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

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Motivation

Large gaps in nominal wages, productivity, and living standards across sectors and locations. Gollin, Lagakos, and Waugh (2014); Gollin, Kirchberger, and Lagakos (2020)

Spatial frictions may have important impacts on the allocation of people across locations.

Bryan and Morten (2019)

Mobility of people entails two broad types of costs:

- Fixed costs (e.g., dislocation of migration, loss of network)
- Variable costs (e.g., bus tickets)

Key idea of this paper: granular data on spatial mobility of individuals is informative about the relevance of different types of costs.

Data for studying migration and mobility

Traditional

- Census or standard household surveys designed to measure longer-term migration flows
- Household travel surveys designed to measure commuting and travel

Newer

- CDR data, smartphone app location data, google maps queries, credit card data

Our data

- Fine-grained, anonymized data on smartphone app locations.
- More than one million devices over an entire year.
- Three African countries: Kenya, Nigeria and Tanzania.

Fixing ideas: data

Data availability has implied that previous literature on mobility has tended to focus on two dimensions that can be documented in surveys:

- Commuting (people mostly work within 1km of their home)
- Migration

Our data allow us to observe a third type of movement in some detail:

- Visits - relatively short-term travel to non-home locations

This type of mobility is common and frequent.

Samples are big enough to pick ordinary residents' movements.

The ubiquity of this type of mobility is potentially informative about the nature of spatial frictions.

To fix ideas - theory

Consider an individual i living in o who can consider one location d to visit getting a return of R_d

- Visiting family or friends, government offices, recreation/leisure activities

The individual has utility

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

- D_{od} represents the driving time between o and d,
- Z_{odi} represents an idiosyncratic preference draw following a Fréchet distribution with scale parameter T and shape parameter ϵ.

To fix ideas - estimation

This gives rise to the simple gravity equation

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

where ϕ_o and δ_d are origin and destination fixed effects.

To estimate Π_{od} we need lots of observations about travel choices.

From our million devices we have 4,739,794 user-days away from home.

This allows us to compute Π_{od} for a large set of people with great precision at a national scale.

Contributions

1. Construct a novel set of metrics for characterizing mobility across space
    - Frequency, spatial extent, densities and places visited
2. Use measures to provide a rich description of mobility in an African context
    - Do we observe much long-distance travel?
    - What patterns of mobility do we observe across cities?
    - Do we observe much connectivity between rural and urban areas?
3. Estimate gravity models to examine variable costs of distance

Related Literature

Importance of within-country frictions for the movements of goods

Arkolakis, Costinot, and Rodríguez-Clare (2012); Costinot and Donaldson (2016); Atkin and Donaldson (2015); Donaldson and Hornbeck (2016); Donaldson (2018); Allen and Arkolakis (2014).

Importance of within-country frictions for the movements of people

Young (2013); Hamory, Kleemans, Li, and Miguel (2020); Bryan, Chowdhury, and Mobarak (2014); Akram, Chowdhury, and Mobarak (2017); Bryan and Morten (2019); Baseler (2019).

Frictions and flow of information

Aker (2010); Jensen (2007).

Related Literature (cont.)

Quantitative urban models

Monte, Redding, and Rossi-Hansberg (2018); Owens, Rossi-Hansberg, and Sarte (2020); Ahlfeldt, Redding, Sturm, and Wolf (2015); Dingel and Tintelnot (2021); Kreindler and Miyauchi (2021); Miyauchi, Nakajima, and Redding (2021)

Literature using smartphone app location, CDR data and other types of 'big data'

Blumenstock (2012); Chen and Rohla (2018); Athey, Ferguson, Gentzkow, and Schmidt (2020); Atkin, Chen, and Popov (2020); Mongey, Pilossoph, and Weinberg (2020); Couture, Dingel, Green, Handbury, and Williams (2020); Giannone, Li, Paixao, and Pang (2020).

Our contribution:

$\rightarrow$ focus on high-frequency mobility on a national scale in developing countries.

Main findings

1. Substantial mobility flows: large fractions of days spent away from home, long distances travelled, several cities visited.
2. Largest cities are magnets for mobility flows originating from everywhere within countries.
3. Secondary cities appear to be substitutes for each other.
4. Costs of distance significant compared to other estimates in the literature but within reasonable ranges.

Data

Each observation is a "ping": smartphone accesses internet via a set of apps (i.e. social, navigation, information).

For each ping we know: device identifier, timestamp and longitude/latitude.

▸ Illustrative data

Start by assigning home locations: modal 0.01 degree cell user is seen between 7pm and 7am; two additional restrictions:

1. User is observed for more than 10 nights
2. User is at inferred home location for at least 50 percent of total nights we observe a user.

High confidence users satisfy both restrictions.

Identify irregularities in the data: mislabelled locations, data sinks.

Our sample: sample and pings per user

	Full sample		High-confidence	
	Users	Pings ratio	Users	Pings ratio
	(1)	(2)	(3)	(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

Our sample: 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

Selection

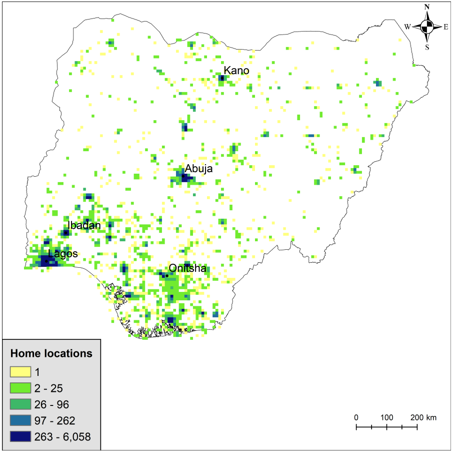
Smartphone app users in no way representative of the population in our setting.

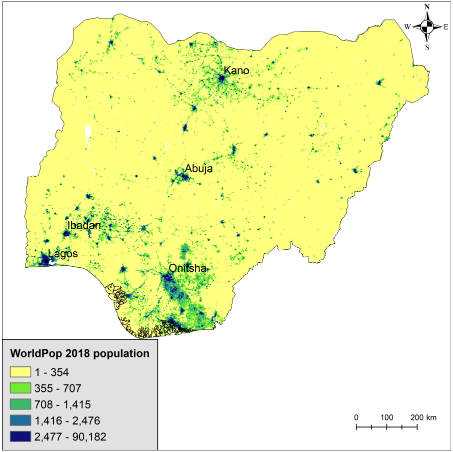
Take three steps to examine representativeness:

1. Match home locations with population density.
2. Use ICT Access and Usage Survey to examine characteristics of users by device ownership.
3. Match home locations with DHS data to examine characteristics of places.

In paper: discuss device = users (device sharing, multiple devices/SIM cards), turned-off devices, smartphone app location data vs CDR data.

Home locations in Nigeria and World Pop population ▸ Kenya ▸ Tanzania

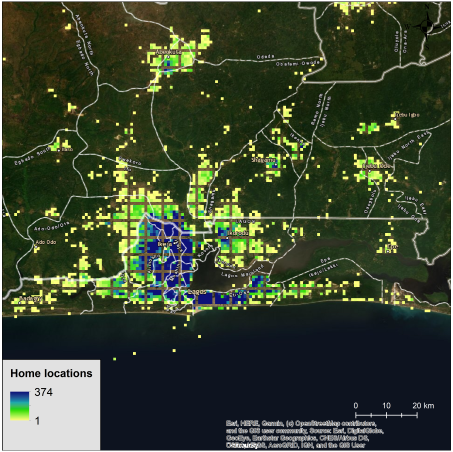


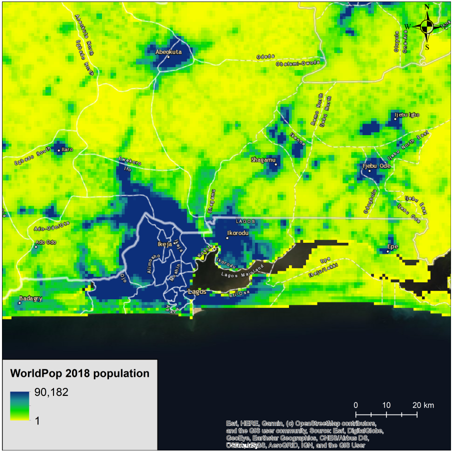


- Coverage of users is broadly national (users in 112/115 regional capitals).
- R-squared between population and users between 0.43 and 0.62 with coefficients of 0.95 (Kenya), 1.69 (Nigeria) and 0.96 (Tanzania).

▸ Coverage Kenya ▸ Coverage Nigeria ▸ Coverage Tanzania

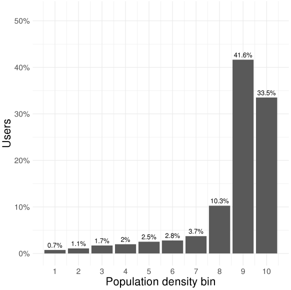
Home locations in Lagos and World Pop population



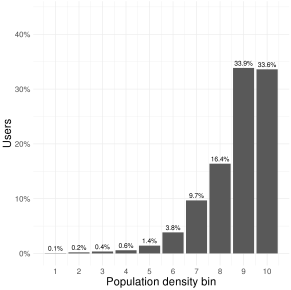


Broad coverage within cities.

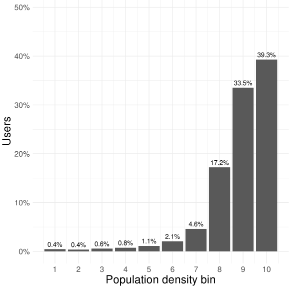
Population density



Kenya



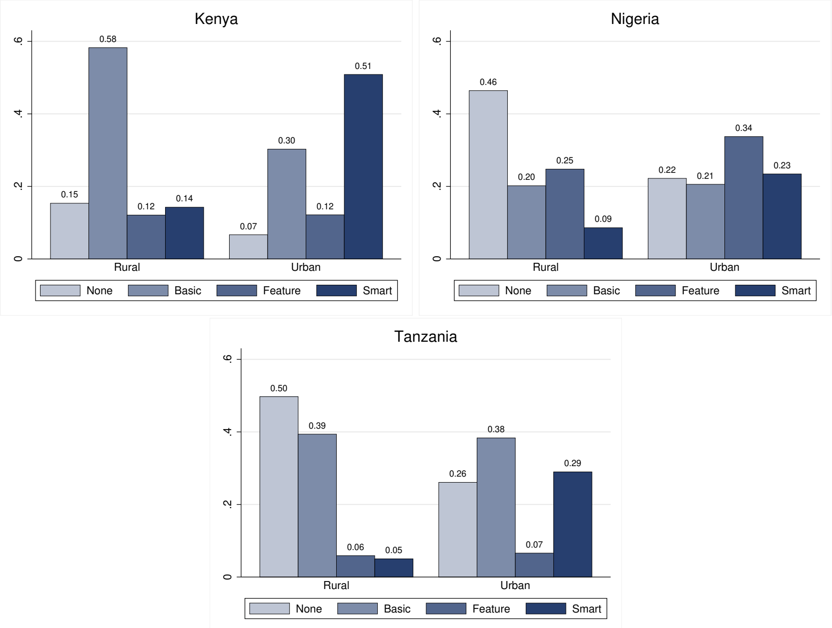
Nigeria



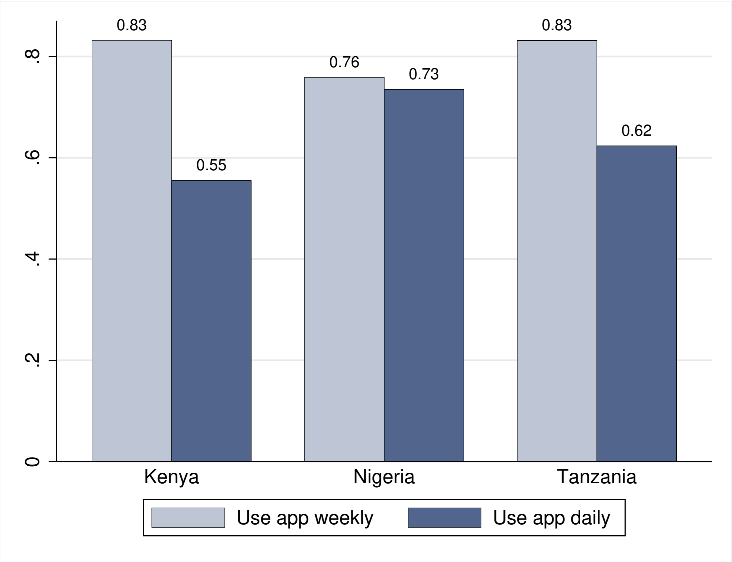
Tanzania

About 70% of users are falling into the highest density bins.

Device ownership by location

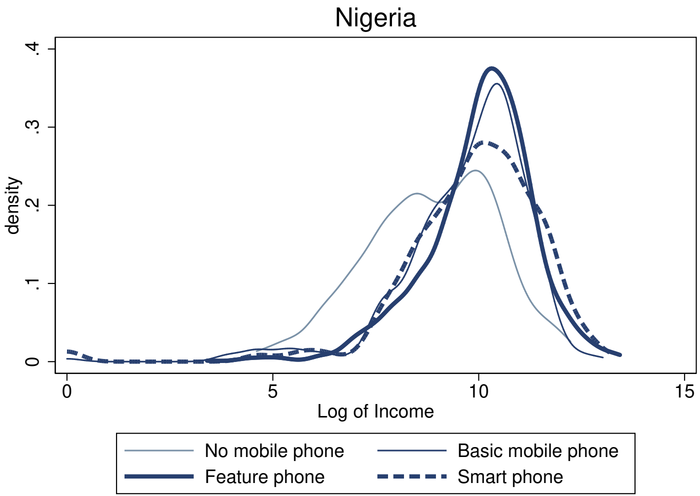


App usage of smartphone users.



Income and mobile phone ownership ‣ Kenya ‣ Tanzania

How different are users from other people?



T-tests for equality of means between DHS and matched DHS samples, Nigeria. ▸ Kenya ▸ Tanzania

	Variable	DHS	Matched DHS	Difference	SE	p-value
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 piped water	0.14	0.14	-0.01	0.01	0.572
	Constructed floor	0.89	0.96	0.08	0.01	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 piped water	0.09	0.14	0.05	0.01	0.000***
	Constructed floor	0.64	0.96	0.32	0.01	0.000***

In almost two-thirds of 66 (11x2x3) comparisons, differences are less than 10 percent.

Selection summary

Users are likely to be more urban, educated, richer. ▸ Kenya ▸ Nigeria ▸ Tanzania

Surely represent more privileged portion, but not just top 10 percent.

Users not nationally representative, but also not wildly atypical once we consider location:

- urban users live in locations that are broadly typical of all urban areas.
- rural users live in locations that are not wildly atypical.

▸ Kenya ▸ Nigeria ▸ Tanzania

Argue that population of users is still informative about patterns of mobility in the broader population.

1 Data and Sample Selection

2 Mobility

3 Gravity

Measuring mobility

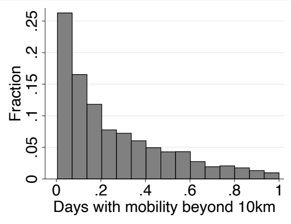
- Characterizing mobility:
  1. Frequency.
  2. Spatial extent.
  3. Densities visited.
  4. Cities visited.
- Characterizing connectedness of locations (e.g. cities):
  1. Incoming flows: number of visitors, frequency of visits, distance travelled, density at origin.
  2. Outgoing flows: number of residents seen outside the area, frequency of movements, spatial extent, densities visited.

Measuring mobility

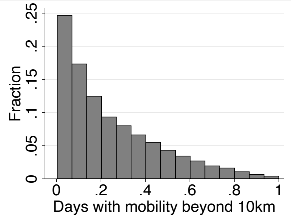
Fraction of days with mobility beyond 10km:

- 13.8% Kenya
- 15.2% Nigeria
- 11.8% Tanzania

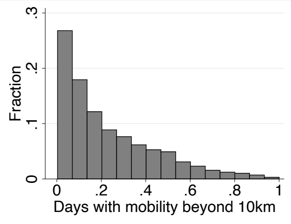
For users with any mobility beyond 10km:



Kenya



Nigeria



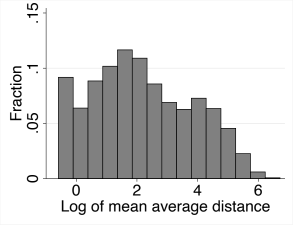
Tanzania

▸ Excluding outliers

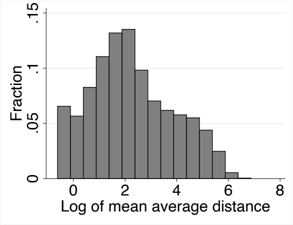
Measuring mobility: mean distance away from home.

Average distance from home for non-home pings (km):

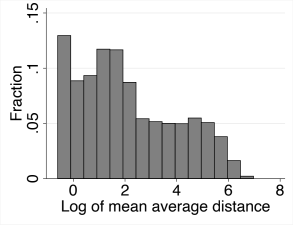
- 33.8 km Kenya
- 45.5 km Nigeria
- 31.8 km Tanzania



Kenya



Nigeria



Tanzania

Excluding outliers

Home-based work is common

Work locations: modal 0.01 degree cell user is seen between 9am and 6pm; two additional restrictions:

1. User is observed for more than 8 distinct weekdays
2. User is at inferred work location for at least 50 percent of total weekdays we observe a user.

High confidence users satisfy both restrictions.

Fraction of users with identical home and work locations in the work subset.

	Overall	**Urban**	**Non-urban**
Kenya	80.2%	78.5%	87.7%
Nigeria	79.8%	79.2%	84.4%
Tanzania	82.6%	80.6%	87.7%
TOTAL	80.4%	79.3%	86.1%

Measuring mobility: Share of users by home bin-visited bin pair

Kenya Tanzania

		Home density bin									
		1	2	3	4	5	6	7	8	9	10
	1	35.7%	19.6%	18.8%	6.8%	6.1%	3.8%	3.3%	3.1%	2.5%	1.5%
	2	23.8%	33.3%	35%	12.1%	12.6%	9.1%	6.8%	6.1%	5.3%	3.2%
	3	26.2%	29%	41.5%	32%	18.9%	13.1%	10.5%	8.8%	7.3%	4.7%
	4	31%	26.8%	45.3%	35.2%	32.6%	22.3%	15%	12%	11.2%	6.9%
Visited	5	23.8%	33.3%	43.6%	45.9%	51.3%	38.1%	27%	21%	20.1%	15.2%
density	6	33.3%	33.3%	37.6%	53.9%	60%	68.7%	45.8%	31.5%	26.8%	17.4%
	7	42.9%	55.8%	50.9%	52.7%	64%	69.9%	76.1%	56.1%	39.8%	25.5%
	8	71.4%	58.7%	54.7%	58.7%	61.5%	60%	72.8%	81.2%	63.7%	37.9%
	9	76.2%	61.6%	62.8%	62.6%	66.8%	64.1%	68.4%	81.2%	91.5%	64.7%
	10	42.9%	44.9%	43.2%	44.7%	50.2%	47.8%	46.9%	46.9%	61.9%	95.3%

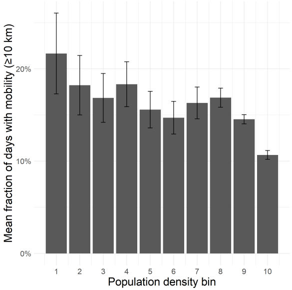
Nigeria

Substantial flows of people across densities.

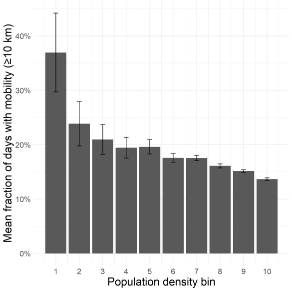
Transit ping filtering algorithm

Kenya, transit pings excluded Nigeria, transit pings excluded Tanzania, transit pings excluded

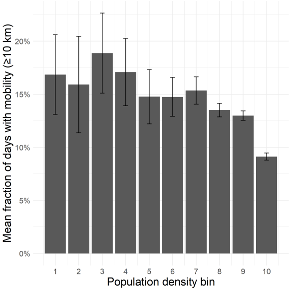
Fraction of days with mobility beyond 10km by density



Kenya



Nigeria

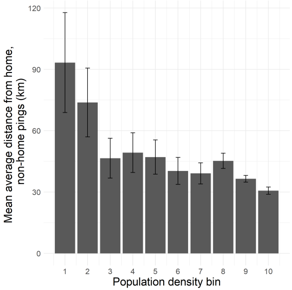


Tanzania

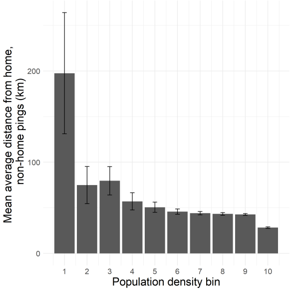
10-20 percent of days we observe users they are further than 10km from home.

▸ Excluding outliers

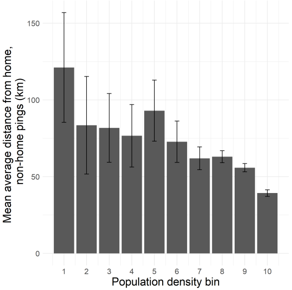
Measuring mobility: mean distance away from home by density bin of home location.



Kenya



Nigeria



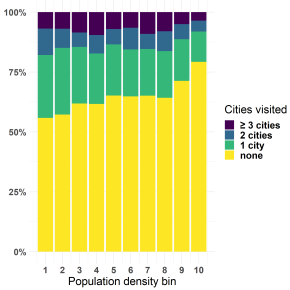
Tanzania

Average distance of non-home pings is 30-100km.

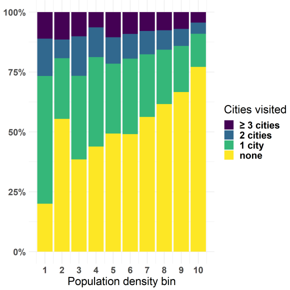
Those in remote areas travel farthest conditional on being away from home.

▸ Excluding outliers

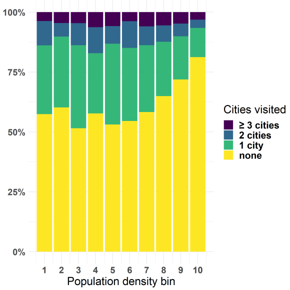
Distribution of users according to the number of non-home cities visited, by population density bin.



Kenya



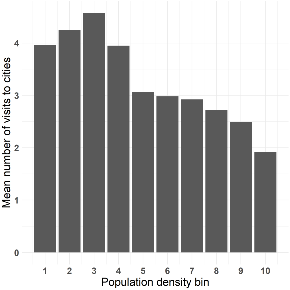
Nigeria



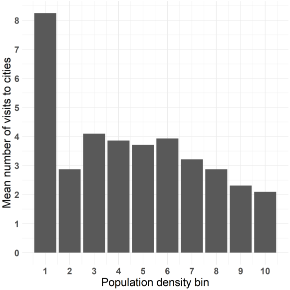
Tanzania

Across all densities a sizeable fraction of individuals make visits to one or more non-home cities.

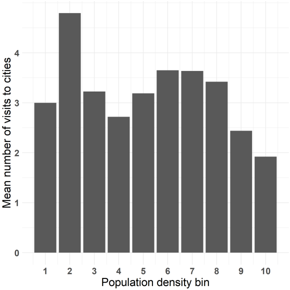
Average number of visits to non-home cities, by population density bin



Kenya



Nigeria



Tanzania

Individuals make multiple visits to non-home cities on average.

Measuring mobility: Origin of visitors in top 5 cities ▸ Kenya ▸ Tanzania

Visitor: observed in city who lives outside city boundaries.

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%

Origin of visitors to major cities, Nigeria

Large fraction of non-urban visitors to largest city (66% of visitors to Nairobi, 61% of visitors to Dar Es Salaam).

Modest flows between secondary cities.

Recap on findings so far

Smartphone users represent a mobile population:

- seen more than 10 km from home between one-sixth and one-tenth 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 venture far when they do.

Across all densities a sizeable fraction of users visit a number of non-home cities on multiple occasions.

Largest cities are magnets for travellers from the entire country.

Secondary cities appear to be substitutes for each other.

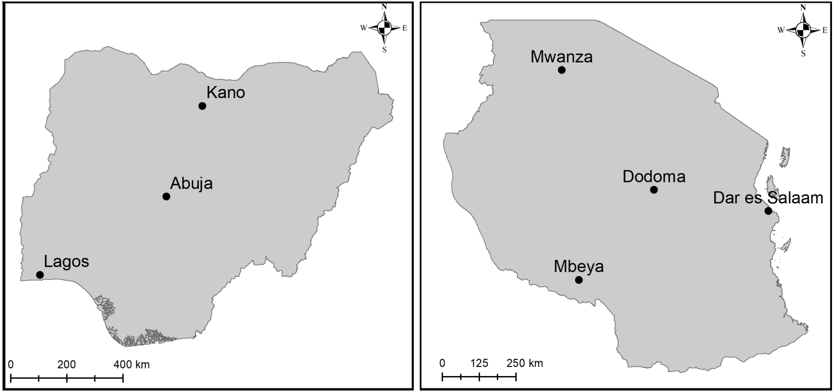
Gravity equation: city-level

Use PPML to estimate the following gravity equation at the city-level

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

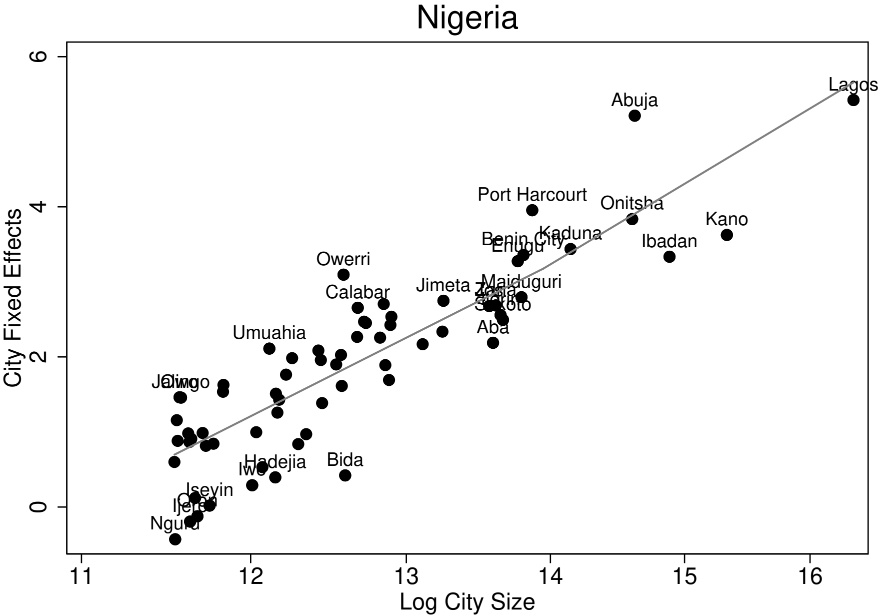
	Kenya	Nigeria	Tanzania
	(1)	(2)	(3)
Gravity Equation			
Log(Traveltime)	-.953***	-1.468***	-1.027***
	(0.061)	(0.092)	(0.04)
Origin FE	YES	YES	YES
Destination FE	YES	YES	YES
Obs.	210	4422	239
R^2	0.975	0.935	0.993

Returns to visiting certain locations: controlling for distance...

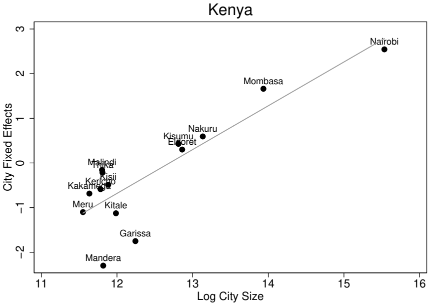


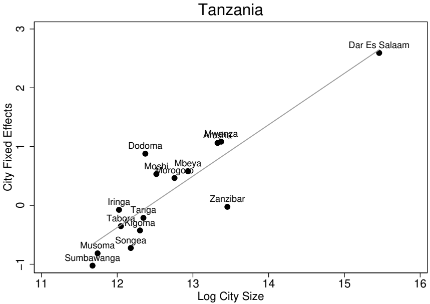
- ...Kano residents are 4 times as likely to visit Lagos but only 1.3 times as likely to visit Abuja than any other city in Nigeria.
- ...Mwanza/Mbeya residents are 3.3 times as likely to visit Dar es Salaam than any other city but only 1.2 times as likely to visit Dodoma.

Destination fixed effects



Destination fixed effects (cont)





	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

Gravity models for movements of people

Paper: estimate gravity models, considering:

- Admin regions and virtual countries (Michalopoulos and Papaioannou, 2013).
- Excluding within-city commuting: remove rows of adjacent cell pairs.
- Sparseness: limit to origin cells with 50 residents or more.
- Estimate at quarterly level.
- Intensive margin: different mobility metrics.

Gravity model results - virtual regions

	all cells		non-adj. cells		non-adj. cells 2	
	(1)	(2)	(3)	(4)	(5)	(6)
log(distance)	-0.894^{***}		-0.794^{***}		-0.790^{***}	
	(0.036)		(0.047)		(0.058)	
log(distance)×Kenya		-0.881^{***}		-0.731^{***}		-0.696^{***}
		(0.061)		(0.078)		(0.104)
log(distance)×Nigeria		-1.085^{***}		-0.982^{***}		-1.001^{***}
		(0.055)		(0.073)		(0.093)
log(distance)×Tanzania		-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

Somewhat higher than Bryan and Morten (2019) who find 0.7 for Indonesia and 0.5 for United States.

Conclusion

Develop methodology to use smartphone app location data to investigate the salience of spatial frictions in low-income countries.

Observe substantial mobility across space: frequent, distant.

Costs of distance within reasonable range and estimates suggest high returns to visiting certain locations.

Cannot prove that flows are sufficient to break down barriers, but difficult to argue that costs are insurmountable and rural areas are cut-off.

Points towards other frictions: a fixed cost explanation would describe the data better than a variable cost story.

Thank you!

Illustrative smartphone data ◂ Return

userID	timestamp	longitude	latitude
id1	2020-03-24 06:00:00	3.34...	6.68...
id1	2020-03-24 08:00:00	3.34...	6.68...
id1	2020-03-24 10:00:00	3.34...	6.68...
id1	2020-03-24 12:00:00	3.34...	6.68...
id2	2020-03-24 06:00:00	3.19...	6.46...
id2	2020-03-24 08:00:00	3.19...	6.46...
id2	2020-03-24 10:00:00	3.88...	7.37...
id2	2020-03-24 12:00:00	3.88...	7.37...
id3	2020-03-24 06:00:00	3.41...	6.61...
id3	2020-03-24 08:00:00	3.64...	8.83...
id3	2020-03-24 10:00:00	3.64...	8.83...
...	...	...	...

Distance from home to work

Conditional on work location different from home location:

Home-to-work median distance (in km).

	Overall	**Urban**	**Non-urban**
Kenya	4.7	5	2.5
Nigeria	4.5	4.6	4
Tanzania	3.3	3.5	1.6
TOTAL	4.4	4.5	3

Gravity equation: city-level

Return

	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

Gravity equation: comparison with estimates in the literature

Estimate region-level gravity equation and get elasticity between 1 and 1.5.

Higher than elasticity of 0.7 for Indonesia and 0.5 for the United States (Bryan and Morten, 2019).

Robustness:

- Virtual countries (Michalopoulos and Papaioannou, 2013).
- Excluding within-city commuting: remove rows of adjacent cell pairs.
- Sparseness: limit to origin cells with 50 residents or more.
- Estimate at quarterly level.
- Intensive margin: different mobility metrics.

Gravity equation: region-level

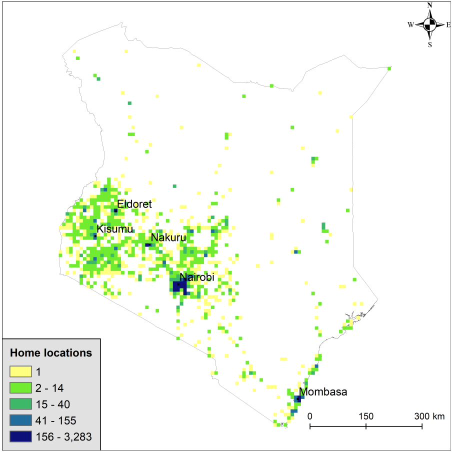
Estimate region-level gravity equation similar to what Bryan and Morten (2019) estimate for Indonesia.

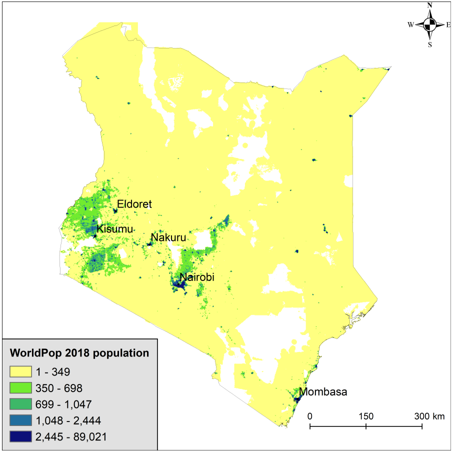
	Kenya	Nigeria	Tanzania
	(1)	(2)	(3)
Log(Distance)	-1.004***	-1.497***	-1.176***
	(0.062)	(0.06)	(0.084)
Origin FE	YES	YES	YES
Destination FE	YES	YES	YES
Obs.	2162	1332	870
R^2	0.983	0.982	0.936

Bryan and Morten (2019) find an elasticity of 0.7 for Indonesia and 0.5 for the United States.

Home locations in Kenya and World Pop population

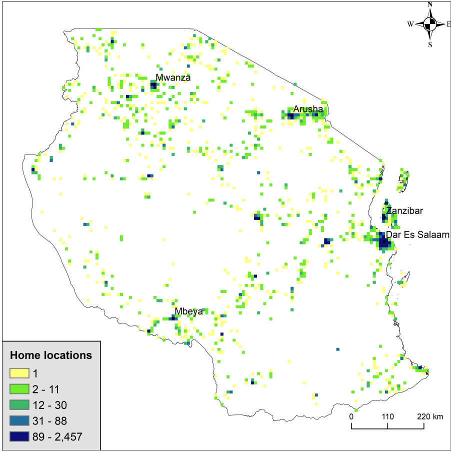
Return

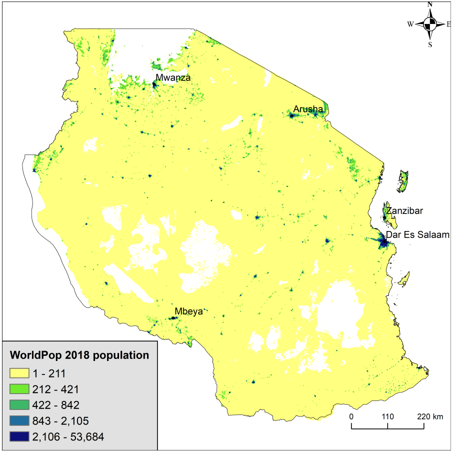




Home locations in Tanzania and World Pop population

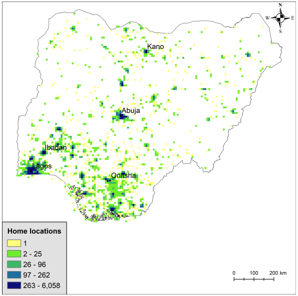
Return

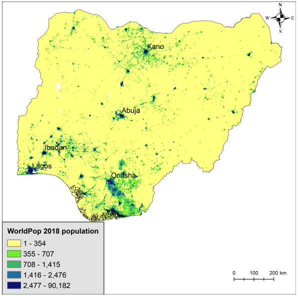


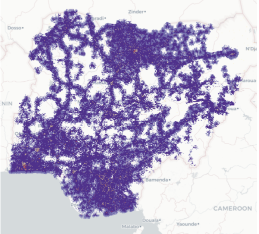


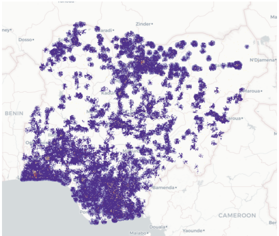
Home locations, population and coverage

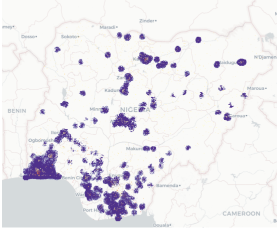
Return







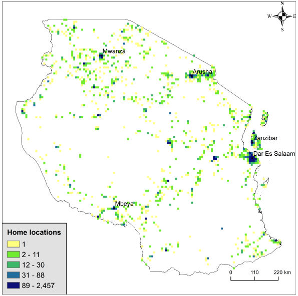


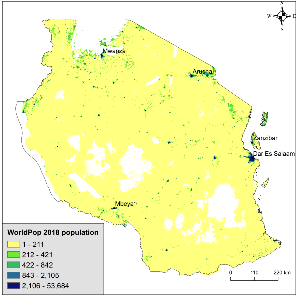


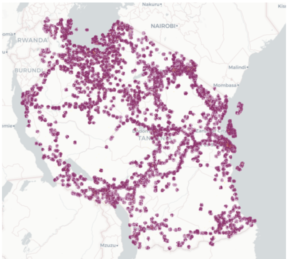
Note: Coverage maps from GSMA.

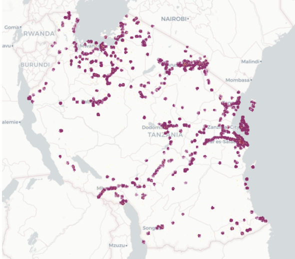
Home locations, population and coverage

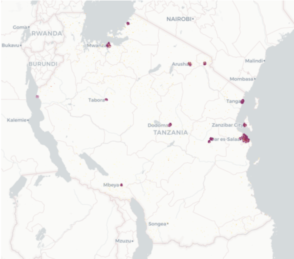
Return







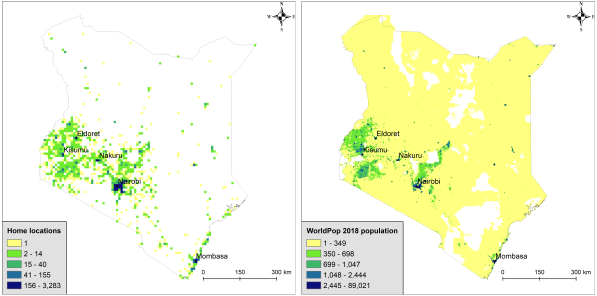


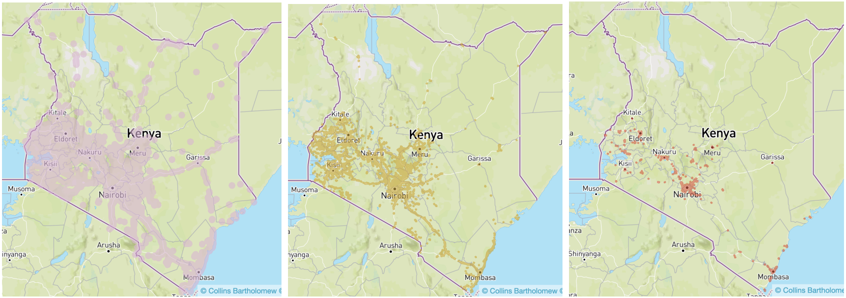


Note: Coverage maps from GSMA.

Home locations, population and coverage

Return





Note: Coverage maps from GSMA.

T-tests for equality of means between DHS and matched DHS samples, Nigeria. ▸ Kenya ▸ Tanzania

	Variable	DHS	Matched DHS	Difference	SE	p-value
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 piped water	0.14	0.14	-0.01	0.01	0.572
	Constructed floor	0.89	0.96	0.08	0.01	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 piped water	0.09	0.14	0.05	0.01	0.000***
	Constructed floor	0.64	0.96	0.32	0.01	0.000***

In almost two-thirds of 66 (11x2x3) comparisons, differences are less than 10 percent.

T-tests for equality of means between DHS and matched DHS samples, Kenya. Return

	Variable	DHS	Matched DHS	Difference	SE	p-value
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 piped water	0.71	0.82	0.11	0.02	0.000***
	Constructed floor	0.82	0.92	0.10	0.01	0.000***
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 piped water	0.24	0.25	0.01	0.02	0.464
	Constructed floor	0.31	0.38	0.07	0.01	0.000***

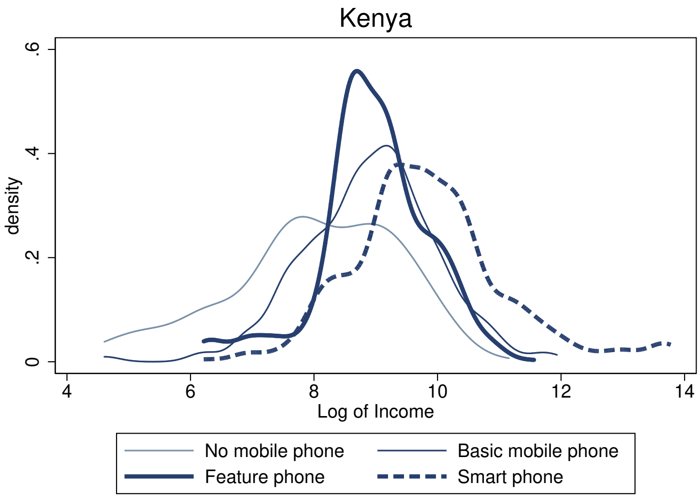
T-tests for equality of means between DHS and matched DHS samples, Tanzania

Return

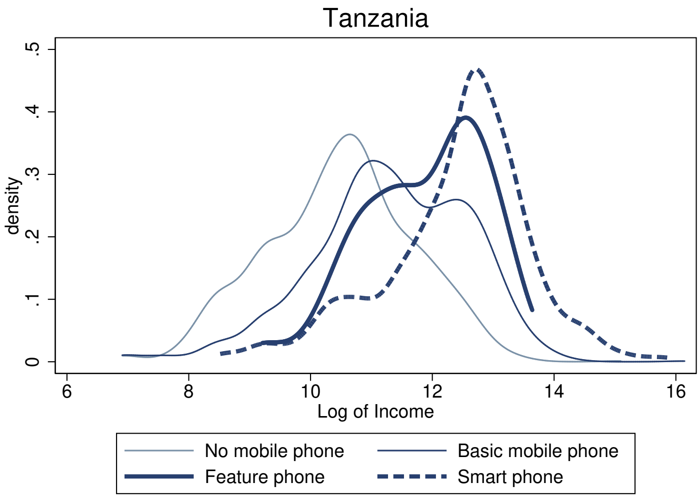
	Variable	DHS	Matched DHS	Difference	SE	p-value
Urban	Household size	4.54	4.30	-0.24	0.07	0.001***
	Age of HH head	42.22	41.56	-0.67	0.37	0.073*
	Education of HH head	8.01	8.40	0.39	0.10	0.000***
	Access to piped water	0.67	0.67	0.00	0.04	0.980
	Constructed floor	0.87	0.96	0.09	0.02	0.000***
Rural	Household 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 piped water	0.27	0.54	0.27	0.03	0.000***
	Constructed floor	0.27	0.65	0.37	0.02	0.000***

Income and mobile phone ownership: Kenya

Return

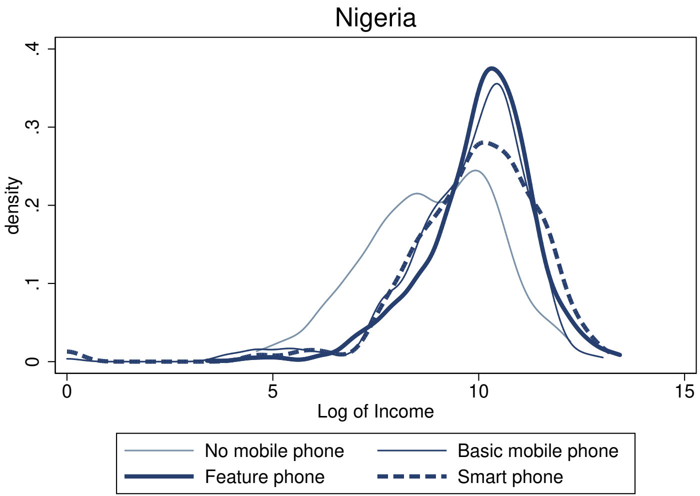


Income and mobile phone ownership: Tanzania ◂ Return



Income and mobile phone ownership ‣ Kenya ‣ Tanzania

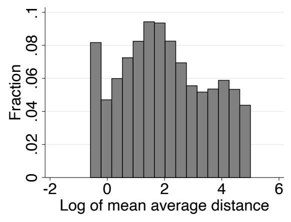
How different are users from other people?



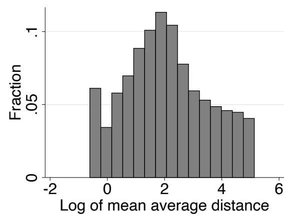
Measuring mobility: mean distance away from home, excluding outliers. Return

Average distance from home for non-home pings (km):

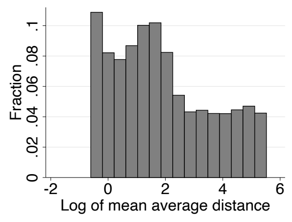
- 21.4 km Kenya
- 21.8 km Nigeria.
- 27.9 km Tanzania



Kenya



Nigeria

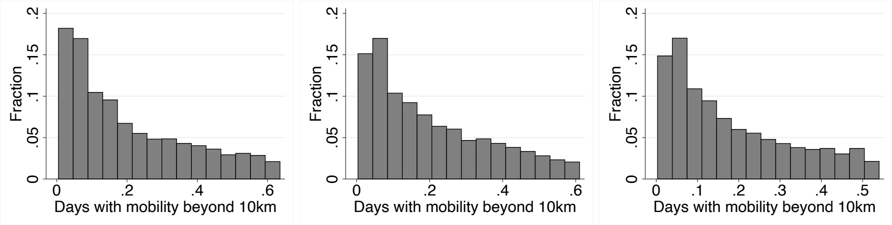


Tanzania

Measuring mobility, excluding outliers ◂ Return

Fraction of days with mobility beyond 10km:

- 10.3% Kenya
- 8.8% Tanzania
- 12.1% Nigeria

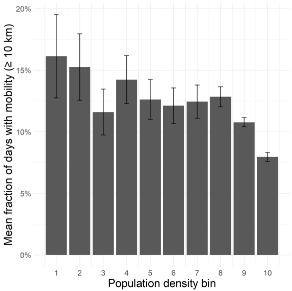


Kenya Nigeria Tanzania

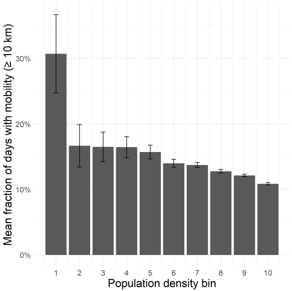
Measuring mobility - excluding outliers

back

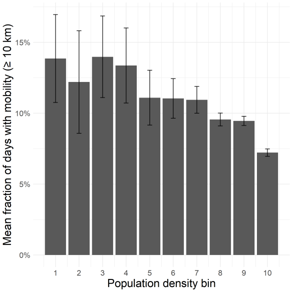
Fraction of days with mobility beyond 10km:



Kenya

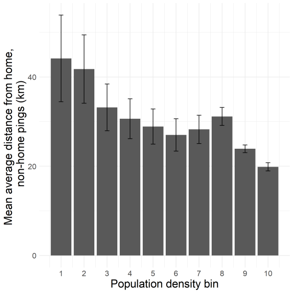


Nigeria

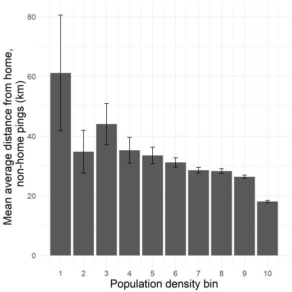


Tanzania

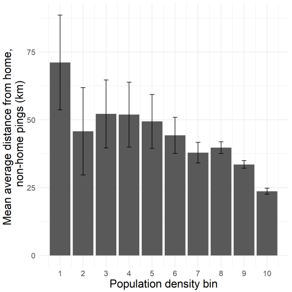
Measuring mobility: mean distance away from home by density bin of home location - excluding outliers. back



Kenya



Nigeria



Tanzania

Measuring mobility: Share of users by home bin-visited bin pair - Kenya. Back

		Home density bin									
		1	2	3	4	5	6	7	8	9	10
	1	72.3%	32.9%	15.1%	11.8%	11.9%	14.7%	13.3%	15.1%	9.5%	6.7%
	2	42.9%	61.4%	38.1%	26.9%	21%	17.5%	18.6%	20.9%	15%	11.4%
	3	25.9%	46.2%	55.5%	43.8%	35.8%	29.6%	28.8%	25.5%	19.4%	14.7%
	4	33.9%	34.2%	52.5%	56.6%	46.9%	39.4%	35.3%	29.6%	23.7%	17.8%
Visited	5	30.4%	25.9%	43%	52.2%	53.6%	49.3%	38.8%	35.7%	25.5%	18.9%
density	6	27.7%	27.2%	30.2%	47.1%	46.6%	55.5%	47.4%	38.3%	26.5%	19.7%
	7	26.8%	28.5%	35.5%	44.8%	45%	56.5%	57.9%	48.5%	35%	24.5%
	8	42%	44.9%	45.7%	56.9%	57.1%	60.8%	68.4%	69.7%	50.8%	36%
	9	55.4%	54.4%	53.6%	66%	65%	67.8%	72.1%	79.8%	89.8%	76%
	10	32.1%	36.1%	30.6%	41.4%	37.5%	40.9%	45.8%	51.7%	70%	88.6%

Kenya.

Measuring mobility: Share of users by home bin-visited bin pair - Kenya, transit pings excluded. Back

		Home density bin									
		1	2	3	4	5	6	7	8	9	10
	1	71.2%	32.9%	14%	11.1%	11.4%	13.2%	12.1%	13.9%	8.7%	5.6%
	2	43.2%	60.8%	37.7%	24.9%	18.9%	17.1%	17.2%	19.3%	13.3%	9.6%
	3	25.2%	45.6%	55.1%	41.1%	34.9%	28.4%	26.5%	24.1%	17.6%	13.2%
	4	34.2%	32.9%	51.3%	56.6%	46.2%	37.7%	33.9%	27.5%	22.1%	16.5%
Visited	5	29.7%	25.3%	42.3%	51.5%	52.4%	48.3%	37.5%	34.3%	24.1%	17.8%
density	6	27%	24.7%	28.7%	46.1%	46.2%	54.6%	46.8%	37.3%	25.5%	18.4%
	7	27%	27.8%	34.7%	42.4%	43.8%	55.8%	57.7%	47.5%	34.1%	23.6%
	8	42.3%	44.3%	45.3%	55.9%	56.8%	60.8%	68.1%	69.3%	50.3%	35.4%
	9	55.9%	53.8%	53.6%	65.3%	65.1%	67.8%	72.1%	79.8%	89.8%	76%
	10	32.4%	36.1%	30.2%	41.4%	37.3%	40.1%	45.4%	51.3%	69.9%	88.6%

Kenya.

Measuring mobility: Share of users by home bin-visited bin pair - Nigeria, transit pings excluded. Back

		Home density bin									
		1	2	3	4	5	6	7	8	9	10
	1	35.7%	18.8%	18.8%	6.3%	5.7%	3.5%	2.9%	2.7%	2.2%	1.3%
	2	23.8%	31.9%	35%	12.2%	12.1%	8.3%	6.2%	5.5%	4.6%	2.8%
	3	26.2%	29%	40.6%	31.6%	18%	12.5%	9.6%	8%	6.5%	4.2%
	4	31%	26.1%	44.9%	35%	31.7%	21.7%	14.1%	11.3%	10.4%	6.4%
Visited	5	23.8%	33.3%	42.7%	45.3%	50.6%	37.1%	26.2%	20.2%	19.4%	14.6%
density	6	33.3%	33.3%	36.8%	53%	59.5%	68.6%	45.2%	30.9%	26.2%	17%
	7	42.9%	55.8%	49.6%	52.8%	63.6%	69.9%	75.9%	55.9%	39.3%	25.1%
	8	71.4%	58%	54.3%	58.4%	61.1%	59.6%	72.5%	81%	63.4%	37.6%
	9	76.2%	61.6%	62.8%	62.5%	66.8%	63.9%	68.3%	81.1%	91.4%	64.5%
	10	42.9%	44.2%	41.9%	44.5%	49.9%	47.7%	46.7%	46.7%	61.7%	95.3%

Nigeria.

Measuring mobility: Share of users by home bin-visited bin pair - Tanzania. Back

		Home density bin									
		1	2	3	4	5	6	7	8	9	10
	1	73.6%	33.8%	18.2%	15%	15.2%	10.3%	11.6%	9.5%	7.9%	4.4%
	2	18.7%	50%	40%	29.3%	22.6%	15.2%	14.9%	11.6%	9.1%	5.4%
	3	13.2%	39.7%	43.6%	38.8%	30%	20.1%	15.4%	13.7%	10.6%	6.3%
	4	14.3%	38.2%	40.9%	42.2%	39.2%	24.2%	20.7%	15.8%	12.3%	7.7%
Visited	5	16.5%	33.8%	42.7%	40.8%	36.9%	43.4%	27.2%	20.3%	14.3%	8.3%
density	6	19.8%	26.5%	35.5%	41.5%	46.5%	51.2%	42.2%	24.5%	17.7%	10.6%
	7	30.8%	38.2%	44.5%	46.9%	41.9%	54.2%	64.4%	42.6%	26.5%	15.8%
	8	42.9%	44.1%	50%	47.6%	51.2%	55%	62.6%	82.6%	56.9%	33.6%
	9	40.7%	51.5%	54.5%	48.3%	55.8%	59.1%	56.1%	68.7%	88.4%	66.2%
	10	40.7%	35.3%	31.8%	38.1%	32.7%	38.8%	39.7%	45%	64.5%	93.5%

Tanzania.

Measuring mobility: Share of users by home bin-visited bin pair - Tanzania, transit pings excluded.

Back

		Home density bin									
		1	2	3	4	5	6	7	8	9	10
	1	73.6%	33.8%	18.2%	14.3%	13.4%	8.5%	10.2%	7.9%	6.5%	3.6%
	2	18.7%	50%	39.1%	27.9%	21.2%	13.1%	13%	9.7%	7.1%	4.1%
	3	11%	38.2%	43.6%	38.8%	29%	18.3%	13.9%	11%	8.6%	5.1%
	4	13.2%	35.3%	40%	40.1%	37.8%	22.4%	19.3%	13.1%	10%	6.4%
Visited	5	16.5%	29.4%	42.7%	39.5%	36.4%	41.4%	25.6%	17.8%	12.2%	7%
density	6	18.7%	22.1%	35.5%	40.8%	45.2%	49.6%	41.1%	22.4%	15.9%	9.3%
	7	29.7%	38.2%	42.7%	46.3%	40.6%	53%	64%	40.8%	25.3%	14.9%
	8	42.9%	42.6%	50%	46.9%	50.2%	54.8%	61.9%	82.3%	56.5%	33.2%
	9	40.7%	50%	54.5%	48.3%	55.3%	58.9%	55.8%	68.5%	88.4%	66%
	10	39.6%	35.3%	30.9%	38.1%	31.8%	38.3%	39.5%	44.7%	64.2%	93.4%

Tanzania.

Transit Pings Filtering Algorithm

Back

Define a visit as a sequence of pings in a 5km cell.

Duration: time between first and last ping.

Classify pings into:

1. stay pings: duration > T_{stay}
2. transit pings: duration < T_{stay} and a speed value greater than 20km/h is observed for at least 25% of pings.

T_{stay} about 21 minutes.

Measuring mobility: Origin of visitors in top 5 cities - Kenya

Back

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%

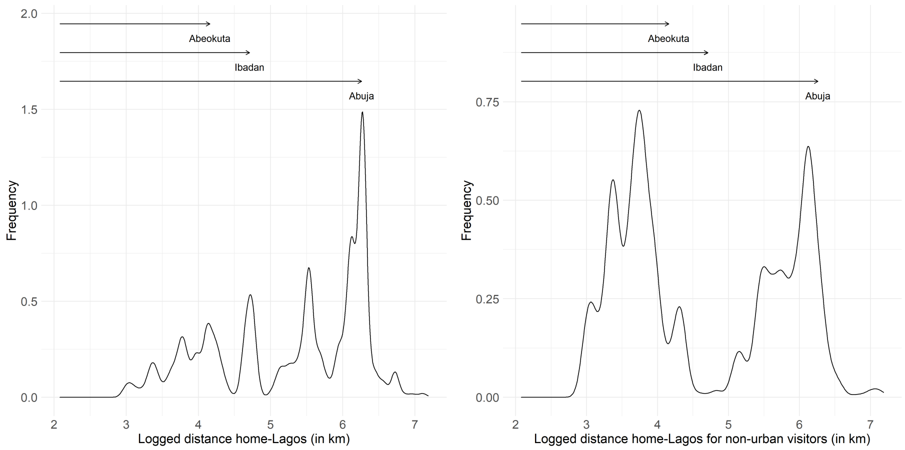
Kenya.

Measuring mobility: Origin of visitors in top 5 cities - Tanzania

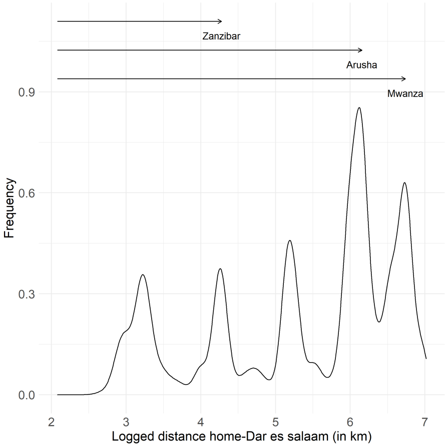
Dar Es Salaam (1,850 visitors)		Zanzibar (743 visitors)		Mwanza (704 visitors)		Arusha (859 visitors)		Mbeya (395 visitors)	
Origin	*Visitors*	*Origin*	*Visitors*	*Origin*	*Visitors*	*Origin*	*Visitors*	*Origin*	*Visitors*
Arusha	9.7%	Dar Es Sa.	53.3%	Dar Es Sa.	32.4%	Dar Es Sa.	39.5%	Dar Es Sa.	38.2%
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%

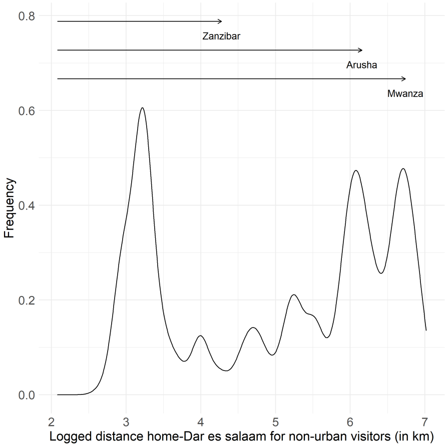
Tanzania.

Distances travelled by visitors to Lagos



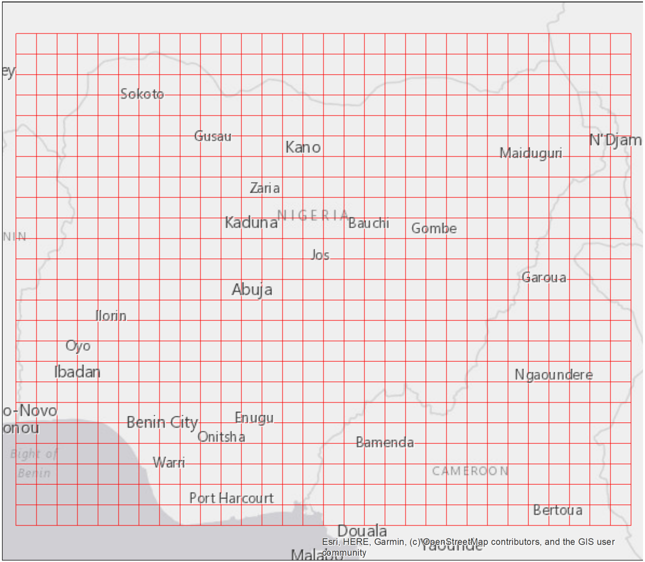
Distances travelled by visitors to Dar Es Salaam





Virtual regions - Nigeria

Return



References

Ahlfeldt, G. M., S. J. Redding, D. M. Sturm, and N. Wolf (2015): "The economics of density: Evidence from the Berlin Wall," *Econometrica*, 83, 2127–2189.

Aker, J. C. (2010): "Information from Markets Near and Far: Mobile Phones and Agricultural Markets in Niger," *American Economic Journal: Applied Economics*, 2, 46–59.

Akram, A. A., S. Chowdhury, and A. M. Mobarak (2017): "Effects of Emigration on Rural Labor Markets," Working Paper 23929, National Bureau of Economic Research.

Allen, T. and C. Arkolakis (2014): "Trade and the Topography of the Spatial Economy," *Quarterly Journal of Economics*, 129, 1085–1140.

Arkolakis, C., A. Costinot, and A. Rodríguez-Clare (2012): "New Trade Models, Same Old Gains?" *American Economic Review*, 102, 94–130.

Athey, S., B. A. Ferguson, M. Gentzkow, and T. Schmidt (2020): "Experienced Segregation," Working Paper 27572, National Bureau of Economic Research.

References (cont.)

Atkin, D., K. Chen, and A. Popov (2020): "The Returns to Serendipity: Knowledge Spillovers in Silicon Valley," Unpublished working paper.

Atkin, D. and D. Donaldson (2015): "Who's Getting Globalized? The Size and Implications of Intra-national Trade Costs," Working Paper 21439, National Bureau of Economic Research.

Baseler, T. (2019): "Hidden Income and the Perceived Returns to Migration: Experimental Evidence from Kenya," Unpublished Working Paper, University of Rochester.

Blumenstock, J. E. (2012): "Inferring Patterns of Internal Migration from Mobile Phone Call Records: Evidence from Rwanda," *Information Technology for Development*, 18, 107–125.

References (cont.)

Bryan, G., S. Chowdhury, and A. M. Mobarak (2014): “Underinvestment in a Profitable Technology: The Case of Seasonal Migration in Bangladesh,” *Econometrica*, 82, 1671–1748.

Bryan, G. and M. Morten (2019): “The Aggregate Productivity Effects of Internal Migration: Evidence from Indonesia,” *Journal of Political Economy*, 127, 2229–2268.

Chen, M. K. and R. Rohla (2018): “The Effect of Partisanship and Political Advertising on Close Family Ties,” *Science*, 360, 1020–1024.

Costinot, A. and D. Donaldson (2016): “How Large Are the Gains from Economic Integration? Theory and Evidence from U.S. Agriculture, 1880-1997,” Working Paper 22946, National Bureau of Economic Research.

Couture, V., J. I. Dingel, A. E. Green, J. Handbury, and K. R. Williams (2020): “Measuring Movement and Social Contact with Smartphone Data: A Real-Time Application to COVID-19,” Working Paper 27560, National Bureau of Economic Research.

References (cont.)

Dingel, J. I. and F. Tintelnot (2021): "Spatial Economics for Granular Settings," .

Donaldson, D. (2018): "Railroads of the Raj: Estimating the Impact of Transportation Infrastructure," *American Economic Review*, 108, 899–934.

Donaldson, D. and R. Hornbeck (2016): "Railroads and American Economic Growth: A "Market Access" Approach," *Quarterly Journal of Economics*, 131, 799–858.

Giannone, E., Q. Li, N. Paixao, and X. Pang (2020): "Unpacking Moving," Unpublished Manuscript.

Gollin, D., M. Kirchberger, and D. Lagakos (2020): "Do Urban Wage Premia Reflect Lower Amenities? Evidence from Africa," Forthcoming, *Journal of Urban Economics*.

Gollin, D., D. Lagakos, and M. E. Waugh (2014): "The Agricultural Productivity Gap," *Quarterly Journal of Economics*, 129, 939–993.

References (cont.)

Hamory, J., M. Kleemans, N. Y. Li, and E. Miguel (2020): "Reevaluating Agricultural Productivity Gaps with Longitudinal Microdata," *Journal of the European Economic Association*, 19, 1522–1555.

Jensen, R. (2007): "The Digital Provide: Information (Technology), Market Performance, and Welfare in the South Indian Fisheries Sector," *The Quarterly Journal of Economics*, 122, 879–924.

Kreindler, G. E. and Y. Miyauchi (2021): "Measuring Commuting and Economic Activity inside Cities with Cell Phone Records," Unpublished Manuscript.

Michalopoulos, S. and E. Papaioannou (2013): "Pre-colonial Ethnic Institutions and Contemporary African Development," *Econometrica*, 81, 113–152.

Miyauchi, Y., K. Nakajima, and S. Redding (2021): "Consumption Access and Agglomeration: Evidence from Smartphone Data," Unpublished Manuscript.

References (cont.)

Mongey, S., L. Pilossoph, and A. Weinberg (2020): "Which Workers Bear the Burden of Social Distancing Policies?" Working Paper 27085, National Bureau of Economic Research.

Monte, F., S. J. Redding, and E. Rossi-Hansberg (2018): "Commuting, Migration, and Local Employment Elasticities," *American Economic Review*, 108, 3855–90.

Owens, Raymond, I., E. Rossi-Hansberg, and P.-D. Sarte (2020): "Rethinking Detroit," *American Economic Journal: Economic Policy*, 12, 258–305.

Young, A. (2013): "Inequality, the Urban-Rural Gap, and Migration," *Quarterly Journal of Economics*, 128, 1727–1785.