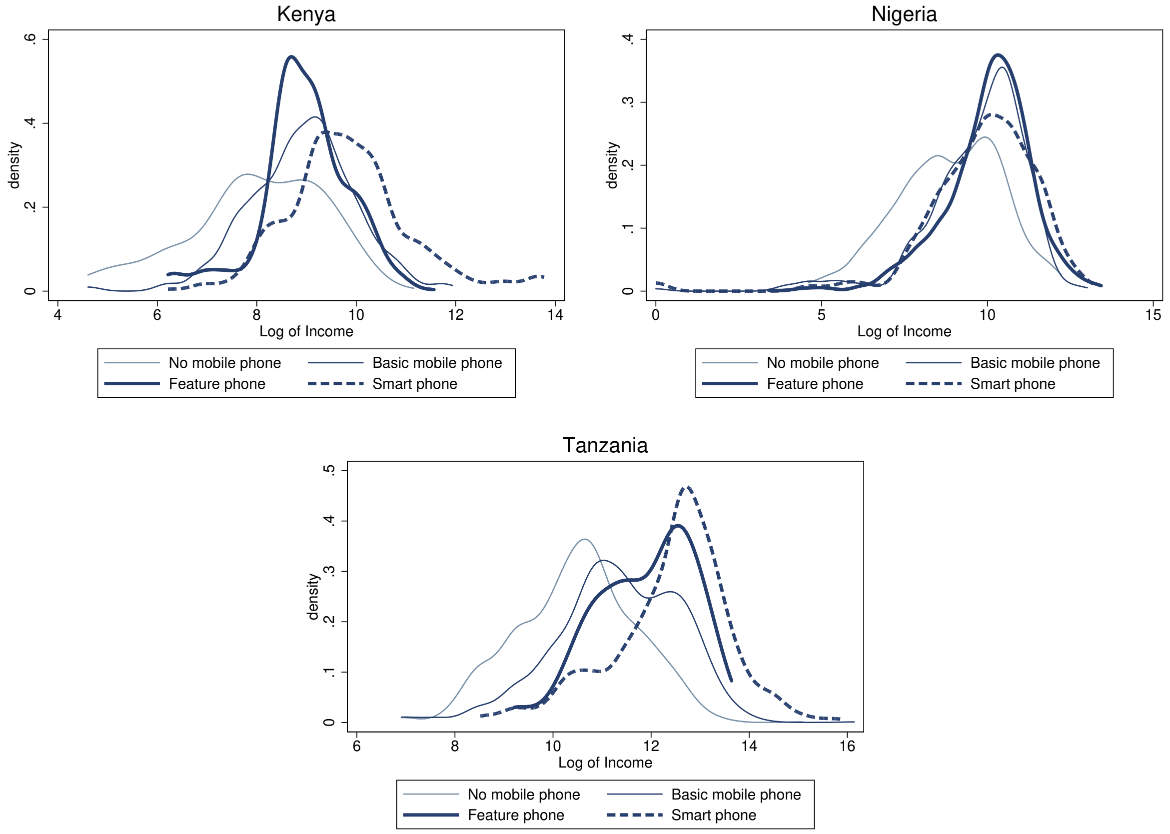
Compared to rural areas, respondents in urban areas are unsurprisingly more likely to own a mobile phone, and the phone is more likely to be a more sophisticated phone. The figure shows that in all countries smartphone ownership is highest in urban areas, with rates between 25 and 46 percent. If we include feature phones, this increases the rate to between 50 and 60 percent. The proportion of individuals with a basic mobile phone ranges between 24 and 40 percent. Across the rural areas of our three countries, smartphone and feature phone ownership is highest in Kenya, at 37 percent penetration, and lowest in Tanzania, with 12 percent. When asking users for the reasons they do not own a smartphone, the main reasons given are affordability and not needing one, because a feature or basic phone

[19] A "feature phone" is defined as one that has a small screen and some rudimentary internet access, but button-based data entry rather than touch screen. It is more complex than a "basic phone," which can only carry out simple calling and texting functions.

is enough.[20]

To examine how owners of these different devices differ from each other – perhaps more important, from those without a device – we compare users by income, age and education. Figure 4 shows that while there are differences in these distributions such that those with no mobile phone tend to have the lowest incomes, the distributions overlap across a large range of monthly incomes. This is particularly the case for individuals that have any type of mobile phone. Figure C.5 compares the number of years of schooling and Figure C.6 shows the age distributions. Both highlight that these distributions are not distinct.

Figure 4: Income and device ownership.

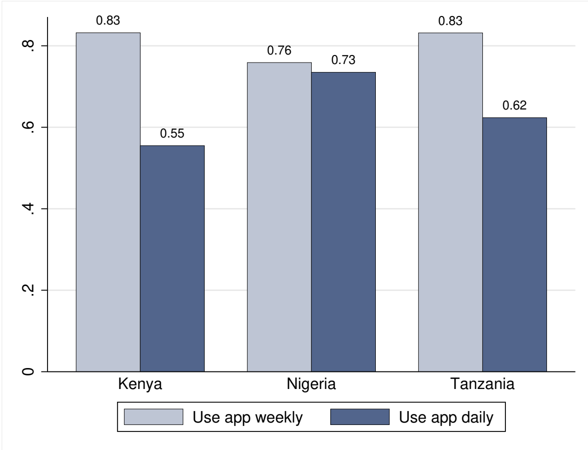


Note: These figures show the distribution of income by device ownership. All figures use the sample weights provided.

The survey also asks respondents about their usage of a range of apps from social networking apps (facebook, Whatsapp, Instagram) to news, weather, trading, business, health and dating apps. Figure 5 shows that between 76 and 83 percent of smartphone owners report using an app weekly on their phones, and more than 55 percent use these apps daily.

[20]This question is available only for a small number of users from Nigeria.

Figure 5: App usage of smartphone users.



Note: These figures show the fraction of smart phone owners using apps weekly or daily. All figures use the sample weights provided.

Our takeaway message from this analysis is that our population of users provides useful information about patterns of mobility in the broader national population. Our users are not statistically representative, but they are also not wildly atypical, at least once we control for the disproportionate concentration in urban areas. Our urban users live in places that are similar to the places where other urban residents live; our rural users live in locations that are not especially different from other rural locations. Within urban locations, smartphone users are a relatively large fraction of the population. Speaking very loosely, they represent the most privileged one-third to one-half of the distribution – but not just the top one percent. Even in rural areas, smartphone users account for over one-third of the Kenyan population, and more than 10 percent in Tanzania. It is true that even within the populations of smartphone owners, our users may be atypical. Our high-quality subset consists of people who use their devices relatively frequently, and this may bias us towards users who are more mobile and more sophisticated than the average. But as people in these countries have begun to use their phones for messaging and social media, one suspects that this distinction – to the extent that it ever held true – may not be very pronounced. In sum, we believe that the evidence supports us in using these data to inform a discussion of human mobility within these three countries. We are almost certainly looking at a subset of the population that is more mobile than the average; but equally, we are looking at only a subset of the total mobility. In other words, the trips that our users have taken are a subset of the total trips made; and the connections that we identify between locations are a subset of the total connections.

To conclude this section of the paper, we take up more fully the potential biases that we may have introduced by equating "devices" with "users." We acknowledge that distinct users may use the same device, and individual users might have multiple devices. We discuss these issues in turn. Unfortunately we do not have data on the extent to which smartphones are shared among contacts. From the ICT Access and Usage Survey we know that between 20 and 35 percent who stated that they do not *own* a mobile phone say that they nevertheless *used* a mobile phone in the past three months. Unfortunately the survey does not ask which type of mobile phone a respondent used, nor are respondents asked whether this was the respondent's own phone at the time.[21] However, it is reasonable to assume that device sharing is frequently likely to occur within households. If so, it would not affect the home locations we determined for our users, nor would it alter the characteristics of home locations we discussed. If several people share a device that is used, for example, to travel to the nearby city, this would lead us to capture travel by several household members rather than just one device user. Given that we are interested in the flow of people between locations (and not necessarily the particular person), this would still give us a reasonable measure of human mobility between locations.

Individuals could also have multiple phones or SIM cards. The latter problem is not a significant concern for us. Our data observe devices, rather than SIM cards; even when the SIM card is swapped, the device identifier remains the same, so our smartphone app data are unaffected. This is an advantage of our data relative to the CDR data widely used in many development applications; although ownership of multiple active SIM cards is relatively rare in Kenya (more than 80 percent of individuals have only one active SIM card), it is fairly common in Nigeria and Tanzania where less than 57 percent of individuals have only one active SIM card.

However, there is some reason for us to be concerned about users who own multiple devices. This would affect our results in the opposite way of device sharing, such that the movement data of these two-device-owners would get a higher weight in our mobility metric calculations. A possible additional complication would arise if a user maintains two devices, with each linked to a different location or set of locations – for example, because different mobile providers may offer better coverage in certain geographies. This would make a highly mobile user look artificially as though she does not move very much. For example, someone who commutes each week from home in a rural area to work in a big city, using a different device in each location, will appear as a relatively immobile individual. Unfortunately, we do not have information on the extent with which users own multiple devices, but given that smartphones are relatively expensive – and given the attachment that people feel to particular devices – it is likely to be a rather small number.

Finally, we note that users may not leave their devices turned on at all times, and they may not connect with apps during all of their travels (e.g., if data charges are high). This would lead to a systematic underestimation of the frequency of travel and the distance travelled. With all these caveats, however, we proceed to analyze the mobility data.

[21] It is possible, for instance, that the respondent lost his/her phone or had it stolen during that time period, or perhaps even that the phone died or was sold.

4. Quantifying mobility

In this section, we develop and implement a number of indicators to measure high-frequency mobility patterns. We consider mobility on two levels: the mobility of individual users across locations, and the connectedness of different locations through these individual movements. We characterize mobility at the user level on three key dimensions: frequency, spatial extent and densities visited. Our preferred indicators in this respect are the fraction of days with mobility beyond 10km away from home (*frequency*), the average distance away from home (*spatial extent*), and the distribution of (non-home) pings/users across population density categories (*densities visited*). We investigate how these vary across subsets of users residing in different population density categories - we use population density deciles as cutoff values to define these density bins. In characterizing the connectivity of locations, we quantify incoming and outgoing flows separately. We characterize incoming mobility flows by their size: the number of distinct visitors during the period of observation, the frequency of visits to the city, the distance travelled, and the population density at visitors' home locations. Similarly, we calculate the size of outgoing flows: i.e., the number of distinct residents seen outside the city during the period, the frequency of movements outside the city, their spatial extent and the population densities visited. In addition, we provide measures of mobility flows for pairs of cities. We examine the origin locations of visitors in the five largest cities in each of our three countries, and we also look at the top destinations visited by their residents. We then disaggregate both the origin and destination locations into densities and summarize our data in the form a spatial transition matrix to examine the connections between remote and dense areas.

We begin by considering the mobility of people beyond their immediate surroundings to evaluate users' frequency of mobility. Some initial notation is helpful. Let $x \in X$ denote a location defined by rounded coordinates, with X the (finite) set of all possible locations within the extent of a given country. For any given user i in the set of users I, we can partition X in two ways. First, we partition X into the home location and non-home locations. Let $d_i(x)$ denote the haversine distance to location x from the home location of user i.[22] Define the distance threshold $\bar{d}$ to be the limit of the home location. Then for user i, the set of locations such that $d_i(x) \leq \bar{d}$ defines a set of locations near home, H_i. Similarly, $d_i(x) > \bar{d}$ defines a set of non-home locations, $\bar{H}_i$. For any user i, it is true that $H_i \cup \bar{H}_i = X$.

A second useful way to partition X for a given user i is into the subset of locations (typically a strict subset) where user i is observed with a ping and those where the user is not observed. We use Z_i to represent the set of locations where we observe a ping from i during the period of observation, and we in turn partition Z_i into those locations that belong to i's home

[22] Strictly speaking, we use the haversine distance between 2-decimal rounded latitude-longitude locations. This is approximately the same as taking the haversine distance between the centroids of two narrowly defined gridcells.

location - as defined by $\bar{d}$ - denoted Z_i^H and those that are non-home locations, denoted $Z_i^{\bar{H}}$. In addition, we denote by Z_{it} the set of locations where we observe a ping from i on any given day t and that we can partition into Z_{it}^H and $Z_{it}^{\bar{H}}$.

As a final notational preliminary, define an integer-valued function $p_i(x)$ that counts the number of pings for user i in each location $x \in X$. Clearly, $p_i(x) \geq 1$ for $x \in Z_i$, and $p_i(x) = 0$ elsewhere. Let $P_i = \sum_{x \in X} p_i(x)$ give the total number of pings for user i.

As our first measure, we use the fraction of days a user is seen more than 10 km away from her home location (i.e., we set $\bar{d} = 10\text{km}$). Let M_{it} be a mobility indicator such that $M_{it} = 1$ on any day, t, if there is at least one ping observed for person i at a location away from home; i.e., $Z_{it}^{\bar{H}} \neq \emptyset$. Define $M_i = \sum_{t=1}^{365} M_{it}$ to be the number of days the user is seen more than 10 km away from her home location. Similarly, let T_{it} be a dummy indicating whether at least one ping is observed for person i at any location on day t; i.e., $T_{it} = 1$ if $Z_{it} \neq \emptyset$; and let $T_i = \sum_{t=1}^{365} T_{it}$ be the number of days over the period of study where at least one ping from user i is observed. Then we define the mobility frequency for user i as:

$$F_i = \frac{M_i}{T_i} \tag{1}$$

In this expression, the numerator denotes the number of days with at least one ping 10 km away from home for user i, and the denominator gives the total number of days on which user i is observed (i.e., days with at least one ping). A limitation of this metric is that it does not allow us to distinguish between users making a lot of short trips and those travelling less but spending more time at their destinations.

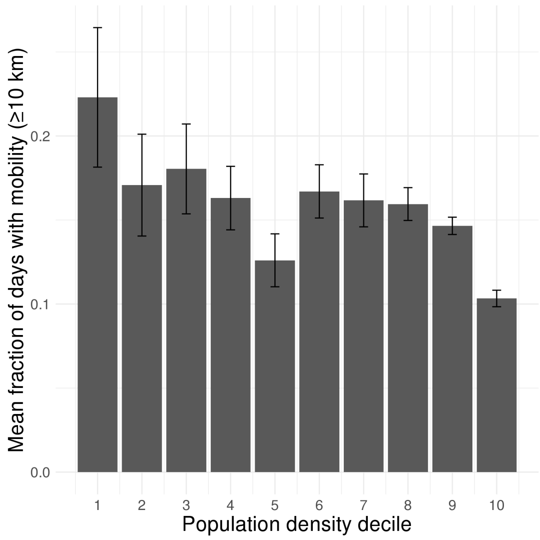
To translate this individual measure into a characteristic of a group of people, we average across the members of that group. For this, it is useful to define some groups of people. As noted above in Section 3, we assign each user to a population density bin, based on the characteristics of the user's home location. For instance, we consider the set of decile-bounded bins, $B = \{b_1, b_2, ..., b_{10}\}$, and we define the corresponding subsets of users $I_1, ..., I_{10}$. Let n_j denote the number of users assigned to bin b_j, i.e. the number of users in I_j. We then compute:

$$F^j = \frac{1}{n_j} \sum_{i \in I_j} F_i. \tag{2}$$

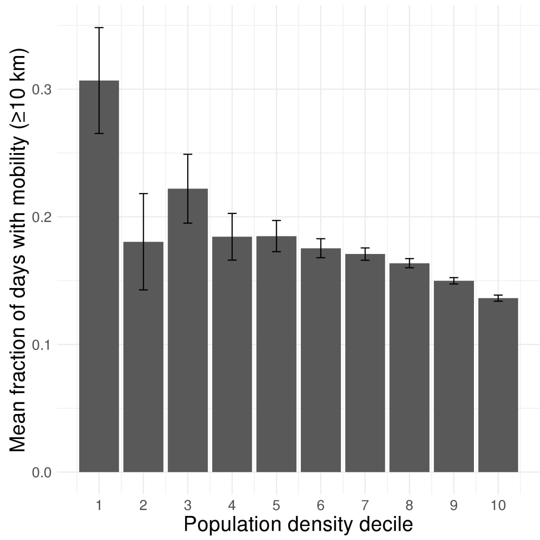
Figure 6 shows this frequency for all three countries, broken down by density bin. The pattern is consistent across countries: on roughly 10-20 percent of the days when we observe them, users appear beyond the 10 km radius from their home locations. There is a distinct pattern, too, in that those who live in the most densely populated areas are the least likely to be observed away from home. We also calculate the fraction of days with mobility beyond

20km and observe similar and even more marked patterns. One plausible interpretation is that those who live in relatively remote areas are likely to travel more frequently than those who live in towns and central cities. We cannot, of course, distinguish between the frequency of trips and the frequency with which users turn to their phones for information. It is possible that users are more likely (or less likely) to use their devices when they are travelling, compared to when they are home; and these patterns may differ for people whose home locations are in different bins of population density. Nevertheless, the data are suggestive both of a relatively high overall frequency of mobility and of differences between rural and urban residents.

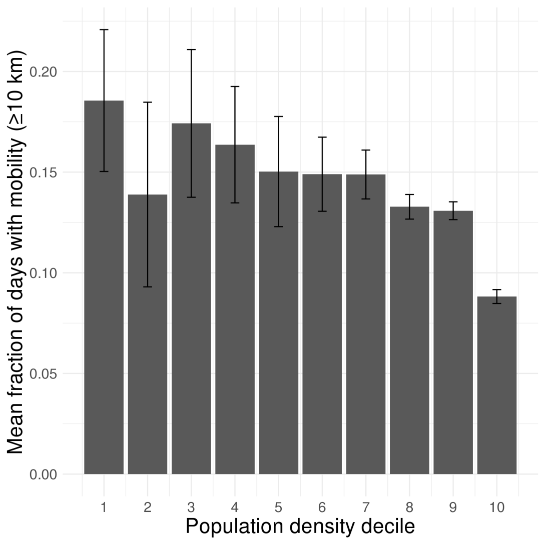
Figure 6: Fraction of days with mobility beyond 10km by density bin.



(a) Kenya



(b) Nigeria



(c) Tanzania

Note: These figures show the fraction of days on which a user is seen more than 10km away from their home location by density decile over the period of a year.

Figure 7 focuses not on the frequency with which people travel, but the distance from home at which they are seen. We define the spatial extent of mobility for user i as the average distance between non-home pings and the home location. Note that for this metric, we take $\bar{d} = 0$ to define the sets of home locations and non-home locations, H_i and $\bar{H}_i$. As before, let $p_i(x)$ be the number of pings we observe for user i at location x. Then let $P_{iH} = \sum_{x \in H_i} p_i(x)$ and $P_{i\bar{H}} = \sum_{x \in \bar{H}_i} p_i(x)$; consistent with our notation above, the total number of pings observed for user i is simply $P_i = P_{iH} + P_{i\bar{H}}$. In simple terms, $P_{i\bar{H}}$ is the number of non-home pings of user i.

Given this, we can construct the spatial extent of user i's mobility, which is the average distance to each of her non-home pings. Thus:

$$S_i = \frac{1}{P_{i\bar{H}}} \sum_{x \in Z_{i\bar{H}}} d_i(x) p_i(x) \tag{3}$$

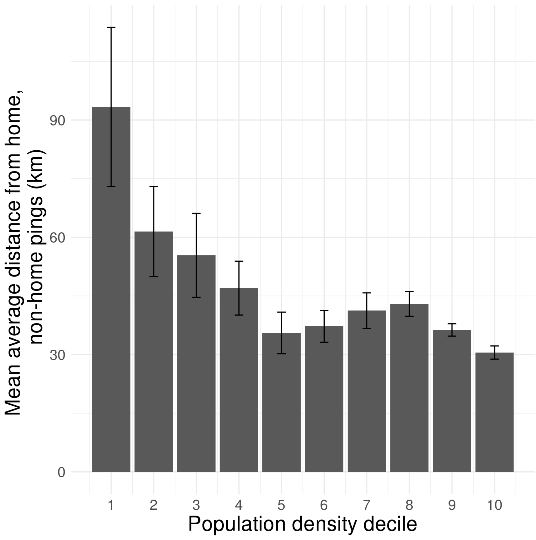
In extrapolating this measure to a group of people, we can once again take an average. For example, we can measure the average of our spatial extent measure for the individuals belonging to a population density bin b_j by simply averaging the individual values of S_i. Thus:

$$S_j = \frac{1}{n_j} \sum_{i \in I_j} S_i \tag{4}$$

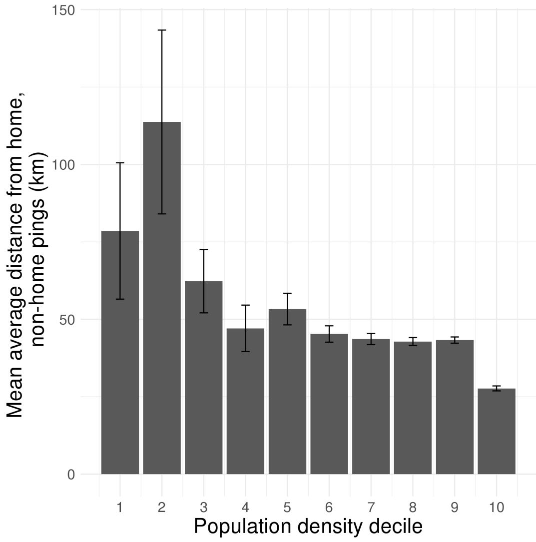
Figure 7 shows that non-home pings are not all highly local. In fact, the average distance – across countries and density bins – ranges from 30-100 km. As in Figure 6, we see a pattern across density bins suggesting that those in relatively sparsely populated areas seem to travel the farthest – in the sense that their average distance away from home (conditional on *being* away from home) is higher than for those in more densely populated locations. It is interesting that both the absolute distances and the relative patterns across density deciles look quite similar across the three countries.

Taken together, Figures 6 and 7 seem suggestive of a pattern in which those from relatively remote areas travel more frequently and farther – possibly to get to towns and cities. To assess this conjecture, we next turn to the third dimension of mobility and construct a first measure that allows us to characterize locations visited by users in terms of population density.

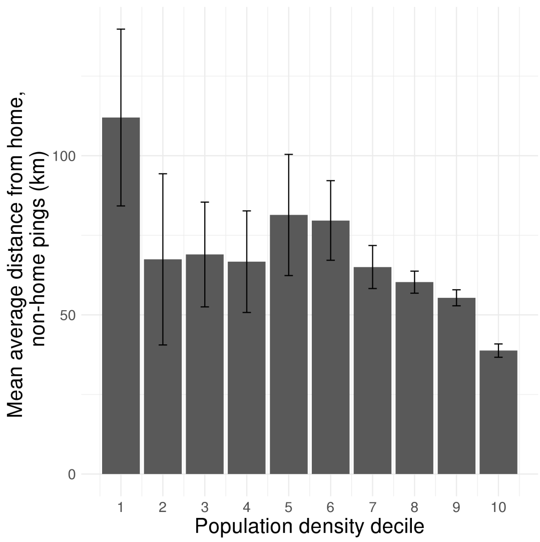
Figure 7: Mean distance away from home by density decile.



(a) Kenya



(b) Nigeria



(c) Tanzania

Note: These figures show the average distance from users' home locations of non-home pings by density decile over the period of a year.

Let $N(x)$ denote the population density at location x. Based on this, let $\tilde{N}(x)$ be an indicator mapping locations into density bins; in other words, $\tilde{N} : X \rightarrow B$. We consider the set of non-home locations pinged by person i, and we assign each ping to a density bin b_j. Then the fraction of visits (i.e., pings in non-home locations) by user i to locations in density bin b_j is given by:

$$v_{ij} = \frac{\sum\limits_{x \in \{x \in \bar{H}_i : \tilde{N}(x) = b_j\}} p_i(x)}{P_{i\bar{H}}} \tag{5}$$

Once again, we summarize our measure at the level of each group I_o of users with home location in density bin of origin b_o by calculating the average fraction of non-home pings in each one of the 10 density bins of destination $(b_d)_{d\in[1;10]}$. Then our measure becomes:

$$V_{od} = \frac{1}{n_o}\sum_{i\in I_o} v_{id} \tag{6}$$

Results are shown in Table 6 for our three countries. Each column j of these tables can be interpreted as the average distribution of non-home pings across density bins for users with home locations in the density bin j.

Alternatively, we construct an aggregate metric at the density bin level to describe the population densities visited at least once by users belonging to each density bin b_j. For each user $i \in I_j$ and each density bin b_k, we define p_{ik} as a dummy indicating whether user i ever visited a location in density bin b_k:

$$p_{ik} = \begin{cases} 1, & \text{if } \exists x \in \{x \in X | \tilde{N}(x) = b_k\} : p_i(x) > 0 \\ 0, & \text{otherwise} \end{cases}$$

Then the fraction of users whose home location is in density bin b_j and who are seen at least once in a location belonging to population density bin b_k is:

$$\Delta_{jk} = \frac{\sum_{i\in I_j} p_{ik}}{n_j} \tag{7}$$

Tables 6 to 7 show more detail about the locations visited by people when they are travelling. Specifically, these tables show, for individuals whose home locations are assigned to different population density bins (across the columns of these tables), the proportion of non-home pings that they record in locations of different population densities.

To give an example, Table 6a shows that for the Kenyan users in our data who live in the least densely populated areas, just over one-third (36.3%) of their non-home pings are recorded in other relatively sparsely populated areas. This would include any observations relatively near to home but outside the immediate home location. But nearly one-fourth of their non-home pings (23.3%) are recorded in locations that fall in the top two deciles of the density distribution. Tables 6b and 6c show comparable data for Nigeria and Tanzania, respectively.

Table 7 offers a slightly different angle on the data. These give the fraction of users residing in a given density bin who are seen over the course of the year on at least one occasion in a non-home location within each of the ten density bins. For instance, this tells us that 6.9% of those Kenyans living in the most densely populated locations in the country, were observed on at least one occasion during the year in a cell that falls within the *least* densely populated parts of the country. At the other end of the distribution, 29.3% of the users whose home locations are in the most sparsely populated areas of the country were observed at least once during the year in the most densely populated parts of the country.

Table 6: Average distribution of pings across visited density bin, by home density bin.

		Home density bin									
		1	2	3	4	5	6	7	8	9	10
	1	36.3%	7.8%	2.7%	2%	1%	1.7%	1.1%	1.2%	0.7%	0.3%
	2	9.3%	24.3%	11.8%	2.9%	2.2%	1.7%	1.5%	1.6%	0.7%	0.4%
	3	4.8%	11.9%	14.5%	7.5%	4.5%	2.4%	3.2%	2.3%	1.2%	0.8%
	4	4.8%	5%	11.5%	12.6%	9.2%	4.6%	4.6%	3.2%	2.2%	1.6%
Visited density	5	5.3%	4.2%	7.5%	10.3%	12.5%	6.3%	7.1%	3.1%	2.3%	1.4%
	6	2.8%	4.5%	7.1%	6.2%	12.2%	11.2%	9.3%	5.6%	5.4%	5%
	7	4.7%	3.3%	4.3%	4.9%	9%	7.4%	13%	9.5%	3.4%	1.6%
	8	8.6%	8.2%	11.4%	11.8%	11.3%	10.6%	18.4%	20.2%	11.4%	5.6%
	9	18.8%	21.8%	23.1%	29.4%	27.8%	36.3%	32%	42.1%	50.8%	40.4%
	10	4.5%	8.9%	6.1%	12.4%	10.3%	17.8%	9.8%	11.3%	21.9%	42.9%

(a) Kenya

		Home density bin									
		1	2	3	4	5	6	7	8	9	10
	1	2.3%	2.7%	2.2%	1.4%	0.5%	0.2%	0.2%	0.1%	0.1%	0.1%
	2	3.7%	12.7%	6%	1.6%	0.8%	0.6%	0.4%	0.2%	0.2%	0.2%
	3	1.5%	9%	6.4%	6.1%	1.2%	1%	0.6%	0.3%	0.2%	0.1%
	4	2.3%	5%	10.8%	5.4%	4.9%	2.6%	1.1%	0.6%	0.5%	0.3%
Visited density	5	2.1%	6.8%	6.2%	9.5%	11.9%	5.9%	2.6%	1.6%	1%	0.5%
	6	4.5%	6.4%	6.8%	12.4%	16%	20.2%	9%	3.7%	2.2%	1.4%
	7	7.3%	12.6%	12.7%	14.6%	15.7%	21.6%	26.2%	12.4%	5.1%	2.6%
	8	20%	13.9%	11.9%	11%	16.2%	15%	24.3%	29.6%	16%	5.3%
	9	42%	19.6%	27.1%	26.4%	20.7%	19.8%	24.7%	40.3%	54.6%	18%
	10	14.4%	11.3%	10%	11.6%	12.1%	13.1%	10.9%	11.2%	20.1%	71.5%

(b) Nigeria

		Home density bin									
		1	2	3	4	5	6	7	8	9	10
	1	32.5%	10.5%	4.7%	2.5%	2.5%	2.3%	1.7%	0.6%	0.4%	0.2%
	2	3%	18.5%	7.2%	3.1%	2.5%	1.7%	0.9%	0.6%	0.3%	0.1%
	3	5.4%	8.2%	8%	8.4%	7.9%	3.4%	1.9%	0.6%	0.5%	0.2%
	4	3.2%	3.2%	8.8%	10.6%	9.6%	5.8%	2.7%	0.8%	0.6%	0.3%
Visited density	5	4.4%	10.4%	6.6%	8.3%	10.2%	5.8%	4%	1.5%	0.8%	0.4%
	6	5%	1.3%	7.1%	9.1%	10.5%	14.4%	11.4%	2.7%	1.4%	0.6%
	7	6.3%	5.7%	8.7%	12.3%	10.5%	18.2%	20.9%	8.6%	3.4%	1.4%
	8	14.6%	16.4%	15.9%	15.8%	17%	19.5%	26.3%	37.1%	17%	6.4%
	9	14.9%	17.3%	19.8%	20.9%	20.5%	20.9%	21.5%	33.2%	49.1%	27.7%
	10	10.7%	8.5%	13%	9%	8.8%	7.9%	8.7%	14.4%	26.5%	62.8%

(c) Tanzania

Note: These matrices show the average fraction of non-home pings of users residing in density bin i for density bin j over the period of a year.

Table 7: Share of users by home bin-visited bin pair.

		Home density bin									
		1	2	3	4	5	6	7	8	9	10
	1	70.7%	31.5%	20.1%	13.6%	13.1%	13.8%	14.5%	14%	10.5%	6.9%
	2	43.1%	57%	39.6%	23.5%	23.5%	18.9%	21.8%	20.4%	16.2%	11.8%
	3	35.8%	50.3%	55.3%	40.6%	35.4%	28.7%	31.4%	27%	23.4%	16.2%
	4	37.4%	37.6%	52%	55.1%	48.8%	38.2%	40%	34.2%	31.3%	24.2%
Visited density	5	34.1%	32.1%	45.4%	50.8%	55.3%	40.3%	44.4%	32.8%	29.5%	20.3%
	6	26.8%	30.9%	43.2%	47.7%	54.2%	48%	52.1%	43.6%	44.3%	37.6%
	7	33.3%	30.3%	37%	40.8%	44.9%	43.1%	54.7%	50.1%	35.3%	23.1%
	8	48.8%	41.8%	52.7%	55.7%	53.7%	53.6%	68.3%	69.8%	58%	39.2%
	9	56.9%	54.5%	59%	67.6%	67.5%	74.5%	72.1%	82.1%	87.9%	79.1%
	10	29.3%	30.9%	33.7%	46.7%	45.6%	54.4%	46.1%	51%	67.9%	84.8%

(a) Kenya

		Home density bin									
		1	2	3	4	5	6	7	8	9	10
	1	19%	22.7%	16.5%	11.9%	7.9%	4.9%	4.6%	4.8%	4.5%	2.6%
	2	27.5%	39.1%	33.8%	20%	14.5%	11.2%	10%	8.9%	10.5%	9.8%
	3	16.2%	34.5%	31.2%	29.4%	19.3%	13.5%	11.3%	9%	7.9%	4.9%
	4	34.5%	25.5%	40.4%	37.3%	32.9%	23.6%	17.7%	14%	14.5%	11%
Visited density	5	31.7%	32.7%	42.3%	43.8%	49.3%	39.4%	26%	20.4%	17.5%	11.8%
	6	40.8%	37.3%	46.2%	56.2%	61.5%	67.7%	48.4%	34%	28.1%	19.8%
	7	61.3%	42.7%	53.8%	59.3%	61.9%	70.1%	75.8%	58.2%	42.7%	28.6%
	8	76.1%	57.3%	59.6%	58.4%	61.5%	62.8%	74.5%	81.2%	66.6%	39.6%
	9	86.6%	54.5%	65.4%	64.7%	62.5%	63.5%	66.9%	82%	90.7%	63.7%
	10	63.4%	34.5%	43.5%	49%	46.2%	47.9%	43.7%	43.7%	57.5%	95.3%

(b) Nigeria

		Home density bin									
		1	2	3	4	5	6	7	8	9	10
	1	67.5%	32.8%	24.4%	18.2%	20.1%	13.6%	13.4%	9.9%	8.2%	4.6%
	2	25%	55.2%	35.8%	26.4%	19.6%	16.6%	13.2%	12.4%	11.2%	7.1%
	3	25.8%	36.2%	37.4%	35.2%	34.1%	22.4%	18.2%	13.8%	11.5%	6.9%
	4	21.7%	20.7%	35.8%	40.3%	37.4%	27.1%	22.9%	16.3%	13.4%	8%
Visited density	5	25.8%	37.9%	37.4%	39%	40.8%	39.9%	27.6%	18.8%	14%	8.1%
	6	32.5%	27.6%	40.7%	40.3%	43.6%	51.3%	41.9%	26.1%	19.4%	11.8%
	7	37.5%	36.2%	40.7%	49.7%	42.5%	57%	60.7%	42.6%	28.8%	17%
	8	49.2%	53.4%	55.3%	55.3%	55.3%	59%	66.3%	80.3%	63.3%	41.3%
	9	45.8%	51.7%	52%	57.2%	54.7%	59.5%	58.1%	72.6%	87.5%	70.4%
	10	39.2%	29.3%	44.7%	38.4%	35.8%	37.4%	37.8%	47.7%	66%	91.9%

(c) Tanzania

Note: These matrices show the proportion of users residing in density bin i that are seen at least once in density bin j over the period of a year.

Taken together, these tables offer a picture of highly mobile populations across all three countries, with people travelling both far (measured in terms of distance) and to locations that differ markedly from their home locations. Nigeria offers a slight exception to the pattern. Pings are heavily concentrated in the most densely populated parts of the country, to a greater degree than in either Kenya or Tanzania, although there still appear (see Table 7b) to be substantial flows of users across locations at different population density levels.

As an alternative to using density deciles for our analysis, we consider in Tables 8 to 10 the "visitors" to the major cities of our three countries.

Table 8: Origin of visitors in top 5 cities, Kenya.

Nairobi (1,699 visitors)		Mombasa (953 visitors)		Nakuru (891 visitors)		Eldoret (448 visitors)		Kisumu (437 visitors)	
Origin	*Visitors*	*Origin*	*Visitors*	*Origin*	*Visitors*	*Origin*	*Visitors*	*Origin*	*Visitors*
Mombasa	20.2%	Nairobi	68.4%	Nairobi	62.5%	Nairobi	51.3%	Nairobi	57%
Nakuru	4.9%	Nakuru	1.5%	Eldoret	3.1%	Mombasa	3.3%	Mombasa	4.6%
Kisumu	4.1%	Kisumu	0.6%	Mombasa	2.9%	Kisumu	2.9%	Eldoret	2.3%
Eldoret	4.1%	Eldoret	0.5%	Kisumu	2%	Nakuru	2.2%	Nakuru	1.4%
Garissa	1.1%	Garissa	0.1%	Garissa	0.1%	-	-	-	-
Non-urban	65.6%	Non-urban	28.9%	Non-urban	29.3%	Non-urban	40.2%	Non-urban	34.8%

Note: This table shows the origin of visitors for the five most populated cities. Origin and destination city boundaries are defined using 3km-buffered GRUMP polygons. Visitors are defined as being seen at least once in a location over the year. "Non-urban" refers to locations outside boundaries of cities with 200,000 or more residents. "Other urb." refers to all cities that are not in the top 5 origin cities.

Table 9: Origin of visitors in top 5 cities, Nigeria.

Lagos (5,258 visitors)		Kano (807 visitors)		Ibadan (2,916 visitors)		Abuja (3,232 visitors)		Kaduna (1,296 visitors)	
Origin	*Visitors*	*Origin*	*Visitors*	*Origin*	*Visitors*	*Origin*	*Visitors*	*Origin*	*Visitors*
Abuja	21.9%	Abuja	43.5%	Lagos	68.7%	Lagos	47%	Abuja	54.9%
Ibadan	13.1%	Lagos	18.5%	Abuja	6.6%	Kaduna	8.8%	Lagos	12%
Abeokuta	7.4%	Kaduna	11%	Abeokuta	3.8%	Port Harc.	5.3%	Kano	10.3%
Shagamu	6.4%	Maiduguri	2.9%	Ilorin	2.9%	Kano	5.2%	Zaria	5.9%
Port Harc.	6.4%	Zaria	2.9%	Shagamu	2.7%	Jos	3.2%	Katsina	1.7%
Other urb.	5.7%	Other urb.	2.5%	Other urb.	2.4%	Other urb.	2.6%	Other urb.	1.2%
Non-urban	39.1%	Non-urban	18.8%	Non-urban	12.9%	Non-urban	27.9%	Non-urban	13.9%

Note: This table shows the origin of visitors for the five most populated cities. Origin and destination city boundaries are defined using 3km-buffered GRUMP polygons. Visitors are defined as being seen at least once in a location over the year. "Non-urban" refers to locations outside boundaries of cities with 200,000 or more residents. "Other urb." refers to all cities that are not in the top 5 origin cities.

Table 10: Origin of visitors in top 5 cities, Tanzania.

Dar Es Salaam (1,850 visitors)		Zanzibar (743 visitors)		Mwanza (704 visitors)		Arusha (859 visitors)		Mbeya (395 visitors)	
Origin	*Visitors*	*Origin*	*Visitors*	*Origin*	*Visitors*	*Origin*	*Visitors*	*Origin*	*Visitors*
Arusha	9.7%	Dar Es Sa.	53.3%	Dar Es Sa.	32.4%	Dar Es Sa.	39.5%	Dar Es Sa.	38.2%
Zanzibar	8.9%	Arusha	4%	Arusha	3.1%	Moshi	10.4%	Mwanza	2.8%
Mwanza	6.7%	Mwanza	0.8%	Dodoma	1.3%	Mwanza	3%	Arusha	2.3%
Morogoro	6%	Moshi	0.8%	Mbeya	0.9%	Dodoma	2.3%	Dodoma	1.8%
Dodoma	4.3%	Dodoma	0.8%	Moshi	0.7%	Zanzibar	2.2%	Morogoro	1.5%
Other urb.	3.5%	Other urb.	0.3%	Other urb.	0.6%	Other urb.	1.6%	Other urb.	0.8%
Non-urban	61%	Non-urban	40%	Non-urban	61.1%	Non-urban	41%	Non-urban	52.7%

Note: This table shows the origin of visitors for the five most populated cities. Origin and destination city boundaries are defined using 3km-buffered GRUMP polygons. Visitors are defined as being seen at least once in a location over the year. "Non-urban" refers to locations outside boundaries of cities with 200,000 or more residents. "Other urb." refers to all cities that are not in the top 5 origin cities.

A visitor is defined here as someone whom we observe in a city whose home location falls outside the city boundaries. We categorize visitors as those who are residents of other major cities in the same country, and then we also consider a group of "non-urban" visitors, who are those who live outside the boundaries of any city of more than 200,000 people.

The data for all three countries show similar and interesting patterns. The largest city consistently has a large number of visitors defined as "non-urban," implying that these cities are magnets for travellers from the entire country. There are consistently large flows from secondary cities to these primate cities, but the proportions fall off sharply to more minor cities. In contrast, the secondary cities typically see large inflows of visitors from the primate cities, along with large inflows from non-urban areas. The flows across and between secondary cities are typically fairly modest, according to this metric. Eldoret has little that Kisumu lacks, and vice versa – so even though these cities are less than 150 km apart, each accounts for less than 3% of the visitors in the other. The same patterns are seen in Nigeria and Tanzania. For Nigeria, to give another example, although visitors from Kano make up 10% of the documented visitors to Kaduna, relatively few of those visiting Kano are from Kaduna. In each city, far more visitors come from towns, villages, and rural areas (together characterized as "non-urban").

We can similarly look at the destinations of those whose home locations are in the major cities of our three countries. For these urban dwellers, we can ask what proportion were seen during the year in other major cities and in non-urban areas (defined as in Table 8. The results of this analysis are shown in Tables 11 to 13.

Table 11: Top 5 destinations of residents from top 5 cities, Kenya.

Nairobi (11,290 residents)		Mombasa (1,683 residents)		Nakuru (413 residents)		Eldoret (340 residents)		Kisumu (258 residents)	
Destination	*Residents*	*Destination*	*Residents*	*Destination*	*Residents*	*Destination*	*Residents*	*Destination*	*Residents*
Mombasa	5.8%	Nairobi	20.4%	Nairobi	20.1%	Nairobi	20.3%	Nairobi	27.1%
Nakuru	4.9%	Nakuru	1.5%	Mombasa	3.4%	Nakuru	8.2%	Nakuru	7%
Kisumu	2.2%	Kisumu	1.2%	Eldoret	2.4%	Kisumu	2.9%	Eldoret	5%
Eldoret	2%	Eldoret	0.9%	Kisumu	1.5%	Mombasa	1.5%	Mombasa	2.3%
Garissa	0.3%	Garissa	0.1%	Garissa	0.2%	Garissa	0.6%	-	-
Non-urban	31.4%	Non-urban	24.4%	Non-urban	37%	Non-urban	38.2%	Non-urban	51.9%

Note: This table shows the destinations of residents for the five most populated cities. Origin and destination city boundaries are defined using 3km-buffered GRUMP polygons. Visitors are defined as being seen at least once in a location over the year. "Non-urban" refers to locations outside boundaries of cities with 200,000 or more residents. "Other urb." refers to all cities that are not in the top 5 origin cities.

Table 12: Top 5 destinations of residents from top 5 cities, Nigeria.

Lagos (35,957 residents)		Kano (1,496 residents)		Ibadan (2,555 residents)		Abuja (7,988 residents)		Kaduna (1,303 residents)	
Destination	*Residents*	*Destination*	*Residents*	*Destination*	*Residents*	*Destination*	*Residents*	*Destination*	*Residents*
Shagamu	5.9%	Abuja	11.2%	Lagos	26.9%	Lagos	14.4%	Abuja	21.8%
Ibadan	5.6%	Kaduna	9%	Shagamu	9.2%	Kaduna	8.9%	Zaria	10.4%
Abuja	4.2%	Lagos	6.7%	Abeokuta	3.8%	Kano	4.4%	Kano	6.8%
Abeokuta	2.8%	Zaria	5.9%	Oshogbo	3.5%	Zaria	3%	Lagos	5.8%
Benin City	2.1%	Katsina	2.2%	Abuja	3.3%	Port Harc.	2.7%	Katsina	2.2%
Other urb.	14.1%	Other urb.	12.1%	Other urb.	20.8%	Other urb.	33.6%	Other urb.	19.1%
Non-urban	20.9%	Non-urban	21.9%	Non-urban	25.5%	Non-urban	32.2%	Non-urban	28.2%

Note: This table shows the destinations of residents for the five most populated cities. Origin and destination city boundaries are defined using 3km-buffered GRUMP polygons. Visitors are defined as being seen at least once in a location over the year. "Non-urban" refers to locations outside boundaries of cities with 200,000 or more residents. "Other urb." refers to all cities that are not in the top 5 origin cities.

Table 13: Top five destinations of residents from largest cities, Tanzania.

Dar Es Salaam (10,370 residents)		Zanzibar (832 residents)		Mwanza (963 residents)		Arusha (1,253 residents)		Mbeya (439 residents)	
Destination	*Residents*	*Destination*	*Residents*	*Destination*	*Residents*	*Destination*	*Residents*	*Destination*	*Residents*
Morogoro	4.9%	Dar Es Sa.	19.8%	Dar Es Sa.	12.9%	Moshi	14.9%	Dar Es Sa.	14.6%
Zanzibar	3.8%	Arusha	2.3%	Dodoma	3.6%	Dar Es Sa.	14.3%	Morogoro	3.4%
Dodoma	3.7%	Dodoma	1.4%	Arusha	2.7%	Dodoma	2.9%	Dodoma	3%
Arusha	3.3%	Tanga	1.3%	Morogoro	1.7%	Zanzibar	2.4%	Arusha	2.5%
Moshi	2.4%	Morogoro	1%	Moshi	1.3%	Mwanza	1.8%	Mwanza	1.4%
Other urb.	5.9%	Other urb.	0.7%	Other urb.	2.4%	Other urb.	3.9%	Other urb.	1.1%
Non-urban	26.4%	Non-urban	36.5%	Non-urban	37.8%	Non-urban	42.9%	Non-urban	36.4%

Note: This table shows the destinations of residents for the five most populated cities. Origin and destination city boundaries are defined using 3km-buffered GRUMP polygons. Visitors are defined as being seen at least once in a location over the year. "Non-urban" refers to locations outside boundaries of cities with 200,000 or more residents. "Other urb." refers to all cities that are not in the top 5 origin cities.

The striking feature of these tables is that a larger fraction of the urban dwellers in our data are seen visiting non-urban areas than other cities. This is true for each of the five largest cities in all three countries; our urban dwellers are more likely to have been seen in a non-urban area than in any other city in the country. Although some of these non-urban areas may be within commuting distance – or at least within relative proximity to the cities of residence – it is striking that our cities appear to be substitutes for one another. In each country, the one or two largest cities serve as magnets, attracting visitors from other cities; but there is relatively little flow between secondary cities. This may reflect a lack of specialization and differentiation between cities – an issue that has been raised previously in sub-Saharan Africa – but even in a country like Nigeria, where there are substantial differences in geography and demographics across cities, there seem to be relatively limited movements of people between cities. This contrasts with more substantial flows connecting cities with smaller towns, villages, and rural areas.

This section has reported on a number of different measures of mobility. These measures point to some consistent stories. The smartphone users in our data represent a mobile population. On average, they are more than 10 km from home on about one-sixth of the days on which they are observed. Those in more sparsely populated areas are more frequently away from home than those who live in city center locations. When they venture from home, they frequently travel far; when we sight them away from home, they are on average more than 50 to 100 km away. Flows are not limited to inter-urban movements of city dwellers visiting other cities; on the contrary, the data show extensive movement across and between many different locations.

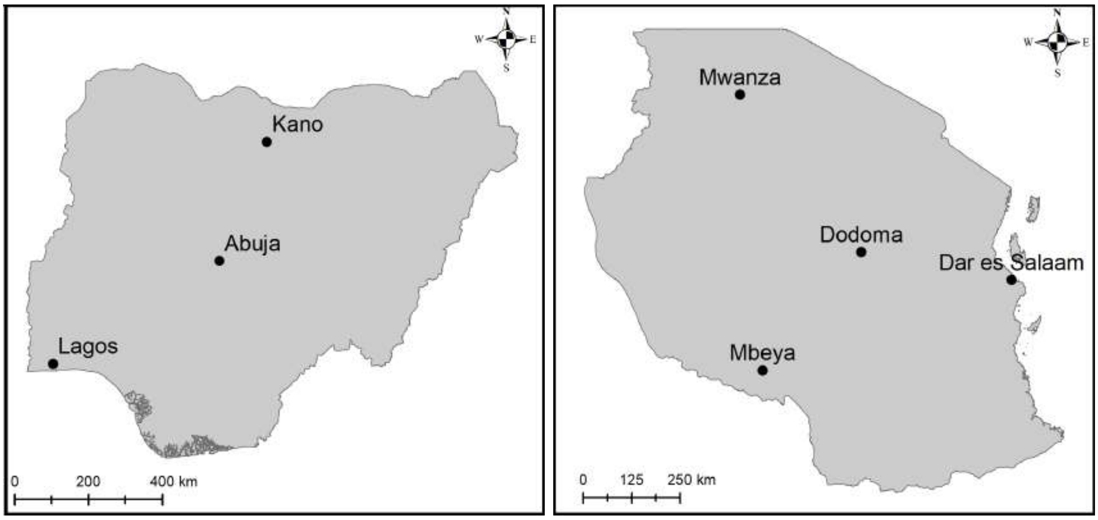
Clearly the data point to a world in which mobility frictions are insufficient to choke off human mobility. At least some subset of the population in our three countries is highly mobile and provides a network of information flows across locations. If individuals are moving, there must also be comparable movement of goods and of information. Even if our data comes from a selected subset of the population, their movements may be sufficient to generate flows of knowledge and information about spatial gaps in living conditions or opportunities. The data provide at least a reason to question frameworks in which spatial gaps arise from a complete failure of information to flow across locations.

5. Agglomeration effects

Our analysis so far illustrates that individuals move a substantial amount across space. One interpretation of this finding is that mobility costs are not insurmountable in our three countries. Another explanation is that movement costs are high but the returns to visiting certain places outweigh the high costs. We do not know what the return of visiting a certain location is for individuals. However, we can say something approximate about the costs as captured by the distance or travel time between two locations. If we see disproportionate amounts of visits to one location while similar locations are within equal or smaller distances, it must be that visitors to this location experience high returns. The intuition is simple: take a resident of New York City who can chose to visit Boston or Washington D.C.. The travel time to each of these cities by car is about three hours and 45 minutes and the approximate distance is 220 miles. If we see twice as many visits to Boston than we see to D.C., we can infer that – by *revealed preference* – this individual experiences twice the return from visiting Boston than they do from visiting Washington D.C..[23]

Taking this logic to our countries, we examine the probability that residents from Kano (located in Nigeria's north) are seen in Abuja (the capital, located in the center) and Lagos (located in the south) compared to the rest of Nigeria's cities (see the illustrative map in Figure 8. The driving distance between Kano and Abuja is about 450km and from Kano to Lagos it is about twice as long. The data suggests that residents from Kano are almost 4 times as likely to go to Lagos than to any other city, but only 1.3 times as likely to go to Abuja. We also repeat this exercise for residents Tanzania analyzing movement patterns

Figure 8: Distances between selected cities in Nigeria and Tanzania



Note: This figure shows the main cities considered in the example given in Section 5. It is apparent that Abuja is far closer to Kano than Lagos; similarly, Dodoma is much closer to Mwanza and Mbeya than Dar Es Salaam. Yet, we see much higher mobility toward Lagos and Dar Es Salaam than to Abuja or Dodoma.

from residents of Mwanza (located in the the north-west of Tanzania), and Mbeya (located in the south) and examine the probability that residents from these cities visit Dodoma (the capital, located in the center), Dar Es Salaam (located in the east), or any other city. The driving distance between Mwanza/Mbeya and Dodoma is about 600-700km and from Mwanza/Mbeya to Dar Es Salaam it is slightly less than twice as far, about 1100km. We find that residents from Mwanza and Mbeya are more than three times as likely to visit Dar Es Salaam than the other cities and only 1.2 times as likely to visit Dodoma. These findings are in line with the descriptive evidence presented in Section 4 which suggested

[23]For this logic to be correct we assume that returns for residents of New York are homogeneous.

that particularly large cities, e.g., Lagos and Dar Es Salaam, attract visitors from throughout the country. Despite larger costs compared to visiting agglomerations that are closer in space, people are voting with their feet to visit these large cities.

We explore this revealed preference argument and use our smartphone app location data to estimate returns to visiting certain destinations relying on the theoretical underpinning of within-city commuting in recent quantitative spatial models (Ahlfeldt, Redding, Sturm, and Wolf, 2015; Kreindler and Miyauchi, 2020).[24] Specifically, consider an individual i living in o who can consider one location d to visit. The individual has the following utility function

$$U_{odi} = \frac{R_d Z_{odi}}{D_{od}^{\tau}} \tag{8}$$

where R_d represents the return from visiting d, D_{od} represents the driving time between o and d, and Z_{odi} represents an idiosyncratic preference draw that follows a Fréchet distribution with scale parameter T and shape parameter ϵ. These shocks allow, for example, for the fact that individuals might have family in one location. Workers observe the shocks and chose the location that maximizes their utility. Conditional on residing in o, Ahlfeldt et al. (2015) show that the probability that an individual visits d is

$$\Pi_{od|o} = \frac{(R_d/D_{od}^{\tau})^{\epsilon}}{\sum_{s=1}^{S}(R_s/D_{os}^{\tau})^{\epsilon}} \tag{9}$$

This is similar to trade models where the enumerator captures 'bilateral resistance' and the denominator 'multilateral resistance'. Taking logs, this becomes

$$\ln \Pi_{od|o} = \epsilon \ln R_d - \epsilon\tau \ln D_{od} - \ln \sum_{s=1}^{S}(R_s/D_{os}^{\tau})^{\epsilon} \tag{10}$$

We then use Quasi Poisson Maximum Likelihood and two-way clustered standard errors to estimate

$$\ln \Pi_{od} = \delta_d - \beta \ln D_{od} + \phi_o + \epsilon_{od} \tag{11}$$

where ϕ_o and δ_d are origin and destination fixed effects. We consider cities above 200,000 residents in Nigeria. Due to the low number of large cities we lower this threshold to 100,000 in Tanzania and Kenya. A resident is classified as living in a city if her home location is within a 3km buffered polygon around GRUMP city polygons. In this part of the analysis, we therefore only consider flows *between* residents of urban locations, abstracting from rural residents. A visitor to a city is a resident seen in a city other than her home city

[24] Couture (2016) uses trip diary data from the National Household Travel Survey to estimate the amenity value of restaurants.

over the specified time span.

Table 14 shows the estimates for the gravity equation. The coefficient on travel time is

Table 14: Gravity model for inter-city mobility.

	Kenya	Nigeria	Tanzania
	(1)	(2)	(3)
Gravity Equation			
Log(Traveltime)	-.953***	-1.468***	-1.027***
	(0.061)	(0.092)	(0.04)
Origin FE	YES	YES	YES
Destination FE	YES	YES	YES
Obs.	210	4422	239
R^2	0.975	0.935	0.993

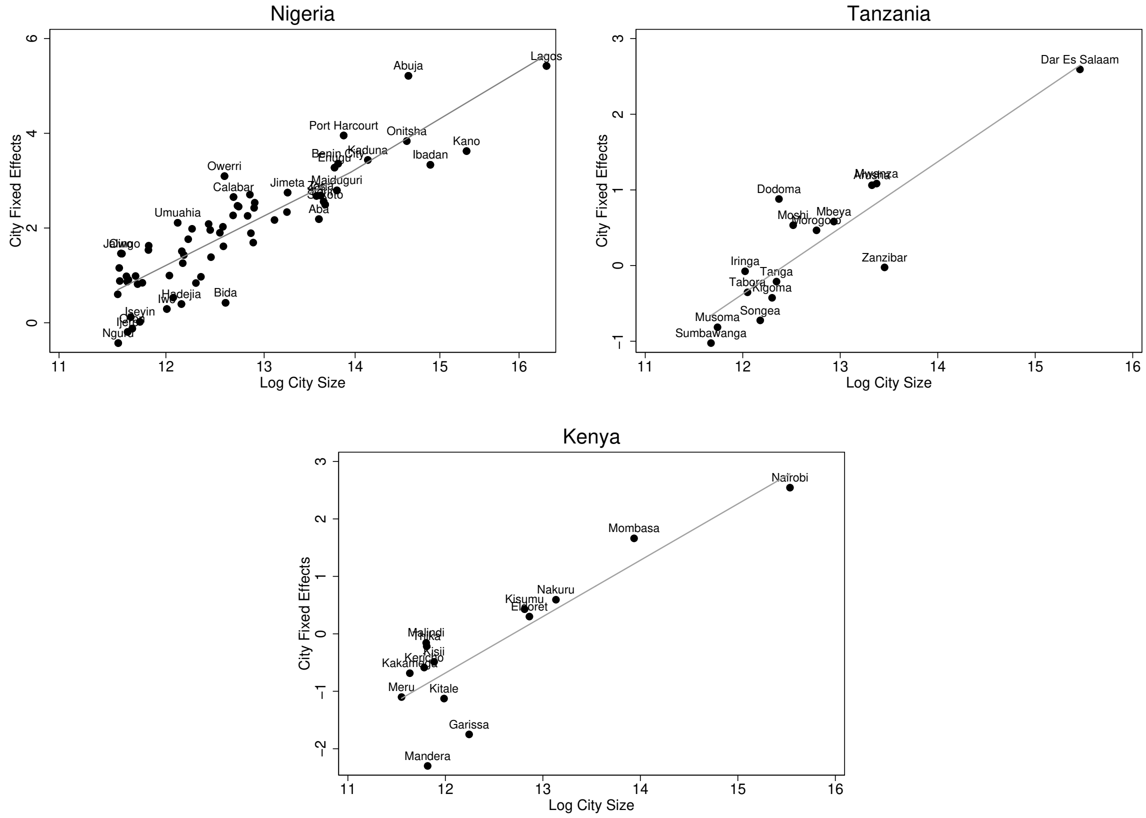
Note: This table estimates equation (11). The dependent variable is the mobility flow between city o and d. Reported standard errors are two-way clustered at the origin and destination levels. *, **, *** denote significance at 10%, 5% and 1% levels.

around one in Kenya and Tanzania and somewhat higher in Nigeria. We next retrieve the estimated destination fixed-effects $\hat{\delta}_d$ which capture returns to visits to a certain city, conditional on the distances between origins o and destinations d, and origin fixed effects. Origin fixed effects capture time-invariant characteristics of residents at the origin, such as income, overall mobility and geographic factors of a location, e.g., remoteness and access to transport infrastructure.

Figure 9 plots the city fixed effects against city size, where we use the smallest city in our sample as the omitted category in each of our countries. A few points are worth highlighting: first, it is remarkable how tightly the city fixed effects correlate with city size. Second, the figures highlight that that Lagos, Dar Es Salaam and Nairobi are outliers in terms of city size; all have the highest city fixed effects, conditional on distances between city pairs and origin city fixed effects. The two recent capitals, Abuja and Dodoma, are well above the predicted regression lines, indicating that that they receive more visits than their population size would predict. Other locations, like Kano and Zanzibar, receive fewer visits than predicted by their population size. The model suggests that Zanzibar, located on an island, clearly would receive more visitors than it does without this barrier. Table 15 shows the results from the regressions of the city fixed effects on log population to investigate the relationship more formally.

The table shows a precisely estimated elasticity of around one for all three countries, indicating that as a city's population doubles, incoming mobility doubles. This underlines the magnetic forces large cities play. This also highlights that as as cities in Africa are expected to double in the coming decades, infrastructure will have to not only accommodate their resident populations, but also the large numbers of people from all over the country who are attracted by these locations.

Figure 9: City fixed effects.



Note: This figure shows the city fixed effects $\hat{\delta}_d$ from equation (11) and log city size.

Table 15: Relationship between city fixed effects and population

	Kenya	Nigeria	Tanzania
	(1)	(2)	(3)
Agglomeration effects			
Log(Population)	0.981***	1.028***	0.874***
	(0.109)	(0.078)	(0.084)
Obs.	14	66	15
R^2	0.735	0.764	0.778

Note: This table regresses the city fixed effects from equation (11) on log city size. Robust standard errors are reported in parentheses. *, **, *** denote significance at 10%, 5% and 1% levels.

Finally, we estimate standard gravity models to link to a previous literature that is structured around gravity models that use distance as a proxy of movement costs (Bryan and Morten, 2019). We follow Bryan and Morten (2019) in estimating these with OLS to be able to compare the estimated coefficients. We test whether the elasticity of mobility with respect to distance is sensitive to different definitions of origin-destination pairs and temporal intervals. Most gravity estimates are constrained by limitations in the data available to define origins and destinations. Much of the literature relies on recall data with relatively low spatial and temporal granularity. For example, some surveys ask respondents to name the region where they were born – which can then be compared with the region where a respondent is currently living. Other surveys may ask whether people were living in a different location five years ago; if so, they are asked to name the place. Matching their responses to identifiable locations sometimes requires artful interpretation. Many standard surveys, such as the Demographic Health Surveys, only classify previous locations or locations at birth into types of places (i.e. city, town, countryside), which makes it impossible to generate origin-destination matrices. Due to the richness of our data, however, we are entirely flexible in defining both the spatial unit for origins and destinations and the time frame we are investigating. We then contrast our estimates with those in the literature.

We start by presenting a basic region-level gravity model over the entire year by linking home locations to administrative units in our countries where the dependent variable is the fraction of users from o that travelled to d in the specified sample period. This is similar to what we would observe in a detailed survey module that contained spatial detail up to the region. The fraction of pairs with non-zero flows between regions amounts to 50% in Kenya, 77.25% in Nigeria and 70% in Tanzania.

Table 16 shows the results for the region-level specification. Reassuringly, distance is negatively related to mobility. Overall, the simple gravity model fits the data well, with distance alone explaining 0.34 percent of mobility between regions. In all specifications, the coefficient on the distance variable is significant and precisely estimated. Including origin and destination fixed effects gives an estimate of the elasticity of mobility with respect to distance of -1.2 for Kenya, -2 for Nigeria and -1.3 for Tanzania. This suggests that a 10 percent increase in movement costs is associated with a 12-20 percent decrease in mobility.

We next define a mobility metric that takes into account the intensive margin as well, by multiplying the number of residents at origin o that are seen at least once at destination d with the number of distinct days these residents are seen in d, and dividing this by the total number of days these residents are seen. Our results are quantitatively robust to including the intensive margin, so that we focus on the extensive mobility measure in the analysis that follows.

Table 16: Gravity model for inter-region mobility at the extensive margin.

	(1)	(2)
log(distance)	-1.499^{***}	
	(0.068)	
log(distance)xKEN		-1.220^{***}
		(0.055)
log(distance)xNGA		-1.953^{***}
		(0.051)
log(distance)xTZA		-1.342^{***}
		(0.109)
Origin FE	Yes	Yes
Dest. FE	Yes	Yes
Observations	2,713	2,713
R^2	0.818	0.834

Note: The dependent variable is the fraction of people at origin o that were seen in d in over the entire sample period. Reported standard errors are two-way clustered at the origin and destination levels. *, **, *** denote significance at 10%, 5% and 1% levels.

Since regions reflect arbitrary boundaries involving irregular geometries, we follow the work of Michalopoulos and Papaioannou (2013) in constructing virtual regions by generating country-level grids of 50km by 50km and using flows between cell pairs as units of analysis.[25] We also examine the robustness of our results to removing one or two rows of adjacent cell pairs in columns (3)-(6) to exclude short trips within cities, for example. Table 17 shows that, as one would expect, movement costs are somewhat lower at lower spatial scales for the three countries but roughly in line with what we found in the region-level analysis.

[25]We count 159, 328 and 313 virtual regions with at least one resident user in Kenya, Nigeria and Tanzania respectively.

Table 17: Gravity model for mobility at the extensive margin between virtual regions.

	(1)	(2)	(3)	(4)	(5)	(6)
log(distance)	-0.894^{***}		-0.794^{***}		-0.790^{***}	
	(0.036)		(0.047)		(0.058)	
log(distance)×KEN		-0.881^{***}		-0.731^{***}		-0.696^{***}
		(0.061)		(0.078)		(0.104)
log(distance)×NGA		-1.085^{***}		-0.982^{***}		-1.001^{***}
		(0.055)		(0.073)		(0.093)
log(distance)×TZA		-0.688^{***}		-0.602^{***}		-0.586^{***}
		(0.042)		(0.054)		(0.063)
Origin FE	Yes	Yes	Yes	Yes	Yes	Yes
Dest. FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,513	16,513	14,100	14,100	11,909	11,909
R^2	0.876	0.880	0.882	0.884	0.889	0.891

Note: The dependent variable is the fraction of people at origin o that were seen in d in over the entire sample period. Columns (1) and (2) report results for all cell pairs with positive mobility. Columns (3)-(4) show results for the subset of non-adjacent cell pairs and columns (5)-(6) provide coefficient estimates for a subset of cell pairs at least two rows/columns apart. Reported standard errors are two-way clustered at the origin and destination levels. *, **, *** denote significance at 10%, 5% and 1% levels.

One concern might be that some regions have few residents so that a handful of residents might lead to large shares. To examine to what degree our results are sensitive to this, Table C.4 limits the sample to origin cells of 50 residents or more.

The general patterns are similar to what we see in Table 17, with slightly higher estimates. So far we have estimated the model over the entire period over which we have data. We next turn to estimating the model at a quarterly level. Columns (2), (4) and (6) in Table 18 show the coefficients for the different quarters for each of our countries. The table suggests that our results are in line with our previous estimates. In brief, the estimates appear to be robust to different spatial and temporal aggregations.

Table 18: Gravity model for mobility at the extensive margin between virtual regions, by quarter.

	(1)	(2)	(3)	(4)	(5)	(6)
log(distance)xKEN	-0.881^{***}		-0.731^{***}		-0.696^{***}	
	(0.061)		(0.078)		(0.104)	
log(distance)xNGA	-1.085^{***}		-0.982^{***}		-1.001^{***}	
	(0.055)		(0.073)		(0.093)	
log(distance)xTZA	-0.688^{***}		-0.602^{***}		-0.586^{***}	
	(0.042)		(0.054)		(0.063)	
log(distance)xKEN-201703		-0.665^{***}		-0.508^{***}		-0.499^{***}
		(0.072)		(0.089)		(0.112)
log(distance)xKEN-201707		-0.826^{***}		-0.664^{***}		-0.646^{***}
		(0.062)		(0.078)		(0.101)
log(distance)xKEN-201711		-0.852^{***}		-0.695^{***}		-0.680^{***}
		(0.059)		(0.075)		(0.098)
log(distance)xNGA-201707		-0.880^{***}		-0.758^{***}		-0.778^{***}
		(0.063)		(0.083)		(0.101)
log(distance)xNGA-201711		-0.976^{***}		-0.857^{***}		-0.877^{***}
		(0.054)		(0.074)		(0.091)
log(distance)xNGA-201803		-1.003^{***}		-0.888^{***}		-0.910^{***}
		(0.050)		(0.070)		(0.087)
log(distance)xTZA-201707		-0.503^{***}		-0.409^{***}		-0.400^{***}
		(0.056)		(0.066)		(0.074)
log(distance)xTZA-201711		-0.623^{***}		-0.528^{***}		-0.516^{***}
		(0.043)		(0.053)		(0.060)
log(distance)xTZA-201803		-0.649^{***}		-0.555^{***}		-0.543^{***}
		(0.039)		(0.049)		(0.056)
Origin FE	Yes	Yes	Yes	Yes	Yes	Yes
Dest. FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	16,513	33,421	14,100	28,032	11,909	23,425
R^2	0.880	0.879	0.884	0.883	0.891	0.891

Note: The dependent variable is the fraction of people at origin o that were seen in d in a particular quarter. Columns (1) and (2) report results for all cell pairs with positive mobility. Columns (3)-(4) show results for the subset of non-adjacent cell pairs and columns (5)-(6) provide coefficient estimates for a subset of cell pairs at least two rows/columns apart. Reported standard errors are two-way clustered at the origin and destination levels. *, **, *** denote significance at 10%, 5% and 1% levels.

While our estimates are not directly comparable to existing estimates in the literature using survey and census data, it is still worthwhile to investigate the magnitudes, while highlighting differences in the time periods covered. Bryan and Morten (2019) look at migration defined as the current location differing from the location at birth and find a value of about 0.7 for Indonesia and 0.5 for the United States, using regencies for Indonesia and states for the United States as spatial units to define origins and destinations. This represents lower movement costs than what we find for our extensive measure of mobility at larger spatial scales such as administrative regions in Table 17. When we define virtual regions of size 50km x 50km our estimates are lower and more in line with the estimates found in Bryan and Morten (2019).

6. Conclusion

Most of our data on human mobility in low-income countries comes from surveys that show migration flows between survey rounds. Often the surveys are several years apart or longer (e.g., decennial censuses). This means that mobility is only evident in these data sources at a very long time horizon. In many studies, we can observe modest flows from rural to urban areas between successive waves of panel data. We can sometimes see in these data that households are connected to family members who have moved to other parts of the country (or even across the world). The data from these surveys are useful and informative in thinking about human mobility, but they provide little information about higher-frequency mobility. The daily and weekly movements of people within countries are crucial to the dissemination of information (e.g., about market opportunities) as well as to the maintenance of family and social cohesion. We know anecdotally that this kind of mobility is both important and ubiquitous; anyone who spends time at a bus station in Accra or Arusha can see first-hand the numbers of people in motion. But we have hitherto had little ability to quantify these flows or to understand their patterns.

In this paper, we use a new data source – pings from smartphone apps – that provides objectively measured observations on the frequency with which people move around within three African countries, and on the locations that they visit. The data reveal a strikingly high degree of mobility – albeit for a non-representative subset of the population. Our smartphone users travel frequently and relatively far. Travel is not limited to peri-urban commuting, nor to city-to-city interchanges. On the contrary, we see substantial flows of people between rural areas and big cities.

Are these flows sufficient to break down information barriers across locations? We have no firm basis on which to answer that question. However, it would be difficult, given these data, to argue that rural areas are completely cut off from cities – or even that rural residents only have access to information about their nearby market towns. On the contrary, we see that the largest cities attract flows of people from the entirety of their countries, serving as magnets of economic activity. Using data on observed trips we estimate high returns to visiting these locations. Returns are increasing with city size which has important implications for future city growth in Africa: cities will have to not only provide infrastructure for their own resident populations but also for a large number of visitors. The analysis of mobility costs reveals that these remain relevant and roughly proportional across different spatial and temporal scales. Costs are also large enough to be highly salient, implying that a reduction in mobility costs (e.g., through improvements in transportation infrastructure) would likely generate an expansion in mobility at all levels.

Our data and analysis suffer from some limitations. We cannot entirely overcome the selection issues that make our sample unrepresentative, and we also cannot distinguish places that people visit deliberately – destinations – from those that they merely pass through.[26] But we benefit from the large number of observations and the large number of users; our smartphone owners are not outliers, even if they are in some degree unrepresentative.

In spite of these limitations, our analysis offers insights that can help guide future work on spatial frictions and their relevance for development. The findings of this paper encourage us to think critically and carefully before invoking models in which human mobility costs are prohibitive (i.e., models in which people are unable to move across locations). The data also suggest that we need to be careful in using models in which information does not flow across locations; even though we observe only a fraction of the total mobility in our three countries, the movements of people seem sufficient to spread information across space. We need to look elsewhere, perhaps, for frictions that seem more capable of explaining persistent sectoral and spatial gaps. For instance, movements from rural to urban areas may involve the loss of social connection or informal insurance, or the loss of claims to land and other resources in rural areas. There may be barriers for rural people – particularly those who are older – in learning new kinds of work or new ways of life. Certainly there is no shortage of potential frictions to consider.

We should also bear in mind that, for the poorest people in our three countries, the story may be very different. Our data shed little light on the mobility of the poor within these countries, and there is much work still to be done to understand the costs of mobility frictions for the poor. Even small monetary costs of mobility can be highly salient for poor people, and information may not flow freely across barriers of ethnicity, social class, age, and other dividing lines. For this reason, we should continue to look for other ways to assess the relevance of mobility frictions for the poor.

[26] In part, this reflects the lack of conceptual clarity between destinations and way points; the underlying distinction is really based on the *intent* of the traveller, rather than on the characteristics of the locations or the trips.

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Appendix (For Online Publication)

A. Details on data smartphone app data

A.1. Construction of the base sample

Our initial samples have 317,420 users in Kenya, 958,207 users in Nigeria and 780,760 users in Tanzania. According to the methodology presented in Section 2, we cannot infer home locations for users never observed at night (7pm-7am) and 121,790, 297,895 and 173,886 users are thus removed in Kenya, Nigeria and Tanzania respectively. Moreover, in Nigeria, inferred home locations with equal latitude and longitude were deemed erroneous which resulted in 905 users being removed. In Tanzania, we identified a data sink of 372,661 users with an inferred home location at (35.75;-6.18), which is located within the city of Dodoma. This represents 52% of the initial sample while we estimated the city of Dodoma to host 0.5% of the population.[27] We entirely remove users with home location coordinates at the data sink from the sample.

A.2. Inferred home locations

The calculation of users' home locations plays a critical role in our analysis of high-frequency mobility patterns. First, home locations are often used as reference locations to observe mobility trajectories. Second, home locations are used to evaluate the spatial coverage of our sample by comparing the spatial distribution of users to the distribution of the population. Third, knowing where our users live help us infer key information allowing to characterize them, e.g. by pairing users with DHS clusters. In our base sample, we define home locations as the most frequently observed 2-decimal rounded coordinates at night (between 7pm and 7am, local time). We consider that the likelihood of correct home location prediction increases with both the number of nights a user is seen and the fraction of these she is observed at the inferred home location. Therefore, we select a subset of users that are seen at least 10 nights, of which at least half are at their home location. We call this subset the "high-confidence" sample and use it as our core sample in the analysis of high-frequency mobility patterns throughout the paper. We also build medium- and low-confidence subsets that include users seen at least 8 and 5 nights respectively in order to evaluate the robustness of our results - the required fraction of nights seen at home is kept at 0.5. The corresponding sample sizes are given in Table A.1. Unsurprisingly, the sample size decreases with the minimum number of observed nights imposed and nearly doubles between the high- and low-confidence subsets.

However, differences in the distributions of users across density deciles between the subsets

[27] We use GRUMP polygons to which we apply a 3km buffer to define the city boundaries and we overlay the WorldPop 2018 population map to estimate the population in Dodoma.

is only minimal, as shown in Figures C.8 to C.10 , which supports the idea that the minimum number of nights criterion used to build our core sample does not imply a selection of atypical users.

Table A.1: Number of users by subset and country

	Base	**High**	**Medium**	**Low**
Kenya	195,630	18,535	23,490	37,249
Nigeria	659,407	78,694	96,954	146,346
Tanzania	234,213	22,728	28,853	46,116
TOTAL	1,089,250	119,957	149,297	229,711

B. Pairing users with DHS information

In Section 3, we link users' home locations with data from the most recently available Demographic and Health Survey (DHS) data to characterize areas where our users live: the 2014 standard DHS in Kenya, the 2018 standard DHS in Nigeria and the 2015-2016 standard DHS in Tanzania.[28] DHS data are geo-referenced at the cluster level and cluster coordinates are randomly displaced to maintain respondents' confidentiality. Urban clusters are displaced by up to 2 kilometers and rural clusters by up to 5 kilometers with 1% of rural clusters being displaced up to 10 kilometers. The displacement is restricted such that clusters stay within the administrative 2 area where the survey was conducted.

We first classify our users within urban and rural categories based on the overlay of users' home location with GRUMP 3-km buffered city polygons (see section **??** for more details on GRUMP city polygons). We then apply two criteria to associate each user with a set of DHS clusters: (i) we select the set of DHS clusters located within a given distance from her home location (10km for urban users and 5km for rural users) and (ii) we calculate the average population density within a 5km buffer - that we call the "experienced density" - for both the user and the selected DHS clusters and we keep the subset of clusters with an experienced density within 25% of the user's. We assume there is some level of spatial continuity in household characteristics conditional on population density to argue that our phone users and DHS respondents selected through the matching procedure are likely to have similar characteristics. Following that methodology, we pair 70% of our users in the high-confidence sample with at least one DHS cluster (90% in Kenya, 66% in Nigeria, 72% in Tanzania). We call the subset of respondents within paired clusters the "matched DHS" sample.[29] Unsurprisingly, unmatched users are found in low density areas where the probability of selection in the DHS is lower by design - the average experienced density for unmatched users is estimated at 2,496 inh./km^2 against 8,835 inh./km^2 for users with at least one paired cluster.

In order to appreciate potential differences between our users and the population as a whole, we conduct t-tests for equality of means between the raw DHS and matched DHS samples on a range of household characteristics. We rely mainly on characteristics for which the spatial continuity is more likely to hold (e.g. housing characteristics (floor, walls, roof, overcrowding), access to public services (electricity, water)). Moreover, we produce results for rural and urban sub-samples separately to account for both the prevalence of urban users in our sample and the lower matching rate in low density areas, which together may lead to results being mainly driven by the urban component of the sample. We produce t-tests

[28] More information on sampling design at https://dhsprogram.com/

[29] Some clusters are paired to more than one user so the matched DHS sample contains a number of duplicates. It is in fact equivalent to the weighted subset of respondents in clusters paired to at least one user, with weights begin equal to the number of users the corresponding cluster is matched to.

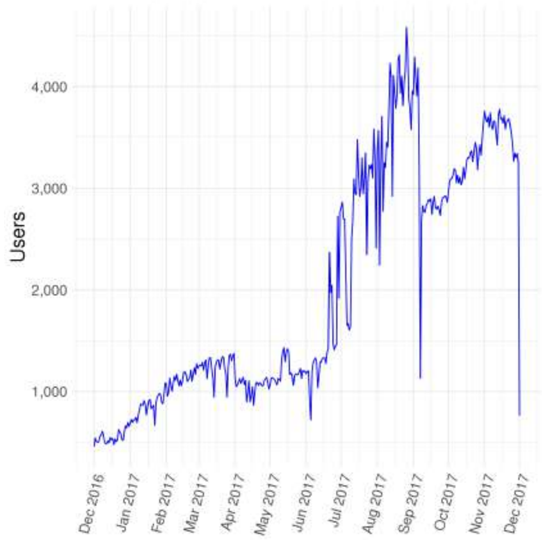
comparing our two weighted data streams, with bootstrapped standard errors robust to heteroskedasticity. The survey weights are used for the reference DHS sample while those of the matched DHS sample correspond to the number of users each cluster is paired with. Definitions for all variables used are given in Table B.1.

Table B.1: Definitions of variables used in mean testing between DHS and matched DHS samples.

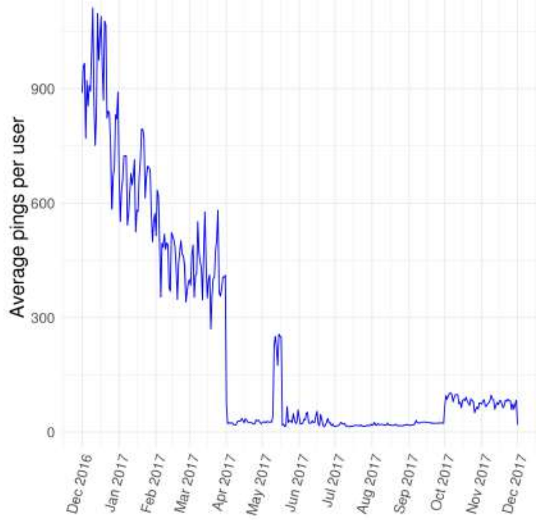
Variable	Definition	Notes
Household size	Total number of (*de jure*) household members	
Age of HH head	Age of the household head	
Education of HH head	Level of education of the household head in single years	
Access to electricity	Dummy equal to 1 if the household has access to electricity	
Radio	Dummy equal to 1 if the household has a radio	
Television	Dummy equal to 1 if the household has a television	
Rooms per adult	Number of rooms used for sleeping divided by the number of household members older than 6	
Access to piped water	Dummy equal to 1 if the household has an access to piped water	Calculated based on the main source of drinking water for household members. Our dummy is equal to 1 if the source of water is one of "piped water", "piped into dwelling", "piped to yard/plot", "public tap/standpipe" or "piped to neighbor".
Constructed floor	Dummy equal to 1 if main material of the floor is not one of "natural", "earth/sand", "dung", "rudimentary", "wood planks", "palm/bamboo"	
Constructed walls	Dummy equal to 1 if main material of the walls is not one of "natural", "no walls", "cane/palm/trunks", "cane/palm/trunks/bamboo", "poles with mud", "dirt", "rudimentary", "dung/mud/sod", "grass", "bamboo with mud"	
Constructed roof	Dummy equal to 1 if main material of the roof is not one of "natural", "grass/thatch/palm leaf", "no roof", "thatch/grass/makuti", "mud", "rudimentary", "rustic mat", "dung/mud/sod", "palm/bamboo", "wood planks", "cardboard"	

C. Additional Tables and Figures

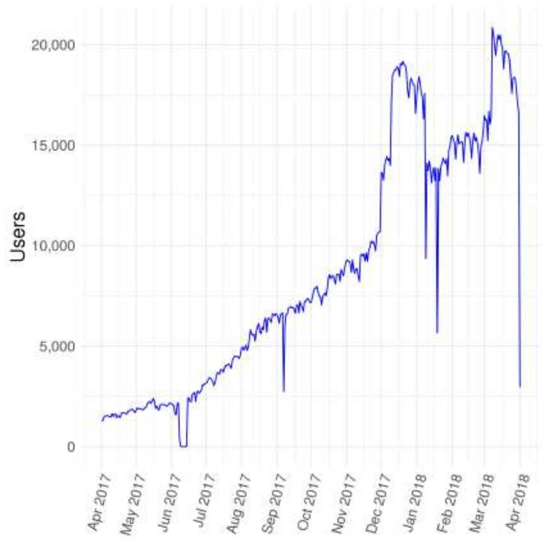
Figure C.1: Users and pings per user over time.



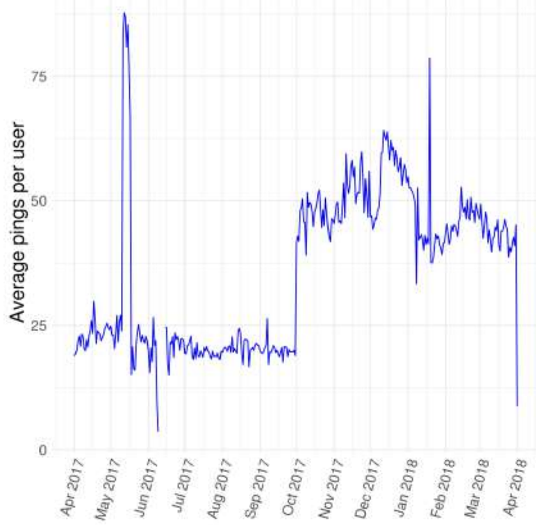
(a) Users - Kenya



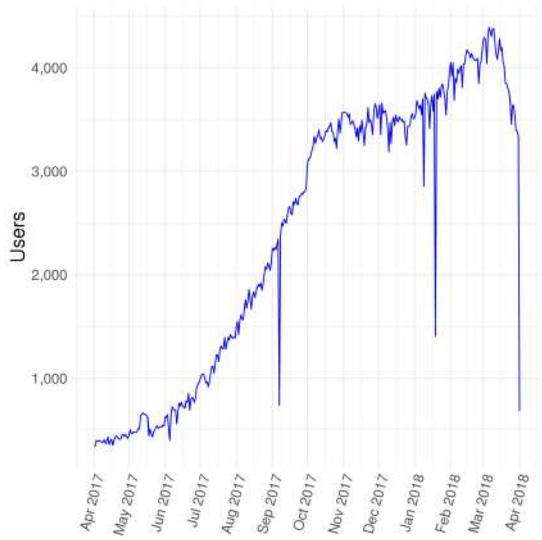
(b) Pings per users - Kenya



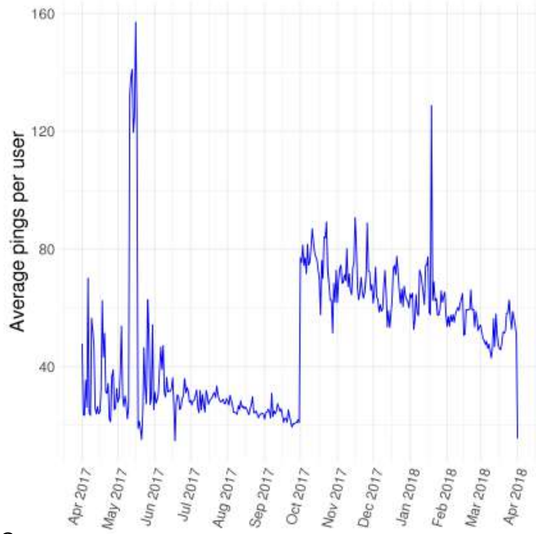
(c) Users - Nigeria



(d) Pings per users - Nigeria

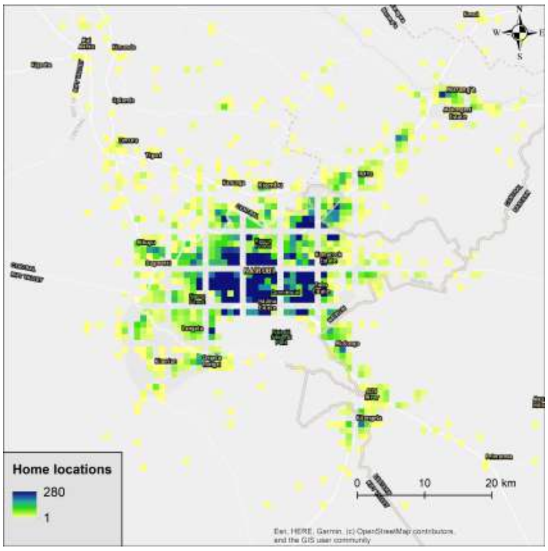


(e) Users - Tanzania

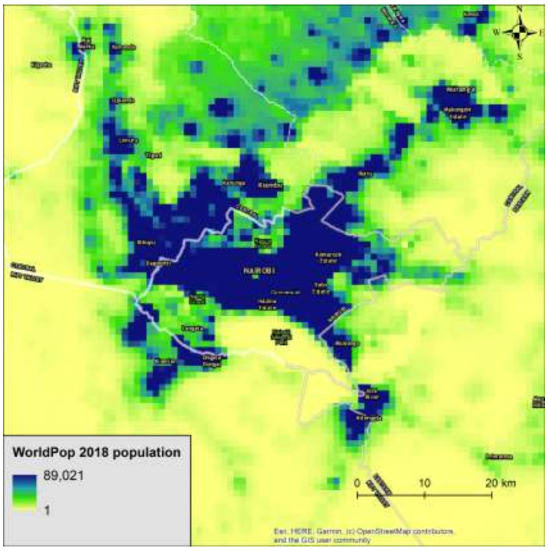


(f) Pings per users - Tanzania

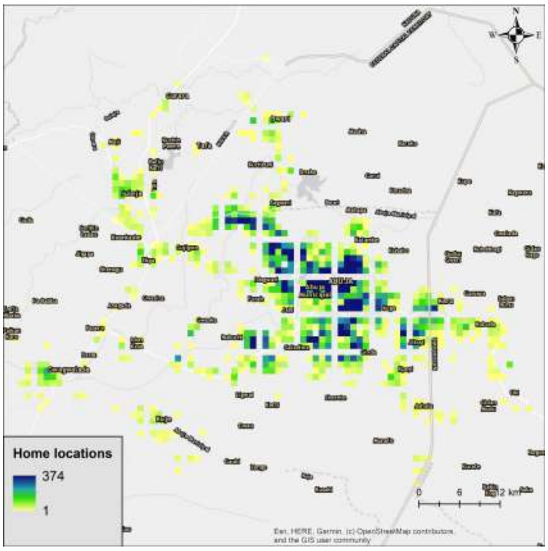
Figure C.2: Distribution of home locations in capital cities, high-confidence sample.



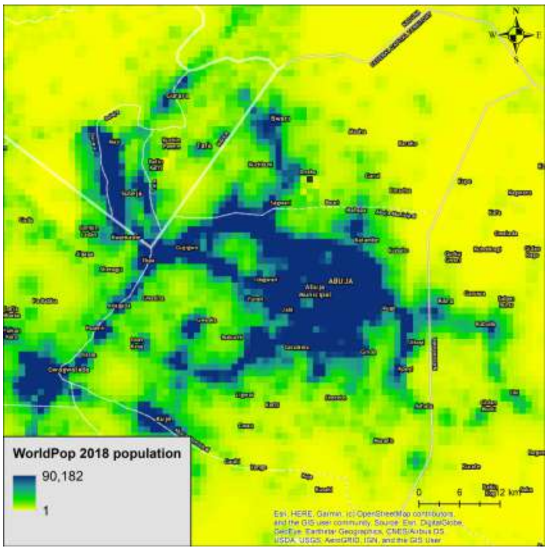
(a) Nairobi



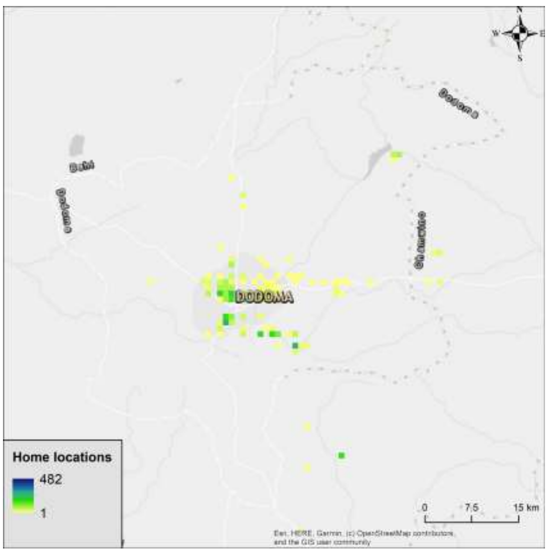
(b) Nairobi



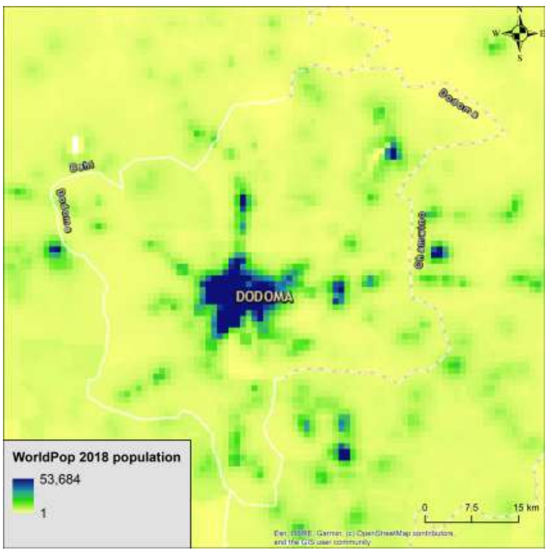
(c) Abuja



(d) Abuja

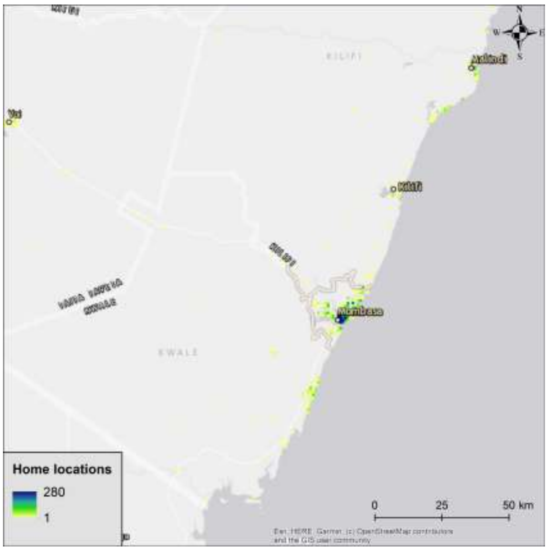


(e) Dodoma

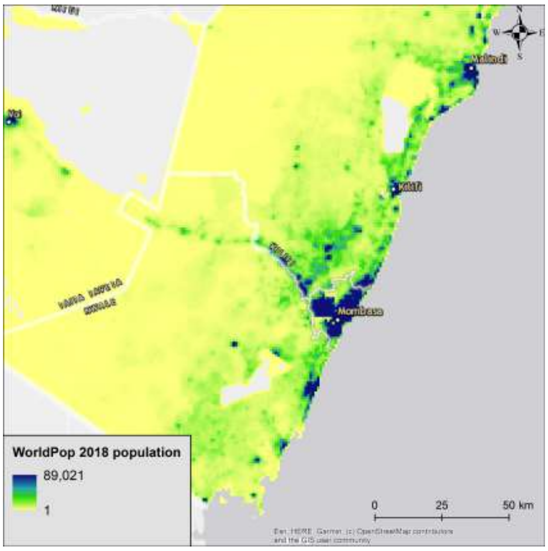


(f) Dodoma

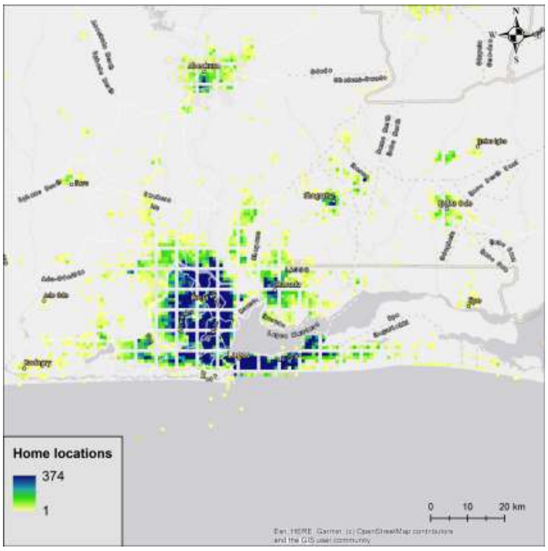
Figure C.3: Distribution of home locations in major cities, high-confidence sample.



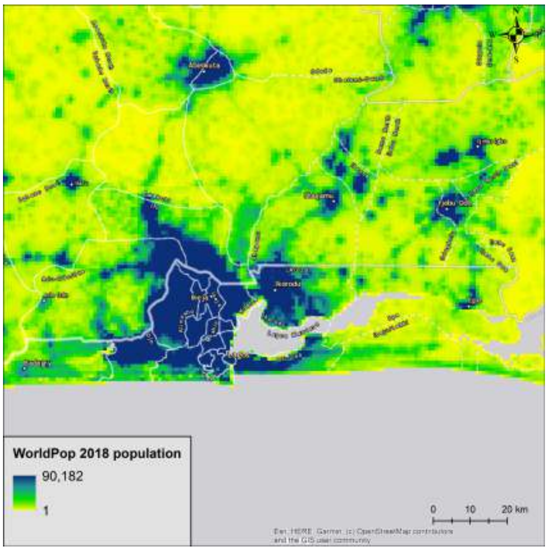
(a) Mombasa



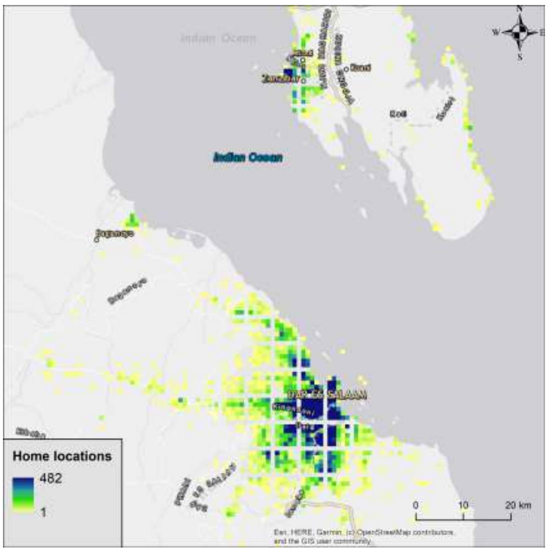
(b) Mombasa



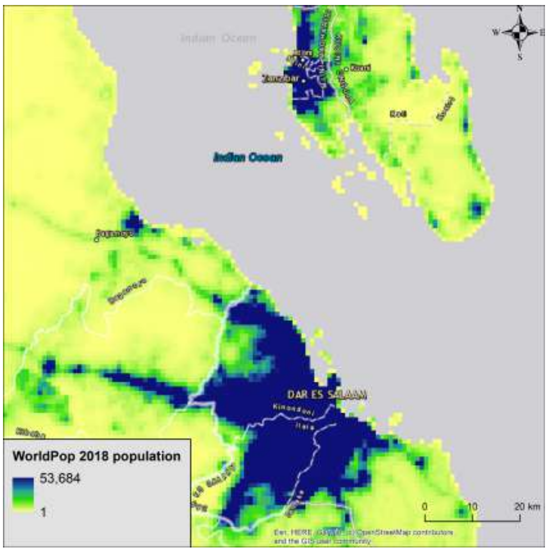
(c) Lagos



(d) Lagos

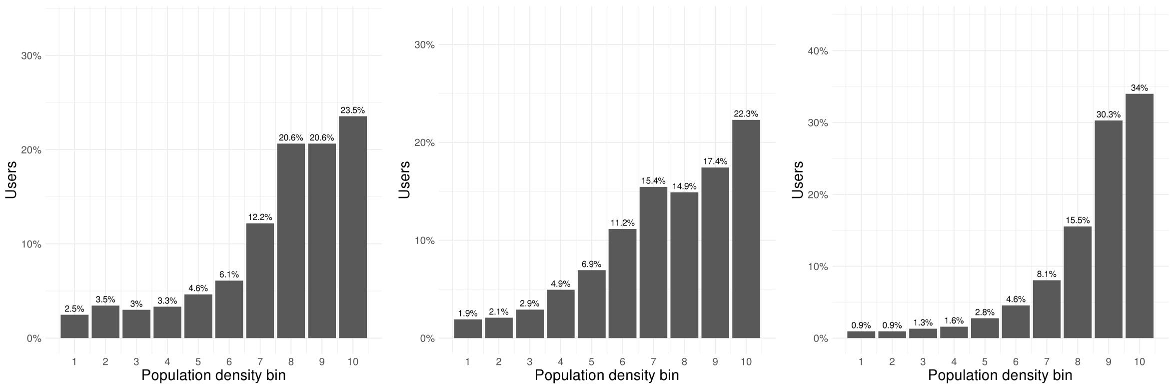


(e) Dar Es Salaam



(f) Dar Es Salaam

Figure C.4: Users by population density decile, Landscan.



(a) Kenya (b) Nigeria (c) Tanzania

Table C.1: T-tests for equality of means between matched DHS and DHS samples, Kenya.

	Variable	DHS	Matched DHS	Difference	SE	p-value
All	Household size	3.99	3.08	-0.91	0.02	0.000***
	Age of HH head	42.93	37.29	-5.64	0.11	0.000***
	Education of HH head	8.00	10.32	2.33	0.03	0.000***
	Access to electricity	0.37	0.80	0.43	0.01	0.000***
	Radio	0.67	0.74	0.06	0.01	0.000***
	Television	0.35	0.64	0.29	0.01	0.000***
	Rooms per adult	0.66	0.66	0.00	0.00	0.522
	Access to piped water	0.44	0.79	0.35	0.01	0.000***
	Constructed floor	0.53	0.90	0.37	0.01	0.000***
	Constructed walls	0.64	0.92	0.28	0.01	0.000***
	Constructed roof	0.89	0.99	0.10	0.01	0.000***
Urban	Household size	3.28	3.02	-0.26	0.03	0.000***
	Age of HH head	38.60	36.82	-1.78	0.17	0.000***
	Education of HH head	9.90	10.46	0.56	0.05	0.000***
	Access to electricity	0.68	0.83	0.15	0.02	0.000***
	Radio	0.74	0.74	0.00	0.01	0.774
	Television	0.56	0.65	0.09	0.02	0.000***
	Rooms per adult	0.68	0.66	-0.02	0.01	0.001***
	Access to piped water	0.71	0.82	0.11	0.02	0.000***
	Constructed floor	0.82	0.92	0.10	0.01	0.000***
	Constructed walls	0.86	0.94	0.07	0.01	0.000***
	Constructed roof	0.98	0.99	0.01	0.00	0.002***
Rural	Household size	4.52	4.33	-0.19	0.02	0.000***
	Age of HH head	46.15	46.60	0.45	0.16	0.005***
	Education of HH head	6.58	7.58	0.99	0.04	0.000***
	Access to electricity	0.13	0.21	0.08	0.01	0.000***
	Radio	0.63	0.70	0.07	0.01	0.000***
	Television	0.19	0.25	0.07	0.01	0.000***
	Rooms per adult	0.64	0.67	0.03	0.00	0.000***
	Access to piped water	0.24	0.25	0.01	0.02	0.464
	Constructed floor	0.31	0.38	0.07	0.01	0.000***
	Constructed walls	0.46	0.46	0.00	0.02	0.949
	Constructed roof	0.82	0.93	0.11	0.01	0.000***

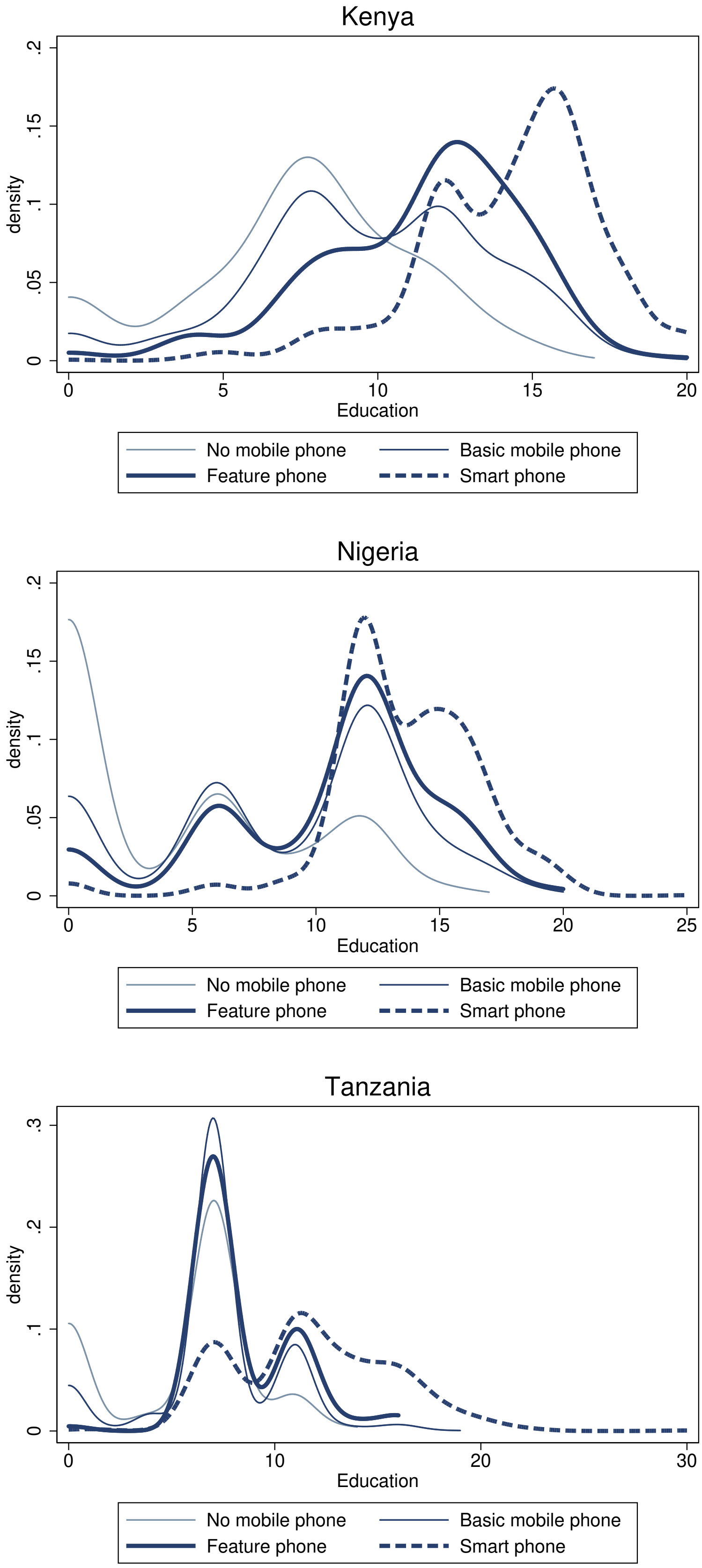
Table C.2: T-tests for equality of means between DHS and matched DHS samples, Nigeria.

	Variable	DHS	Matched DHS	Difference	SE	p-value
All	Household size	4.69	3.83	-0.86	0.02	0.000***
	Age of HH head	45.29	45.17	-0.12	0.12	0.344
	Education of HH head	7.43	11.52	4.10	0.04	0.000***
	Access to electricity	0.60	0.98	0.39	0.01	0.000***
	Radio	0.61	0.84	0.24	0.01	0.000***
	Television	0.49	0.90	0.41	0.01	0.000***
	Rooms per adult	0.74	0.65	-0.09	0.00	0.000***
	Access to piped water	0.11	0.14	0.03	0.01	0.003***
	Constructed floor	0.74	0.96	0.23	0.01	0.000***
	Constructed walls	0.84	1.00	0.16	0.01	0.000***
	Constructed roof	0.89	1.00	0.11	0.01	0.000***
Urban	Household size	4.44	3.83	-0.61	0.03	0.000***
	Age of HH head	45.21	45.18	-0.02	0.18	0.900
	Education of HH head	9.66	11.56	1.91	0.06	0.000***
	Access to electricity	0.88	0.99	0.11	0.01	0.000***
	Radio	0.72	0.85	0.13	0.01	0.000***
	Television	0.73	0.90	0.18	0.01	0.000***
	Rooms per adult	0.72	0.65	-0.08	0.01	0.000***
	Access to piped water	0.14	0.14	-0.01	0.01	0.572
	Constructed floor	0.89	0.96	0.08	0.01	0.000***
	Constructed walls	0.95	1.00	0.04	0.01	0.000***
	Constructed roof	0.98	1.00	0.02	0.00	0.000***
Rural	Household size	4.85	3.92	-0.93	0.03	0.000***
	Age of HH head	45.34	44.77	-0.57	0.16	0.000***
	Education of HH head	6.03	10.23	4.20	0.06	0.000***
	Access to electricity	0.42	0.84	0.42	0.02	0.000***
	Radio	0.54	0.67	0.14	0.01	0.000***
	Television	0.35	0.77	0.43	0.01	0.000***
	Rooms per adult	0.75	0.75	0.01	0.01	0.503
	Access to piped water	0.09	0.14	0.05	0.01	0.000***
	Constructed floor	0.64	0.96	0.32	0.01	0.000***
	Constructed walls	0.77	0.98	0.21	0.01	0.000***
	Constructed roof	0.83	0.99	0.16	0.01	0.000***

Table C.3: T-tests for equality of means between DHS and matched DHS samples, Tanzania.

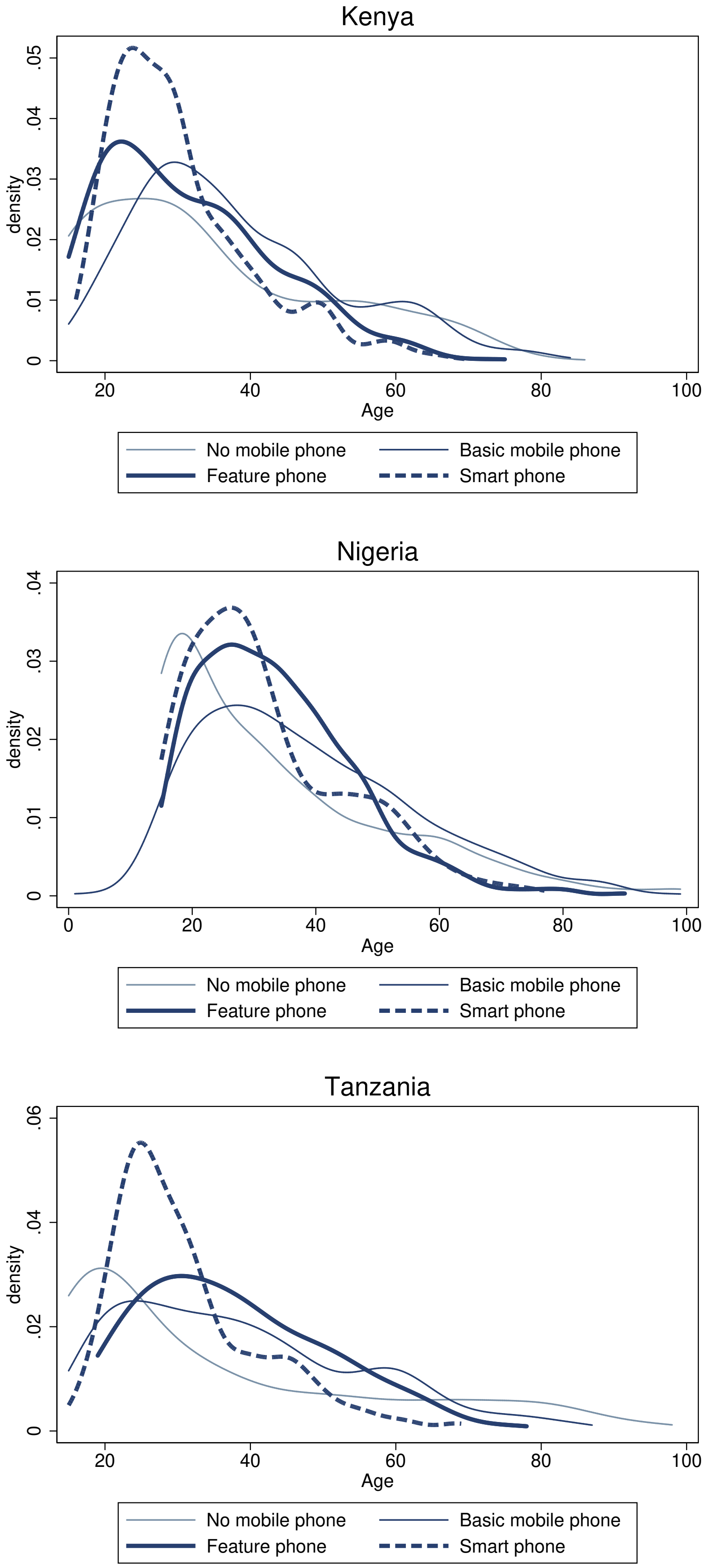
	Variable	DHS	Matched DHS	Difference	SE	p-value
All	Household size	5.03	4.33	-0.70	0.04	0.000***
	Age of HH head	45.43	41.66	-3.77	0.22	0.000***
	Education of HH head	5.90	8.33	2.42	0.05	0.000***
	Access to electricity	0.23	0.78	0.55	0.02	0.000***
	Radio	0.52	0.66	0.14	0.01	0.000***
	Television	0.21	0.65	0.44	0.02	0.000***
	Rooms per adult	0.61	0.59	-0.02	0.00	0.000***
	Access to piped water	0.38	0.67	0.29	0.02	0.000***
	Constructed floor	0.44	0.95	0.51	0.02	0.000***
	Constructed walls	0.80	0.98	0.18	0.01	0.000***
	Constructed roof	0.75	0.99	0.24	0.01	0.000***
Urban	Household size	4.54	4.30	-0.24	0.07	0.001***
	Age of HH head	42.22	41.56	-0.67	0.37	0.073*
	Education of HH head	8.01	8.40	0.39	0.10	0.000***
	Access to electricity	0.63	0.80	0.17	0.03	0.000***
	Radio	0.65	0.66	0.01	0.02	0.462
	Television	0.52	0.67	0.14	0.03	0.000***
	Rooms per adult	0.62	0.59	-0.03	0.01	0.000***
	Access to piped water	0.67	0.67	0.00	0.04	0.980
	Constructed floor	0.87	0.96	0.09	0.02	0.000***
	Constructed walls	0.96	0.98	0.03	0.01	0.005***
	Constructed roof	0.97	0.99	0.02	0.01	0.002***
Rural	Household size	5.21	5.04	-0.16	0.05	0.002***
	Age of HH head	46.61	44.40	-2.21	0.27	0.000***
	Education of HH head	5.13	6.28	1.14	0.07	0.000***
	Access to electricity	0.08	0.31	0.23	0.02	0.000***
	Radio	0.47	0.59	0.12	0.01	0.000***
	Television	0.09	0.29	0.20	0.02	0.000***
	Rooms per adult	0.61	0.63	0.03	0.01	0.000***
	Access to piped water	0.27	0.54	0.27	0.03	0.000***
	Constructed floor	0.27	0.65	0.37	0.02	0.000***
	Constructed walls	0.73	0.85	0.12	0.02	0.000***
	Constructed roof	0.67	0.89	0.22	0.02	0.000***

Figure C.5: Education and device ownership.



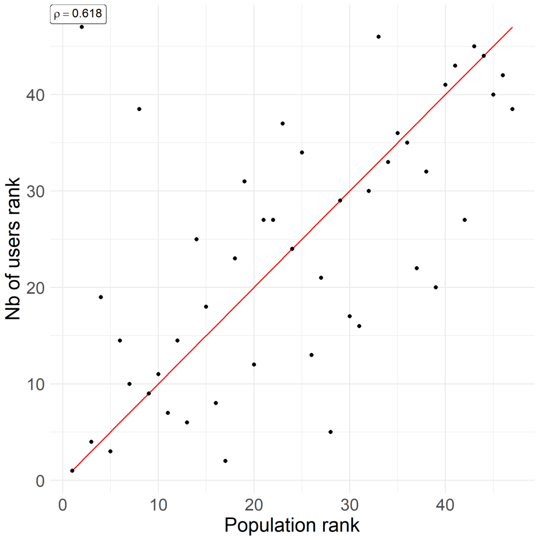
Note: These figures show the distribution of education by device ownership. All figures use the sample weights provided.

Figure C.6: Age and device ownership.

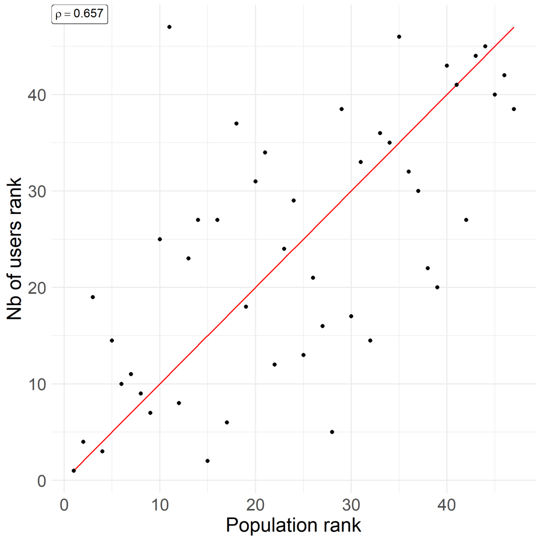


Note: These figures show the distribution of age by device ownership. All figures use the sample weights provided.

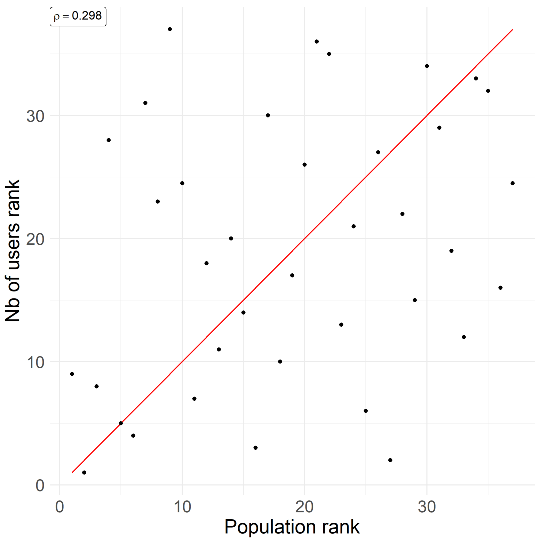
Figure C.7: Comparing user and population ranks at the first administrative level.



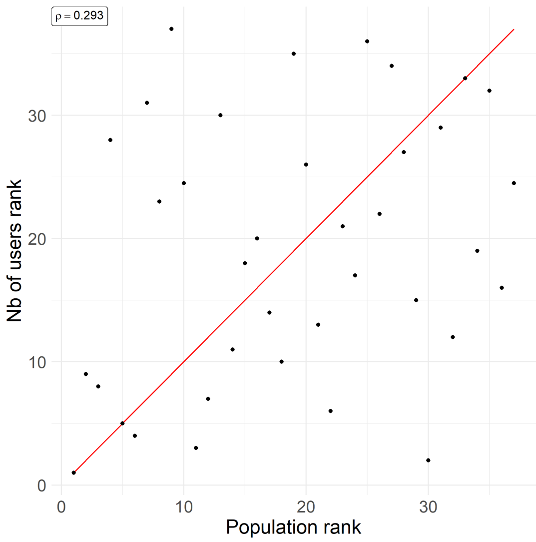
(a) World Pop, Kenya



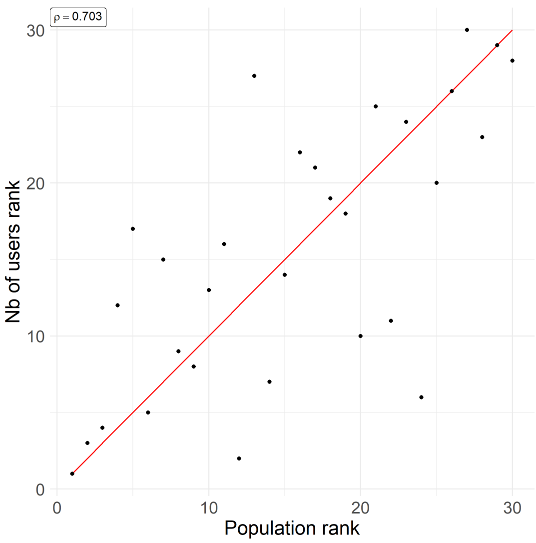
(b) Lanscan, Kenya



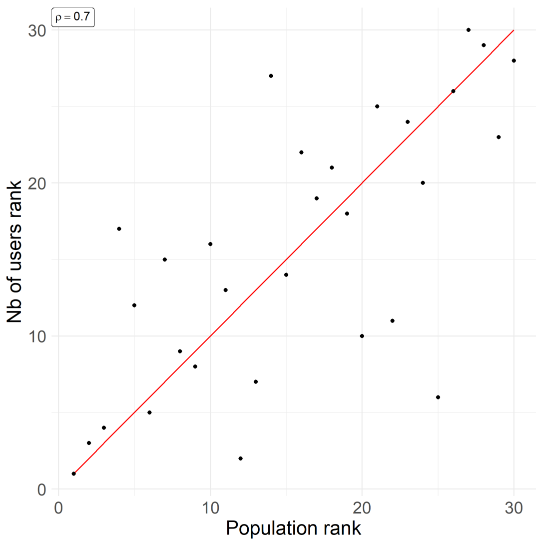
(c) World Pop, Nigeria



(d) Lanscan, Nigeria



(e) World Pop, Tanzania



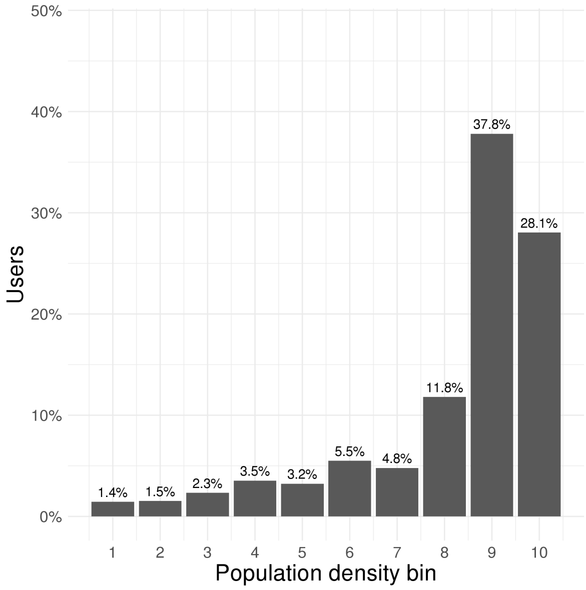
(f) Lanscan, Tanzania

Table C.4: Gravity model for mobility at the extensive margin between virtual regions, origin cells of 50 residents or more.

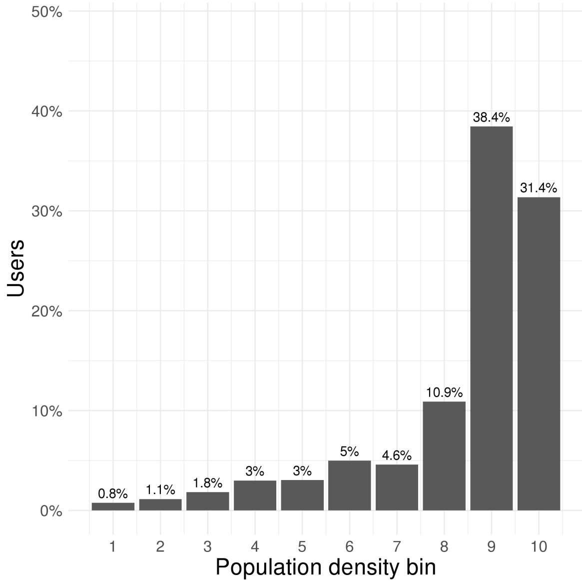
	Dependent variable:					
	(1)	(2)	(3)	(4)	(5)	(6)
log(distance)	-1.079^{***}		-0.964^{***}		-0.958^{***}	
	(0.039)		(0.052)		(0.066)	
log(distance)×KEN		-1.018^{***}		-0.829^{***}		-0.794^{***}
		(0.058)		(0.080)		(0.115)
log(distance)×NGA		-1.246^{***}		-1.129^{***}		-1.136^{***}
		(0.051)		(0.073)		(0.095)
log(distance)×TZA		-0.863^{***}		-0.770^{***}		-0.750^{***}
		(0.043)		(0.063)		(0.073)
Origin FE	Yes	Yes	Yes	Yes	Yes	Yes
Dest. FE	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,015	11,015	9,954	9,954	8,674	8,674
R^2	0.825	0.830	0.818	0.821	0.827	0.830

Note: Columns (1) and (2) report results for all cell pairs with positive mobility. Columns (3)-(4) show results for the subset of non-adjacent cell pairs and columns (5)-(6) provide coefficient estimates for a subset of cell pairs at least two rows/columns apart. Reported standard errors are two-way clustered at the origin and destination levels. *, **, *** denote significance at 10%, 5% and 1% levels.

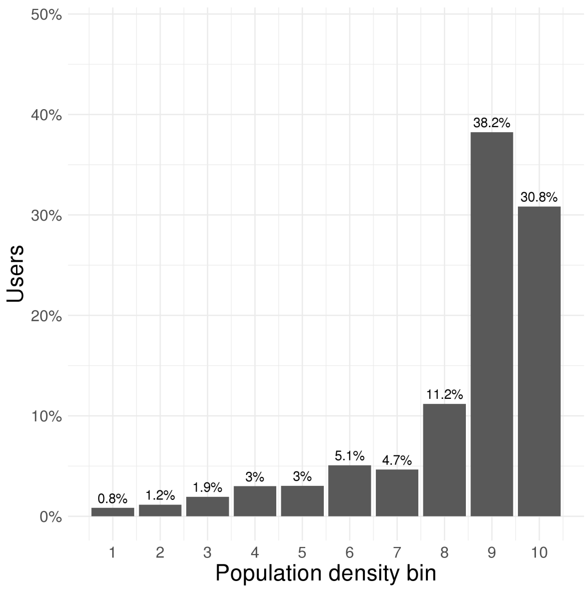
Figure C.8: Fraction of users by population density deciles in Kenya.



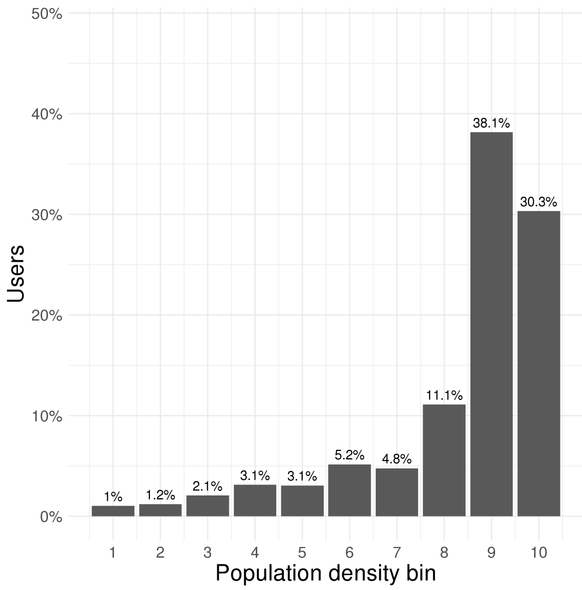
(a) Base sample



(b) High-confidence subset

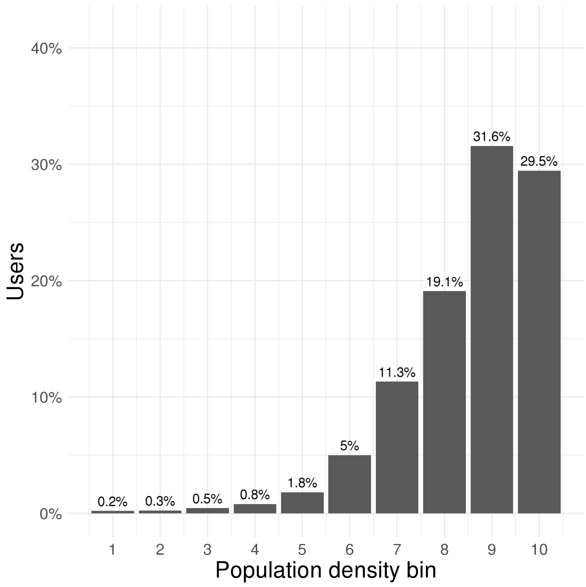


(c) Medium-confidence subset

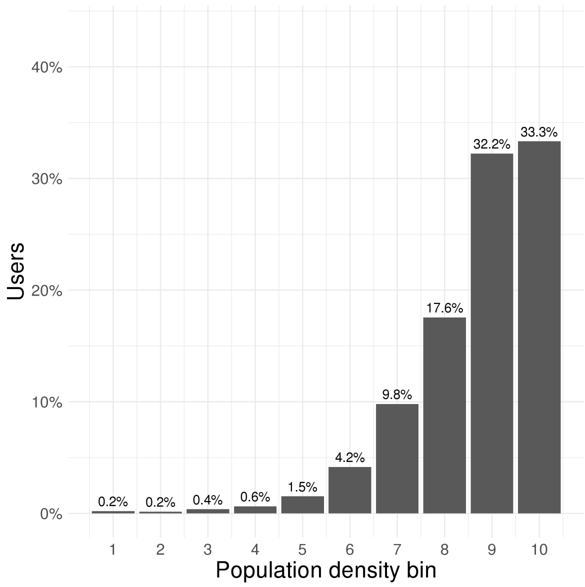


(d) Low-confidence subset

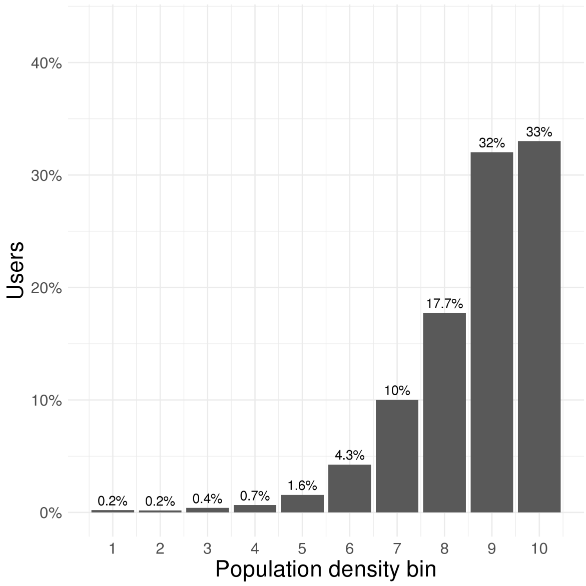
Figure C.9: Fraction of users by population density deciles in Nigeria.



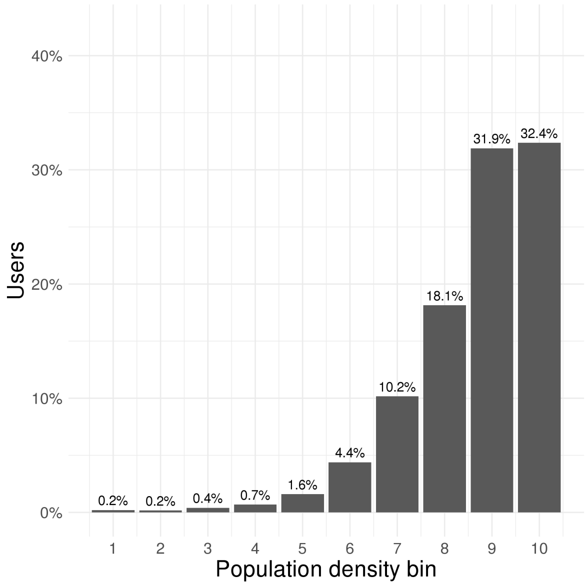
(a) Base sample



(b) High-confidence subset

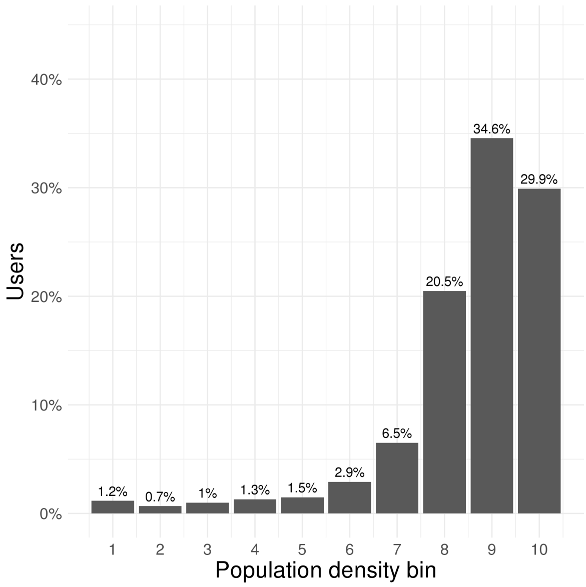


(c) Medium-confidence subset

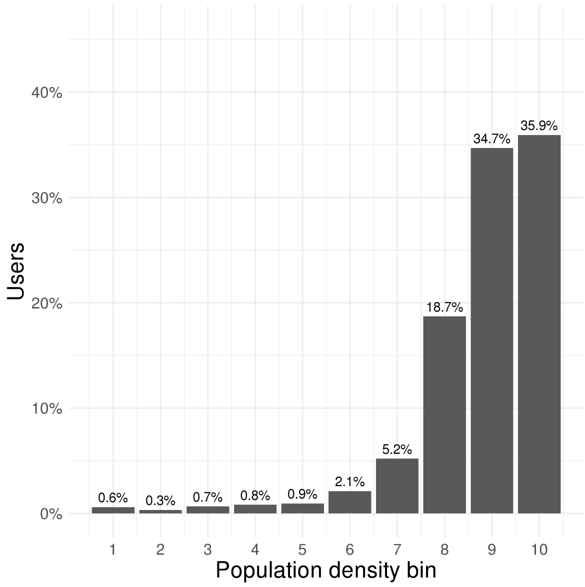


(d) Low-confidence subset

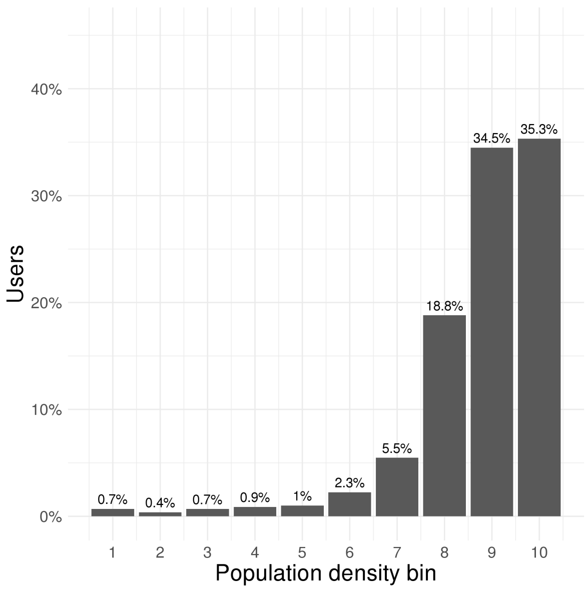
Figure C.10: Fraction of users by population density deciles in Tanzania.



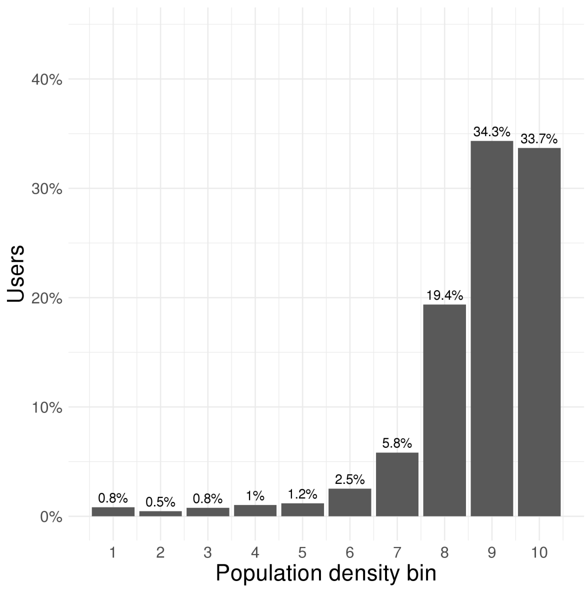
(a) Base sample



(b) High-confidence subset



(c) Medium-confidence subset



(d) Low-confidence subset

Table C.5: Origin of visitors in top 5 cities, Kenya.

Nairobi (1,598 visitors)		Mombasa (942 visitors)		Nakuru (858 visitors)		Eldoret (437 visitors)		Kisumu (426 visitors)	
Origin	*Visitors*	*Origin*	*Visitors*	*Origin*	*Visitors*	*Origin*	*Visitors*	*Origin*	*Visitors*
Mombasa	21.5%	Nairobi	69.2%	Nairobi	64.9%	Nairobi	52.6%	Nairobi	58.5%
Thika	5.7%	Malindi	3.4%	Eldoret	3.3%	Kitale	4.1%	Mombasa	4.7%
Nakuru	5.2%	Nakuru	1.5%	Mombasa	3%	Mombasa	3.4%	Kakamega	2.8%
Kisumu	4.4%	Thika	1%	Kisumu	2.1%	Kisumu	3%	Eldoret	2.3%
Eldoret	4.3%	Kisumu	0.6%	Naivasha	1.4%	Nakuru	2.3%	Nakuru	1.4%
Other urb.	1.6%	Other urb.	0.5%	Other urb.	1.3%	Other urb.	0.9%	Other urb.	0.9%
Non-urban	57.3%	Non-urban	23.8%	Non-urban	24%	Non-urban	33.6%	Non-urban	29.3%

Note: Details provided in Table 8 note.

Table C.6: Origin of visitors in top 5 cities, Nigeria.

Lagos (4,921 visitors)		Kano (769 visitors)		Ibadan (2,842 visitors)		Abuja (3,075 visitors)		Onitsha (1,777 visitors)	
Origin	*Visitors*	*Origin*	*Visitors*	*Origin*	*Visitors*	*Origin*	*Visitors*	*Origin*	*Visitors*
Abuja	23.5%	Abuja	45.6%	Lagos	70.5%	Lagos	49.4%	Lagos	43.3%
Ibadan	14%	Lagos	19.5%	Abuja	6.8%	Kaduna	9.2%	Abuja	11.8%
Abeokuta	8.1%	Kaduna	11.6%	Abeokuta	3.9%	Port harc.	5.6%	Enugu	8.2%
Port harc.	6.8%	Maiduguri	3%	Ilorin	3%	Kano	5.5%	Port harc.	5.9%
Benin city	6.1%	Zaria	3%	Oshogbo	2.5%	Jos	3.3%	Owerri	4.8%
Other urb.	4.6%	Other urb.	2.6%	Other urb.	2.3%	Other urb.	2.7%	Other urb.	3.7%
Non-urban	36.9%	Non-urban	14.7%	Non-urban	11.1%	Non-urban	24.2%	Non-urban	22.3%

Note: Details provided in Table 8 note.

Table C.7: Origin of visitors in top 5 cities, Tanzania.

Dar es salaam (1,753 visitors)		Zanzibar (738 visitors)		Mwanza (688 visitors)		Arusha (832 visitors)		Mbeya (378 visitors)	
Origin	*Visitors*	*Origin*	*Visitors*	*Origin*	*Visitors*	*Origin*	*Visitors*	*Origin*	*Visitors*
Arusha	10.2%	Dar es sa.	53.7%	Dar es sa.	33.1%	Dar es sa.	40.7%	Dar es sa.	39.9%
Zanzibar	9.4%	Arusha	4.1%	Arusha	3.2%	Moshi	10.7%	Mwanza	2.9%
Mwanza	7.1%	Mwanza	0.8%	Musoma	2.5%	Mwanza	3.1%	Iringa	2.4%
Morogoro	6.3%	Moshi	0.8%	Tabora	1.7%	Dodoma	2.4%	Arusha	2.4%
Dodoma	4.5%	Dodoma	0.8%	Dodoma	1.3%	Zanzibar	2.3%	Sumbawanga	2.4%
Other urb.	3.7%	Other urb.	0.4%	Other urb.	0.9%	Other urb.	1.7%	Other urb.	1.9%
Non-urban	58.8%	Non-urban	39.4%	Non-urban	57.3%	Non-urban	39.1%	Non-urban	48.1%

Note: Details provided in Table 8 note.