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Mobile Phones and HIV Testing:

Multi-country Evidence from Sub-Saharan Africa

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Abstract

This study investigates the role of mobile phone connectivity on HIV testing in sub-Saharan Africa. We make use of the novel and comprehensive OpencellID cell tower database, and DHS geocoded information for over 400,000 women in 28 Sub-Saharan African countries. We examine whether women's community distance from the closest cell-tower influences knowledge about HIV testing facilities and the likelihood of ever been tested for HIV. After finding a negative and significant impact of distance on our main outcomes, we investigate the mechanisms through which such effects might occur. Our analysis shows that proximity to a cell tower increases HIV-related knowledge as well as reproductive health knowledge. Similar results are observed when the analysis is performed at community level. Results suggest that the effect of mobile phone connectivity is channelled through increased knowledge of HIV, STIs, and modern contraceptive methods. Further analysis shows that cell phone ownership has an even larger impact on HIV testing and knowledge. This paper adds to recent literature on the impact of mobile-based HIV prevention schemes by showing through large-scale analysis that better mobile network access is a powerful tool to spread reproductive health knowledge and increase HIV awareness.

Keywords

Mobile technology; public health; HIV; reproductive health

JEL

D83; I15; I18; O33

1. Introduction

Sub-Saharan Africa carries a disproportionate burden of HIV infections and AIDS related diseases. In 2016, of the 6000 new HIV infections happening globally every day, two out of three occurred in Sub-Saharan Africa (Kharsany and Karim, 2016). Global AIDS-related deaths have sharply decreased in the past decade, with sub-Saharan African countries leading this downward trend (UNAIDS, 2019), largely due to the increased access to anti-retroviral drugs. AIDS-related mortality has decreased by approximately 40% since 2010, and by 60% since it reached its peak in 2004 (UNAIDS, 2019). However, the number of new infections has not decreased at the same pace. Although the number of new HIV infections decreased by approximately 23% worldwide since 2010, with southern and eastern Africa showing the largest reduction, in 2019 there were over 1.7 million new infections, of which 1.4 million happened in Sub-Saharan Africa (and 59% of whom are women) (UNAIDS, 2019). More importantly, not every person living with HIV is aware of her condition (UNAIDS, 2018). Estimates for people aware of their condition in Sub-Saharan African countries range between 45% (Sweat and Fonner, 2016) and 65% (UNAIDS, 2018), hence, the numbers of infected individuals are potentially being underestimated by the hundreds of thousands. In order to increase the capacity of governments to correctly identify HIV-infected individuals and therefore reduce the spreading of the virus, standard HIV-testing facilities and awareness raising campaigns are being paired with alternative methods such as community-based testing, self-test kits, and point-of-care testing for early infants (UNAIDS, 2018). Major barriers to testing (e.g. stigma, inaccessibility of services, and low awareness) are being gradually overcome thanks to these new techniques which are currently being rolled-out in numerous Sub-Saharan countries (Jani et al., 2018; Sweat and Fonner, 2016; UNAIDS, 2018). Expanding HIV-related knowledge and introducing optimised HIV-testing techniques such as community-based testing and self-testing can potentially increase the returns from national anti-HIV programs (Swann, 2018).

Sub-Saharan Africa has proven to be a technological hothouse when it comes to the expansion of mobile phone coverage and use. The rapid increase in mobile subscribers' numbers and the expansion of network penetration has resulted in SSA becoming the world's fastest-growing mobile region.[1] Mobile phones, facilitate individuals' access to information from sources that would otherwise be unreachable or costly and enable near-instant communication through voice and text (or video, in the case of smartphones). Mobile phone penetration had a pivotal role in the region, influencing economic growth human development (Asongu et al., 2016; Lee et al., 2012). It has been argued that the "communication" component of mobile phones holds the most potential of supporting economic development, by creating knowledge-sharing

[1] Data from GSMA Intelligence. Accessed via https://www.gsma.com/ [Accessed 4 October 2019]

networks (Aker and Mbiti, 2010; Donner, 2006; Nakato et al., 2016). Recently, researchers have been investigating the role of mobile phones in public health and found them to be powerful awareness raising tools and facilitators of individuals' communication with health workers and other patients (Anstey Watkins et al., 2018; Kaplan, 2006). For mobile phone users, new information is, therefore, acquired mostly through communication with other individuals. However, mobile phones can also facilitate access to institutional resources (e.g. by receiving informative text messages from a health clinic, listening to radio, or, for those with access to smartphone, surfing the internet). Evidence from rural Indonesia has shown that midwives' use of mobile phones increased access to institutional resources and, consequently, fostered better reproductive health knowledge. Further, access to peer resources was associated with higher self-efficacy, which was as well positively associated with health knowledge (Lee et al., 2011). Phones have also been used in recent years as a new way of reaching HIV-infected and at-risk individuals with awareness raising campaigns.[2]

Some studies have focused on investigating mobile-based awareness-raising messaging and adherence to HIV/AIDS treatment programmes through randomized control trials (Amankwaa et al., 2018; Gross et al., 2019; Lester et al., 2010). Lester et al. (2010), in a seminal study on this topic, examined the association between higher adherence to antiretroviral treatment (ART) and SMS-based support in Kenya. More recent studies have questioned the role of SMS-based support as a "silver bullet" in resource-limited settings, especially after second-line ART failure, although it still remains a valuable tool for promoting higher participation in anti-HIV/AIDS programmes in general (Gross et al., 2019). A study on the role of mobile apps for newly diagnosed HIV-positive patients found that young individuals in particular are more responsive to mobile-based treatment adherence campaigns (Venter et al., 2019). However, the impact of mobile technology on HIV, and HIV-testing knowledge and uptake might go way beyond the effectiveness of SMS-based or app-based support. The lack of literature on the topic makes it difficult to formulate hypotheses on the role played by cellular phones, although it has been shown that innovative mobile-based awareness-raising campaigns at community- and individual-level represent an economically sensible alternative to traditional awareness raising campaigns (UNAIDS, 2018). Moreover, mobile technology-enabled networks facilitate peer-to-peer communication, which has been proven to increase HIV knowledge and treatment adherence, while reducing HIV risk (Kaponda et al., 2009; Mbeba et al., 2011). Finally, mobile devices may accord privacy in communication, which could facilitate the discussion of a topic such as HIV prevention which is still stigmatized. Considering the high number of new infections that happen every year in Sub-Saharan African countries, and the fact that a large portion of people leaving with HIV

[2] See Project Masiluleke in South Africa (https://www.innovations.harvard.edu/project-masiluleke) and Text to Change in Uganda (http://images.aarogya.com/aids/pdf/unandzain.pdf).

are still unaware of their condition, it is crucial to better understand if and how mobile technology can support HIV prevention and testing. Although there is an emerging body of evidence linking mobile phones with health promotion and awareness, to our knowledge, evidence on the role played by mobile phone ownership or connectivity on HIV-testing knowledge and attitudes is lacking. Our study seeks to address this knowledge gap.

Our study examines the role mobile connectivity can play in promoting HIV testing through multi-country analysis in Sub-Sahara Africa. We focus on mobile connectivity instead of mobile ownership to account for the fact that phone sharing is very common in Sub-Saharan African countries (Aker and Mbiti, 2010; Kaplan, 2006). Our study is, to our knowledge, the first of its kind to establish a connection between widespread access to mobile phone network and knowledge of HIV testing facilities and ultimately HIV testing uptake. We utilize recent data on cell-tower locations and data on women's HIV testing and knowledge in 28 sub-Saharan African countries. In our paper, we also explore the mechanisms through which mobile phone connectivity affects HIV testing knowledge and uptake. We test if mobile connectivity has a direct effect on levels of HIV knowledge, and whether it influences overall knowledge about reproductive health (i.e. knowledge about other sexually transmissible diseases (STIs) and about contraceptive methods). We find that indeed mobile connectivity influences general knowledge about HIV and reproductive health.

With our research, we establish a causal link between mobile network connectivity and HIV testing knowledge and practices using individual-level data from 28 African countries and we shed a light on potential mechanisms for these results.

2. Data and Methodology

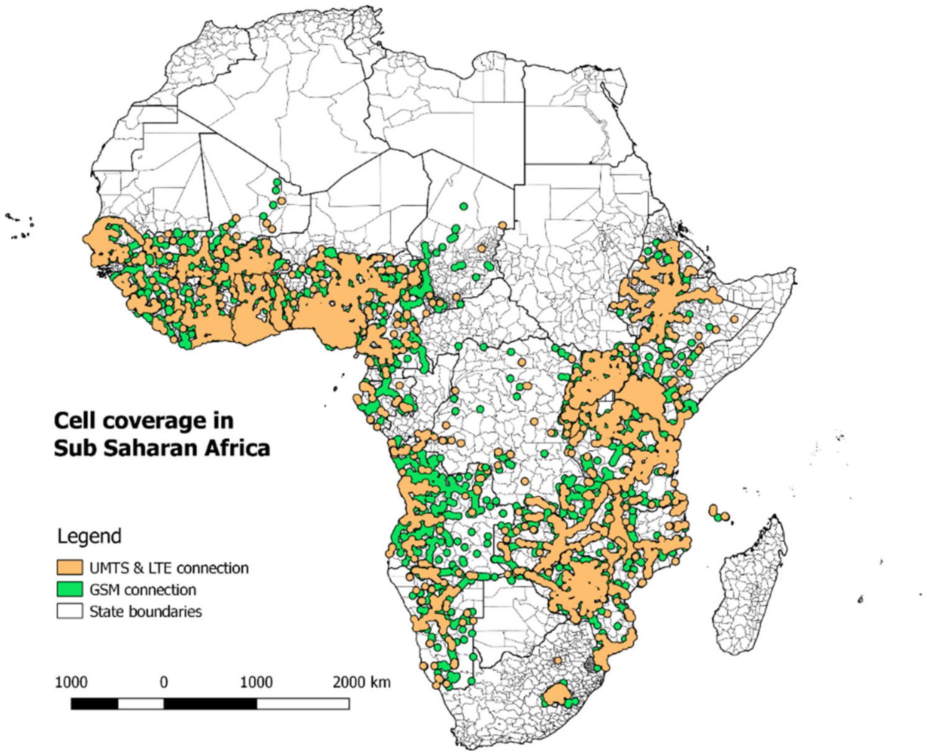
Several data sources have been used to build the dataset used in our analysis.

2.1 Cell connectivity information

Information on cell towers location is derived from OpenCellid dataset. OpenCellid is the largest, daily updated, publicly available database of cell towers. Linear distance between household clusters and the nearest cell tower is calculated in kilometres and serves as a proxy for cell connectivity and signal strength and as our main explanatory variable. OpenCellid datasets reports location, operator, and type of signal for over 40 million towers world-wide.[3] Database entries for the African continent start in 2008. Unfortunately, the date of entry does not unequivocally represent the date of construction of a tower. Because of this, many countries show total absence of cell towers before year 2013, a clearly misleading representation. This is why we calculate distance from nearest cell tower including all cell towers in each country regardless of the date in which they have been added to OpenCellid dataset, under the assumption that towers have been built before their date of entry in the dataset. Since this is a very strong assumption, we test its robustness by running our analysis again, this time limiting the number of cell towers per country to those added to OpenCellid before the year in which individual survey data was collected. As we will show in a later section, results remain consistent even when the number of cell towers (and, therefore, of countries) is reduced. One more issue with OpenCellid data is that tower location is not verified after it is inserted in the database, which might result in a discrepancy between reported and actual location. However, one study comparing independently collected data on cell towers coordinates and OpenCellid information on the same towers shows that the localization error estimated from OpenCellid data agrees well with the experimental error distribution (Ulm et al., 2015). As an extra precaution, however, we consider only towers which coordinates' maximum error (reported by OpenCellid) lies within one square kilometre.

[3] Additional information at https://opencellid.org/ [Accessed 20 June 2019]

Figure 1. Cell phone coverage in Sub Saharan African countries included in our study



Note: Coverage is calculated as a buffer of 35 km around each cell tower for the 28 countries included in the dataset.
Source: OpenCellid and Authors' elaboration on QGIS.

2.2 Individual and community level data

Individual data is obtained from the Demographic and Health Survey (DHS) Program from 28 African countries[4]. DHS provides cross-sectional information on women and household access to health and health status together with demographic and labour statistics. Besides women's demographic and employment information, we take from DHS our main dependent variables: a dummy for knowledge of facilities where women could be tested for HIV and a dummy for ever been tested for HIV. We use additional variables on knowledge of reproductive health to test our hypothesis on possible impact pathways. Individual-level characteristics are added to the analysis to serve as confounders (full list present in Table 1). For each country, DHS surveys included in this study have been conducted between 2010 and 2016. The final sample comprises 407,000 women grouped in 19,603 clusters, of who approximately 350,000 are included in the main analysis.

[4] Namely: Angola, Benin, Burkina Faso, Burundi, Cameroon, Chad, Comoros, Ivory Coast, Democratic Republic of Congo, Ethiopia, Gabon, Ghana, Guinea, Kenya, Lesotho, Liberia, Malawi, Mali, Mozambique, Namibia, Nigeria, Rwanda, Senegal, Sierra Leone, Tanzania, Togo, Uganda, Zambia, and Zimbabwe.

Geospatial information of households in DHS datasets is clustered to guarantee respondents' privacy. For these clusters, DHS provides spatial information retrieved from secondary sources within a buffer of 10km for rural communities, and 2km for urban ones. We include in the analysis community-level (i.e. cluster-level) information on average travel time to the nearest settlement and population density, and use terrain slope as to build an instrumental variable for distance to cell-tower (see Methodology section). We also use household-level information on access to electricity to generate a community-level electrification rate indicator. This indicator is simply the percentage of households that have access to electricity within a cluster.

More isolated communities could have lower level of HIV testing regardless of their use of mobile phones (Susan et al., 2002). To better measure community isolation, and to control for it in the analysis, we calculate the linear distance of each cluster from the nearest primary or secondary road. Information on roads in the African continent is obtained through the Digital Chart of the World (DCW) vector base map. Although last updated in 1998, DCW remains a very detailed map of Africa's road system.[5] Distance to road is used, together with distance to nearest settlement and community-level electrification rate, as a proxy for community isolation.

2.3 Sample characteristics

Table 1 reports descriptive statistics from the sample. The average community distance from cell tower is 13 km. Average woman's age is 28 years old, with 5 years of education. About 28% of interviewed women live in a female-headed household, 72% are exposed to at least one type of media (i.e. radio, television, newspaper), 59% are currently working, and 35% live in an urban area. Half of the women in the sample report to have visited a health facility in the last 12 months, although distance from said facility is considered a problem by 41% of them. Over 70% of sampled women have given birth to at least one child. The average population density in the communities was 1290 people per square kilometre (this is considering a buffer of 2 km^2 for urban areas and 10 km^2 for rural areas, 2015 population data). Distance from closest road is 6 km on average and average travel time to closest settlement is about 77 minutes.

[5] Authors have considered using more recent street maps for the analysis, however they ultimately decided to make use of DCW due to its reliability. NASA gROADS (http://tiny.cc/5grl8y) data set, although more recent, does not provide users the chance to adequately distinguish types of roads in the African continent. However, for those countries in which comparison between DCW and gROADS was possible (e.g. Zimbabwe), the authors verified that primary roads reported in the latter were also present in the former (graphical representation in Figure A1 in appendix).

Table 1. Descriptive statistics of the sample

	Values	N
Variables		
Distance from nearest cell tower (Km)	13.06	517,290
Woman age	28.46	517,290
Woman years of education	5.18	517,110
Female-headed households (%)	28.34	517,290
Woman exposed to any type of media (%)	72.05	517,257
Woman currently working (%)	58.6	500,001
Ever had a child (%)	72.66	517,290
Number of lifetime sex partners	2.16	407,542
Woman in union (%)	52.34	517,284
Living in urban area (%)	35.4%	517,290
Population density in community (2015) ǂ	1290.64	516,411
Wealth Index quintiles		517,290
Poorest (%)	19.42	
Poorer (%)	18.56	
Middle (%)	19.01	
Richer (%)	19.96	
Richest (%)	23.05	
Average travel time to closest settlement (min) ǂ	77.48	516,411
Distance from closest road (km) ǂ	6.12	517,290
Visited a health facility in the past 12 months (%)	50.31	499,767
Distance to health facility is considered a problem (%)	41.04	458,976
Electrification (cluster-level) ǂ (%)	31.81	517,290

Note: ǂ Values are reported at community-level.

2.4 Methodology

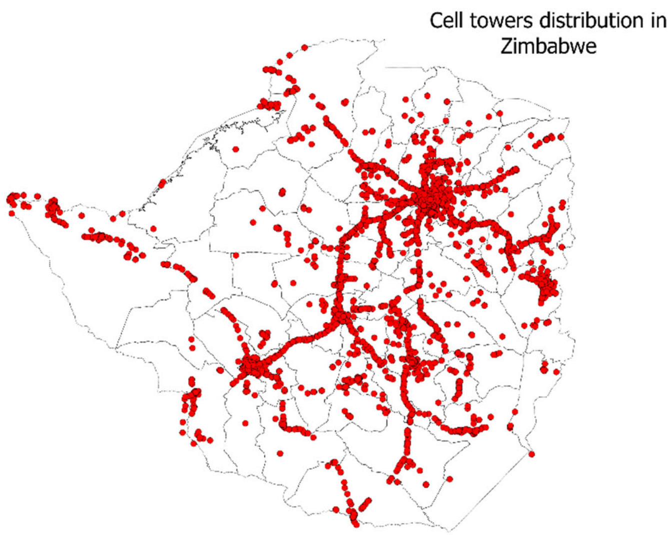
Using probit and OLS regressions, we design a naïve model at first.

$$(1) \quad \boldsymbol{HIVt_i} = \beta_0 + \boldsymbol{\beta_1 D_i} + \beta_2 Z_i + \beta_3 C + u_i$$

Where $\boldsymbol{HIVt_i}$ is a dummy variable indicating if either woman knows where HIV testing facility is or has ever been tested for HIV. β_1 is a vector of our main explanatory variable, or distance to nearest cell tower $\boldsymbol{D}$ for woman *i*. and β_2 is a vector of covariates Z for woman *i*. A full list of covariates is present in Table 1. Finally, β_3 is a vector of community-level characteristics and country-fixed effects C. Location information, from which distance from cell towers was calculated, could only be obtained at community level. Community clusters contain between 1 and 92 households each. In order to address intra-cluster correlation, we cluster standard errors at community level in each regression. De-normalised individual sample weights are included.

As Klonner and Nolen (2008) observe, cell towers' distribution is not exogenous over a country's territory. It might follow an established path (i.e. roads) and be affected by power supply and other infrastructural needs. Moreover, network providers might consider certain areas not profitable enough to repay them of the investment of building a cell tower. Figure 2 shows this endogenous distribution in the context of Zimbabwe.

Figure 2. Cell towers distribution in Zimbabwe



Source: OpenCellid and Authors' elaboration on QGIS.

In order to deal with endogeneity, we look for an instrument that could influence towers' location but is uncorrelated with our dependent variable error terms. Following Dinkelman et al. (2011), we utilize average community land gradient as an instrumental variable. Terrain slope raises the costs of electric line routing and antennas' building (Batzilis et al., 2016; Klonner and Nolen, 2008), acting as a disincentive for mobile network companies to build cell towers in areas with higher land gradient. On the contrary, more competitive markets in Sub-Saharan Africa can lead to a considerable increase in cell-phone area coverage (Buys et al., 2009). Proxies for market competition have been used in the past in tandem with terrain roughness to explain cell towers' positioning (Pierskalla and Hollenbach, 2013). We build our instrumental variable interacting land gradient and number of phone service providers in each country following Berman et al. (Bernam et al., 2017).[6] We also add to the list of covariates information on household electrification to

[6] In their study, Berman et al. (2017) divide the African continent into grid cells and then estimate an interaction term between time variant cell characteristics and time invariant yearly prices of minerals. In our multi cross-sectional dataset, number of mobile network providers is constant for each cluster in the same country, while land gradient varies by cluster. We create our new instrument by interacting country-variant cluster characteristics with country-invariant mobile providers' information.

control for effects related only to access to electricity and not to access to cell-phone network. Our second model, a two-stage regression is, therefore:

$$(2) \quad D_i = \pi_0 + \boldsymbol{\pi_1 Slope * Network\ Providers_i} + \pi_2 Z_i + \pi_3 Elec_i + \pi_4 C + \varepsilon_i$$

$$(3) \quad HIVt_i = \beta_0 + \boldsymbol{\beta_1 \widehat{D}_i} + \beta_2 Z_i + \beta_3 Elec_i + \beta_4 C + u_i$$

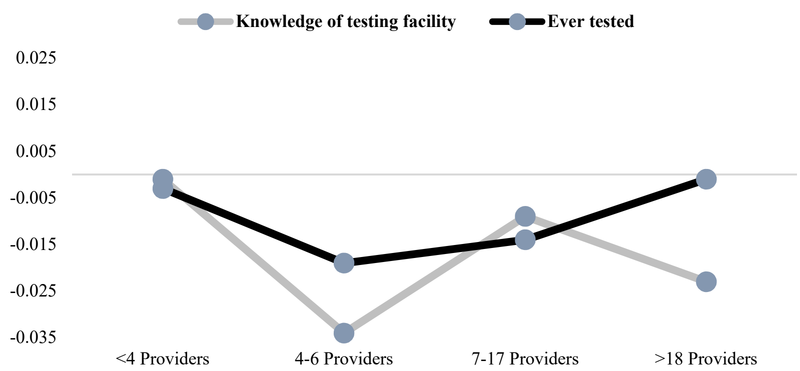
In equation (2), the measure of land gradient *Slope* multiplied by number of *Network Providers* is the exogenous regressors. Electrification *Elec,* ranges between 0 and 1 and represents the percentage of households that have access to electricity in the community. Equation (3) is similar to equation (1), although here distance *D* has been instrumented by *Slope* * *Network Providers.* Land gradient is calculated by DHS based on United States Geological Survey Global 30 Arc-Second elevation model (GTOPO30) (Mayala et al., 2018), and we consider it invariant through time (or, at least, within the same geological era). This model is estimated via two stage least squares (2SLS).

The identification assumption is that conditional on individual and community characteristics, our instrumental variable does not directly affect knowledge of facilities or decision to test for HIV, and only does so through the distance from the nearest cell tower. To check our assumption, we perform several placebo tests. Mobile phone signal spreads unevenly in the area surrounding cell towers due to a variety of factors. Given the geographical extent of our analysis, we are not able to calculate network coverage exactly. However, technical limitations of standard GSM towers set their maximum signal range to a 35 Km radius,[7] therefore communities located more than 35 Km away from the closest cell tower (9.2% of the sample) can be considered not covered by mobile network. Using this cut-off point, which theoretically divides the sample into connected and non-connected communities, we examine whether our instrumental variable only affects outcomes when communities are covered by a mobile network. Results (Table A1 in appendix) demonstrate that our instrument is only significantly correlated with outcomes in network-covered communities. Our second test investigates whether the instrumental variable or instrumented distance from cell tower are in any way correlated to proxies of communities' remoteness, a factor that could in turn affect knowledge of HIV testing place and test uptake. We select three different

[7] The 35 km maximum range is the one imposed by technical limitations on GSM towers; however, it does not take into account barriers to signal that might be present within the radius of the cell tower. This is why the dummy build with this cut-off point is used only as an addition to our main explanatory variable (i.e. distance from cell tower). See https://www.3gpp.org/technologies for additional information on timing advance and TDMA technology, and the way they influence GSM towers range. For the sake of standardisation, we assume towers do not possess features to extend their range.

proxies: distance from nearest road (excluding trails and unpaved roads), exposure to any type of media as proxies for remoteness; and average population density in the community as a proxy for dispersion. Both the instrument and the instrumented distance from nearest cell tower show no significant correlation with any of the proxies, supporting our initial assumption that longer distance from a cell tower does not necessary results from the remoteness of a community (Table A2 in appendix for full results). Lastly, we test the sensibility of our instrumental variable. Our results might be driven by countries where markets are more accessible for mobile phone providers. Competition might decrease mobile technology consumption costs and facilitate knowledge sharing. We run our models once again, this time dividing the sample based on the number of mobile network providers in country of residence. Results remain consistently negative throughout the models (see Figure 3), confirming that the relationship between distance from cell towers and our outcomes does not change based on mobile network market characteristics.

Figure 3. Placebo test



Note: Number of providers correspond, from left to right, to the 50th percentile of the sample, the 75th percentile, the 90th percentile, and the 100th percentile.

3. Results

3.1 Mobile phone connectivity and knowledge of HIV-testing facilities

Our analysis examines whether better mobile connectivity is correlated with women's knowledge of which facilities offer HIV testing. Results from are presented in Table 2. Probit regression results show a strong negative correlation ($p<0.01$) between distance from cell tower and knowledge of an HIV testing facility. Results from the 2SLS estimation are consistent with our Probit results. For each unit increase in distance to the nearest cell tower, the probability of knowing where one can be tested for HIV is 0.7 percentage points lower (0.2 p.p. for Probit analysis). Due to the nature of the variables, interpreting the magnitude of the impact is not straightforward. To facilitate the process, we report (in Figure A1 in Appendix) a graphical illustration of our IV model's predicted share of women knowledgeable about testing facilities by deciles of distance to nearest cell tower. As it can be noticed, 90% or more of women living in the top deciles are knowledgeable about HIV testing facilities locations. The share starts dropping starting from the 4th decile, going below 80% in the bottom two deciles (i.e. with a distance >15km), and reaching 40% in the lowest decile (i.e. distance >33km).

The clustering of households' coordinates allows us to calculate distance from nearest cell-tower at community-level only. To check whether this might affect our results, we perform community-level analysis by averaging women characteristics at community level. The impact of distance to cell towers remains highly significant (p<01). The magnitude of the impact also remains consistent, with a 0.8 p.p. decrease in the probability of knowing testing facility (0.1 p.p. for Probit). Underidentification and weak-instrument (Kleibergen-Paap Wald *F statistic*) tests for all IV regressions show that our instrument is relevant and reasonably strong.

Table 2. Impact of phone connectivity on knowledge of HIV testing facilities.

	Knowledge of HIV testing facility			
	Individual-level		*Community-level*	
	Probit	IV (2SLS)	Probit	IV (2SLS)
Distance from nearest cell (km)	-0.002***	-0.007***	-0.001***	-0.008***
	[<0.001]	[0.002]	[<0.001]	[0.002]
Individual-level characteristic	Yes	Yes	/	/
Community-level characteristics	Yes	Yes	Yes	Yes
Country-year-fixed effects	Yes	Yes	Yes	Yes
Constant	-0.471***	0.509***	0.305***	0.399***
	[0.058]	[0.025]	[0.021]	[0.038]
Observations	351,613	351,488	18,441	18,431
R-squared	0.304	0.184	0.682	0.402
Underidentification (p-value)		<0.001		<0.001

Kleibergen-Paap rk Wald F statistic	31.75	28.74

Note: Cluster-robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1. Underidentification and weak-instrument (Kleibergen-Paap rk Wald F statistic) tests reported at bottom of the table for IV regressions.

3.2 From knowledge to action – mobile connectivity and HIV testing

We have identified a significantly positive effect of proximity to cell towers on knowledge of HIV testing facilities. It is important to also determine whether knowledge acquired through mobile phones ultimately translates into a behavioural change. We therefore investigate whether women living closer to cell towers not only acquire knowledge on where HIV testing can be conducted, but also get tested.

Newly acquired knowledge affects individuals' health behaviour through what has been called the knowledge-attitude-behaviour continuum (Bettinghaus, 1986). Studies show that when agents act on the way information is processed by individuals, one could expect desired behavioural changes to ultimately happen (Bettinghaus, 1986). Activities aimed at increasing knowledge about HIV transmission among pregnant women have been shown to change attitudes and behaviour towards HIV testing (Mahmoud et al., 2007; Rahbar et al., 2007). At the same time, access to peer networks can influence individuals' attitudes towards HIV testing. Studies in the past have found that peer-based interventions can increase HIV knowledge and adherence to AIDS treatment (Broadhead et al., 2002; Pearlman et al., 2002).

We examine whether better mobile connectivity has a direct effect on women's probability of ever been tested for HIV. Our analysis is operationalised in a variation of equations (1) and (3) where having tested for HIV is now the dependent variable and the explanatory variable is distance from nearest cell tower. Table 3 reports the results of our analysis. We find that a unit increase in distance from cell towers significantly reduces women's probability of ever been tested for HIV by 0.5 p.p. in the individual-level model and by 0.4 p.p. in the community-level model. Again, we present in Figure A1 in Appendix a graphical illustration of our IV model's predicted share of women tested by deciles of distance to nearest cell tower. Similarly to knowledge of testing facilities, share of tested women is constant at around 70% in the top four deciles. At the start of the bottom two deciles, share of tested women is already below 60% and it reaches approximately 10% in the lowest decile.

Table 3. Impact of phone connectivity on HIV testing uptake

	Ever tested for HIV			
	Individual-level		*Community-level*	
	Probit	IV	Probit	IV
Distance from nearest cell (km)	-0.005***	-0.005**	-0.001***	-0.004***
	[0.001]	[0.002]	[<0.001]	[0.002]
Individual-level characteristic	Yes	Yes	/	/
Community-level characteristics	Yes	Yes	Yes	Yes
Country-year-fixed effects	Yes	Yes	Yes	Yes
Constant	-1.337***	0.153***	-0.035*	0.070***
	[0.050]	[0.024]	[0.019]	[0.026]
Observations	365,108	364,982	18,480	18,474
R-squared	0.322	0.343	0.791	0.747
Underidentification (p-value)		<0.001		<0.001
Kleibergen-Paap rk Wald F statistic		33.83		28.52

Note: Cluster-robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1. Underidentification and weak-instrument (Kleibergen-Paap rk Wald F statistic) tests reported at bottom of the table for IV regressions

3.3 Robustness checks

3.3.1 Reduced number of cell towers

As a first robustness check, we examine whether the results remain significant when distance from nearest cell tower is calculated using only the cell towers inserted in the OpenCellid dataset starting from the year in which each DHS survey was collected. Several countries are dropped from this analysis due to the complete absence of data on cell towers from the year of the survey onwards, namely: Cameroon, Comoros, Gabon, Guinea, Mozambique, and Senegal. However, figures presented in Table 3 show that results remain significant and consistent with previous findings.

Table 4. Impact of phone connectivity on HIV testing (restricted cell towers' sample)

	Knowledge of HIV testing facility				**Ever tested for HIV**			
	Individual-level		*Community-level*		*Individual-level*		*Community-level*	
	OLS	IV	OLS	IV	OLS	IV	OLS	IV
Distance from nearest cell (km)	-<0.001	-0.003***	-<0.001***	-0.002***	-<0.001***	-0.002**	-<0.001***	-0.001**
	[<0.001]	[0.001]	[<0.001]	[<0.001]	[<0.001]	[0.001]	[<0.001]	[<0.001]
Individual-level characteristic	Yes	Yes	/	/	Yes	Yes	/	/
Community-level characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-0.469***	0.479***	0.336***	0.453***	-1.465***	0.123***	-0.040*	0.052*
	[0.065]	[0.024]	[0.025]	[0.042]	[0.059]	[0.021]	[0.022]	[0.028]
Observations	247,902	247,777	12,867	12,864	261,802	261,676	12,910	12,907
(pseudo) R-squared	0.308	0.094	0.675	0.261	0.351	0.314	0.812	0.711
Underidentification (p-value)		<0.001		<0.001		<0.001		<0.001
Kleibergen-Paap rk Wald F statistic		39.38		12.43		41.80		12.29

Note: Cluster-robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1. Underidentification and weak-instrument (Kleibergen-Paap rk Wald F statistic) tests reported at bottom of the table for IV regressions.

3.3.2 Impact on other health care seeking and utilization

One question that can arise when looking at our results is whether the impact of mobile connectivity on knowledge of HIV testing facilities and testing uptake is driven by a general impact of access to mobile phones on health seeking and utilization. For example, better connectivity may increase demand for health services from the population while at the same time reducing costs to access such services (e.g. increased knowledge and better networking may provide individuals with more options for obtaining health care). To test whether this is the case, we repeat our analysis and replace our outcomes of interest with dummy variables for having health insurance and having delivered one's last child in a safe structure.[8] The results, presented in Table A4 in appendix, are not statistically significant in any of our preferred models (i.e. 2SLS estimations). These results suggest that increased mobile connectivity does not have a general impact on healthcare seeking and utilization

3.3.3 Alternative instrumental variable

As we have shown in our methodology section, terrain roughness and market competition are often associated with infrastructural development. However, there are additional characteristics that influence cell tower positioning in developed and developing countries alike. As an additional robustness check, we test the validity of lightning intensity and cost of mobile phone usage as alternative instruments.

Frequent electrostatic discharges damage mobile phone infrastructures and negatively affect connectivity. Areas with high lightning intensity represent a risk for mobile phone provides since power surge protection for cell towers is costly and reduces profits from their investments. Being Africa the continent with the highest lightning intensity in the world, evidence has showed that 1 standard deviation increase in lightning intensity leads to a lower penetration rate of mobile phone technology of approximately 0.43 percentage points per year (Manacorda and Tesei, 2020). Mobile phone usage depends on a variety of factors, of which cost is surely one of the most important (World Bank, 2016). Higher costs might be driven by low competition and, at the same time, act as an incentive for new companies to provide network access to a larger share of the population.

[8] "Safe structure" is defined here as either a public or a private health center.

We interact average intensity of lightning strikes in a 10km radius around each DHS cluster with country-level monthly cost of running a mobile phone as a percentage of per-capita income.[9] A slight modification to equation (2) produces

$$(4) \quad D_i = \pi_0 + \boldsymbol{\pi_1 Flash\ intensity * Mobile\ cost_i} + \pi_2 Z_i + \pi_3 Elec_i + \pi_4 C + \varepsilon_i$$

Analysis conducted using the alternative instrumental variable produces results consistent with previous findings which remain statistically significant.[10]

3.4 Mobile phone ownership instead of connectivity

We have focused our analysis on the impact of mobile network connectivity on women's HIV and health knowledge and practices regardless of their ownership of a cellular phone. We did so because evidence has shown that mobile phone sharing is a common practice in Sub-Saharan Africa (Aker and Mbiti, 2010). It is the intention of the authors to argue for the potential of better phone connectivity regardless of increased ownership, and our results have supported our claims. However, it is logical to think that the easier the access to a mobile phone the more relevant its impact on our outcomes of interest should be, and ownership of a mobile phone grants a much higher exposure to mobile technology than borrowing. DHS surveys have recently started including questions on mobile phone ownership in their questionnaires as part of individuals' and households' assets. This provides us with a reduced sample of women that reported whether or not they own a cellular phone.[11]

To analyse the role of phone ownership, we make use of Probit models as in equation (1), while we specify a new Probit-2SLS model for the instrumental variable analysis (in this case, we use the same instrument from our main analysis, the interaction between land gradient and number of network providers). Given the binary nature of the phone ownership variable, a binary probit model for the first stage regression is more adequate. We present results in Table 5. According to our IV estimation, phone ownership increases the chance of knowing a facility that conducts HIV tests by

[9] Lighting strikes intensity data is publicly available at https://ghrc.nsstc.nasa.gov/lightning/ [Accessed 04 December 2019]. The satellite data is collected by NASA's Global Hydrology Resource Center. We included in our analysis yearly average lighting strikes for countries included in the analysis for 2010. Lightning strike incidence is proved to be stable through years, making the yearly average for 2010 a good proxy for the subsequent decade (Manacorda and Tesei, 2020). Information on monthly cost of running mobile phone by country is retrieved from 2015 ITU report on Measuring the Information Society, available at https://www.itu.int/en/ITU-D/Statistics/Documents/publications/misr2015/MISR2015-w5.pdf [Accessed 20 January 2020]

[10] Results are available upon request

[11] Information on phone ownership is present for Angola (2015), Burundi (2016), Ethiopia (2016), Malawi (2015), Tanzania (2015), Uganda (2016), and Zimbabwe (2015)

14 p.p., and it increases the chance of ever been tested for HIV by approximately 8 p.p. Considering the percentage of people knowledgeable about HIV testing place and ever tested for HIV who do not own a phone, our percentage points translate into a 16% higher chance of knowing a testing facility and a 13% higher chance of having tested for HIV for mobile phone owners.

Table 5. Phone ownership and HIV testing

	Knowledge of HIV testing facility		Ever tested for HIV	
	Probit	IV	Probit	IV
Mobile phone owner	0.253*** [0.028]	0.141*** [0.025]	0.238*** [0.040]	0.077*** [0.016]
Individual-level characteristic	Yes	Yes	Yes	Yes
Community-level characteristics	Yes	Yes	Yes	Yes
Country-year-fixed effect	Yes	Yes	Yes	Yes
Constant	-1.546*** [0.103]	0.187*** [0.015]	-0.567*** [0.148]	0.706*** [0.012]
Observations	81,048	81,048	76,241	76,241
(pseudo) R-squared	0.315	0.320	0.297	0.183

Note: Cluster-robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1.

3.5 Mechanisms for impact

Cell phone connectivity has been found to positively impact probability of knowing HIV testing facilities and of ever been tested for HIV. Through which mechanisms such impact is achieved is what we investigate in this section. To do so, we need to understand the barriers to HIV testing that mobile phone connectivity might help overcome. Studies have shown that stigma, both self- and social-, remains the most significant barrier to HIV testing in Sub-Saharan Africa (Ayieko et al., 2018; Mohlabane et al., 2016). Provision of HIV counselling for high-risk subjects has yielded good results among adolescents thanks to increased knowledge and awareness, although cultural change is hard to achieve (Chikwari et al., 2018). Physical barriers to HIV testing are also limiting the effectiveness of awareness raising programs. Distance from health facilities, inconvenient opening hours, and long waiting lines are among the reasons cited for low test uptake (Chikwari et al., 2018).

Mobile connectivity has been proven to be a powerful tool to spread information and increase social cohesion in the Global South (Ling and Horst, 2011). Mobile phones also facilitate knowledge diffusion which in turn reduces information asymmetry (Asongu et al., 2016; Asongu and Nwachukwu, 2016). We argue that, while better mobile phone connectivity might do little to reduce physical barriers to HIV testing, it can increase women’s knowledge of HIV related symptoms, can help fight HIV misconception, and foster reproductive health’s knowledge.

To test our hypotheses, we perform analysis on the role of distance from nearest cell tower on several intermediate outcomes. We use as dependent variables knowledge of HIV and sexually transmittable infections (STIs), and knowledge of modern contraceptive methods. HIV knowledge is measured as an index ranging from 0 to 1 measuring knowledge of HIV symptoms and of preventive measures (Wang et al., 2012).[12] Knowledge of STIs and modern contraceptive methods are dummies assigning value 1 to knowledgeable women. Results of the analysis are presented in Table 6.

Distance from cell towers appears to have a significantly negative impact on HIV- and STI-related knowledge. In the same way, it also reduces the chance that a woman would be knowledgeable about modern contraceptive methods. These results seem to confirm our hypothesis that better cellular connectivity facilitates acquisition of knowledge on reproductive health and sexually transmittable diseases. These findings are supported by previous evidence on the role played by mobile phones in knowledge-sharing and learning (Aker et al., 2012; Lee et al., 2011; Qureshi, 2013).

Table 6. Analysis of mechanisms of cell connectivity and HIV testing correlation

	Knowledge of HIV		**Knowledge of STIs**		**Knowledge of contraceptive method**	
	OLS	IV	Probit	IV	Probit	IV
Distance from nearest cell (km)	<-0.001**	-0.004***	-0.003***	-0.002***	-0.002***	-0.004***
	[<0.001]	[0.001]	[<0.001]	[0.001]	[<0.001]	[0.001]
Individual-level characteristic	Yes	Yes	Yes	Yes	Yes	Yes
Community-level characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Country-year-fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.577***	0.754***	-0.154**	0.740***	-0.622***	0.641***
	[0.012]	[0.017]	[0.075]	[0.016]	[0.067]	[0.018]
Observations	340,062	339,965	368,938	368,812	369,000	368,874
(pseudo) R-squared	0.222	0.114	0.258	0.0496	0.344	0.0789
Underidentification (p-value)		<0.001		<0.001		<0.001
Kleibergen-Paap rk Wald F statistic		31.20		33.63		33.63

Note: Cluster-robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1. Underidentification and weak-instrument (Kleibergen-Paap rk Wald F statistic) tests reported at bottom of the table for IV regressions.

[12] The index is a standardised principal component analysis build out of 6 different indicators of HIV misconception: 1) whether or not HIV is caused by witchcraft; 2) whether or not HIV is caused by mosquito bites; 3) whether or not having fewer sexual partners reduces the chance of contracting HIV; 4) whether or not using condoms reduces the chance of contracting HIV; 5) whether or not HIV can be transmitted through food; 6) whether or not healthy looking people might suffer from HIV. Indicator's recoding followed DHS guidelines retrievable at: https://dhsprogram.com/data/Guide-to-DHS Statistics/Comprehensive_Knowledge_about_HIV_Total_and_Youth.htm [Accessed 20 June 2019]

To complete our analysis on mechanisms, we test whether results remain consistent when considering mobile phone ownership instead of mobile connectivity. Findings are reported in Table 7. Our results show that phone ownership significantly increases knowledge about sexual transmittable infections and modern contraceptive methods, while it seems to have no statistically significant impact on general knowledge of HIV.

Recent evidence has shown that mobile phone ownership might have an impact on contraceptive use and knowledge about family planning (Jadhav and Weis, 2019), and facilitate the spread of reproductive, maternal, newborn and child health in vulnerable settings (Alami et al., 2019). At the same time, some research has argued that better outcomes for phone owners are mostly driven by their economic status (Nie et al., 2016). In our analysis we control for additional factors that could influence women's knowledge, such as media exposure, education, asset-based wealth, and place of residence, and the effect of mobile ownership remains statistically significant.

Table 7. Phone ownership and mechanisms

	Knowledge of HIV		**Knowledge of STIs**		**Knowledge of contraceptive method**	
	Probit	IV	Probit	IV	Probit	IV
Mobile phone owner	-0.098 [0.118]	0.005 [0.013]	0.258*** [0.050]	0.053*** [0.016]	0.193*** [0.051]	0.088*** [0.015]
Individual-level characteristic	Yes	Yes	Yes	Yes	Yes	Yes
Community-level characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Country-year-fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Constant	2.011*** [0.400]	0.781*** [0.008]	-0.409*** [0.124]	0.721*** [0.014]	-0.297** [0.132]	0.727*** [0.014]
Observations	66,344	66,344	81,048	81,048	81,048	81,048
Pseudo-R^2	0.224		0.323		0.478	
R-squared		0.239		0.174		0.235

Note: Cluster-robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1.

4. Discussion

This paper analyses the impact of cell phone connectivity on women HIV testing knowledge and behaviour in 28 Sub-Saharan African countries. We used distance from the nearest cell tower as a proxy for phone connectivity strength and quality and we estimated how increasing distance from said cell tower affects the probability of knowing where one can be tested for HIV and the probability of having taken such a test at least once in one's life. With this study, we attempt to expand on the work that has been done on a smaller scale on the role played by mobile technology on HIV awareness-raising and testing (Amankwaa et al., 2018; Gross et al., 2019).

Results show that mobile connectivity has a statistically significant and positive impact on the knowledge of HIV testing facilities and having been tested for HIV. We find evidence that the impact of mobile phone connectivity on HIV testing knowledge and behaviour might be driven by improved knowledge of HIV, STIs, and contraceptive methods. Moreover, we find that the positive effects of mobile technology are even greater when we consider phone ownership as the explanatory variable.

Our results are in agreement with previous evidence that shows the role that mobile technology can play in raising awareness about HIV and HIV testing (Venter et al., 2018). The study also fits well into the new body of literature investigating mHealth and the role it could play in developing countries. Promising evidence shows how informal mHealth and access to mobile phones among young Africans can help bridge healthcare gaps in countries like Ghana, Malawi, and South Africa (Cilliers et al., 2018; Hampshire et al., 2015). Not only mobile phones, but all digital technology has been found to be beneficial for treating and preventing mental disorders in low-income and middle-income countries (Naslund et al., 2017). Our results support the idea that stronger mobile connectivity can foster HIV testing practices in Sub-Saharan Africa.

Our study is not exempt from limitations. First, although we are able to establish a link between mobile connectivity and knowledge of HIV testing facilities and mobile connectivity and HIV testing uptake, due to data limitations we cannot dig deeper into the way mobile connectivity shapes women's attitudes toward testing through better knowledge, since no questions were asked to interviewed women about their opinion of HIV testing. Second, OpenCellid dataset is a relatively new dataset that might be lacking detail especially for remote areas. Missing information on the date in which cell towers are built also poses a limitation. We addressed both these issues by only including cell towers with the most reliable GPS coordinates and by performing robustness checks that aligned the building year of the cell towers with the year of the survey. When and if data will be available in the future, additional longitudinal analysis could be conducted to investigate the evolution of HIV testing behaviour through time for women with better mobile connectivity. A third limitation is represented by the clustering of individuals' position under one GPS coordinate representing the community. This clustering allows distance from cell tower to be calculated only at community-level. We show, however, that our results remain significant even if individual figures are averaged at cluster level and community-level analysis is performed.

Our study provides useful insights on the potential that new communication technologies represent to foster better reproductive health practices in Sub-Saharan Africa, and paves the way for future analysis on how mobile phones enhance knowledge-sharing around HIV/AIDS knowledge, behaviour and practices.

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6. Appendix

Figure A1. Predicted knowledge of testing facilities and testing attitude by deciles of distance to nearest cell tower

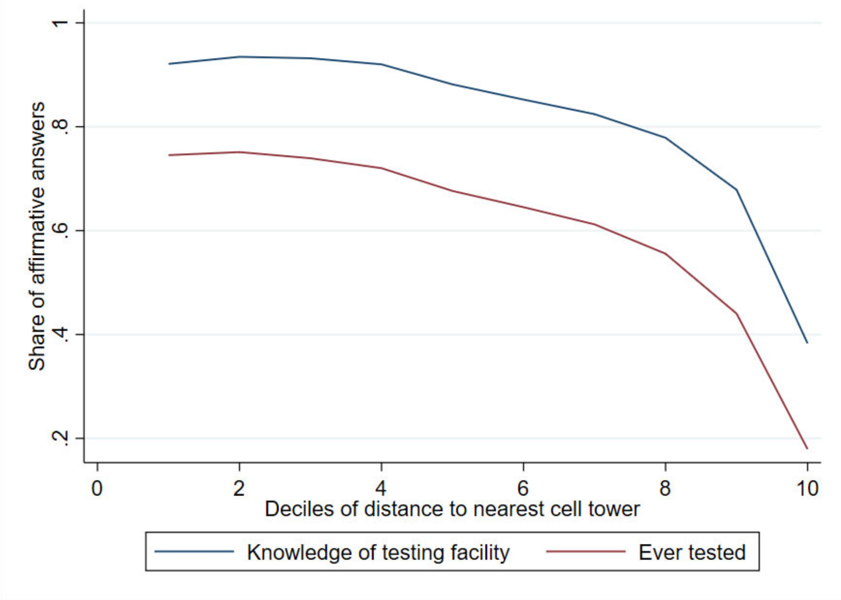


Table A1. First placebo test

	Knowledge of HIV testing facility		Ever tested for HIV	
	Covered	*Non-covered*	*Covered*	*Non-covered*
	OLS	OLS	OLS	OLS
IV	0.001***	-<0.001	0.001**	<-0.001
	[0.001]	[0.001]	[<0.001]	[0.001]
Individual-level characteristic	Yes	Yes	Yes	Yes
Community-level characteristics	Yes	Yes	Yes	Yes
Country-year-fixed effects	Yes	Yes	Yes	Yes
Constant	0.466***	0.258***	0.121***	0.040
	[0.015]	[0.075]	[0.014]	[0.047]
Observations	322,902	28,586	332,153	32,829

Note: "Covered" and "Non-covered" refer to whether the area is covered or not by mobile network. Cluster-robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Table A2. Second placebo test

	Exposed to any type of media		Distance to nearest road (km)		Population density	
	OLS	IV	OLS	IV	OLS	IV
IV	<0.001		0.007		-2.441	
	[0.001]		[0.010]		[2.751]	
Distance from nearest cell (km)		-0.002		-0.135		49.073
		[0.004]		[0.221]		[60.993]
Individual-level characteristic	Yes	Yes	Yes	Yes	Yes	Yes
Community-level characteristics	Yes	Yes	Yes	Yes	Yes	Yes
Country-year-fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Constant	0.394***	0.440	4.972***	8.043	1,136**	23.587
	[0.011]	[0.090]	[0.352]	[4.934]	[497.392]	[1,426]
Observations	404,586	404,586	404,611	404,611	404,611	404,611

Note: Cluster-robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1.

Table A3. Alternative instrumental variable

	Knowledge of HIV testing facility	Ever tested for HIV
	IV	IV
Distance from nearest cell (km)	-0.002*	-0.002***
	[0.001]	[0.001]
Individual-level characteristic	Yes	Yes
Community-level characteristics	Yes	Yes
Country-year-fixed effects	Yes	Yes
Constant	0.462***	0.132***
	[0.017]	[0.016]
Observations	351,613	365,108
R-squared	0.272	0.365
Underidentification (p-value)	<0.001	<0.001
Kleibergen-Paap rk Wald F statistic	32.36	29.28

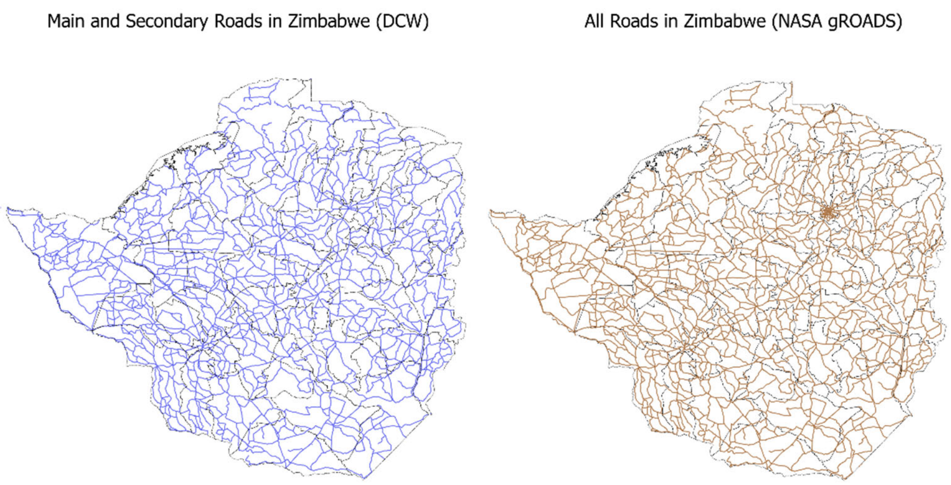
Note: Cluster-robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1. Underidentification and weak-instrument (Kleibergen-Paap rk Wald F statistic) tests reported at bottom of the table for IV regressions.

Table A4. Alternative outcomes for healthcare demand

	Has health insurance		Safe delivery of last pregnancy	
	Probit	IV	Probit	IV
Distance from nearest cell (km)	-0.003***	<-0.001	-0.004***	<0.001
	[<0.001]	[0.001]	[0.001]	[0.001]
Individual-level characteristic	Yes	Yes	Yes	Yes
Community-level characteristics	Yes	Yes	Yes	Yes
Country-year-fixed effect	Yes	Yes	Yes	Yes
Constant	-2.645***	-0.019**	-0.915***	0.221***
	[0.077]	[0.009]	[0.050]	[0.018]
Observations	330,496	330,370	232,334	232,269
(pseudo) R-squared	0.338	0.269	0.334	0.377
Underidentification (p-value)		<0.001		<0.001
Kleibergen-Paap rk Wald F statistic		33.83		34.10

Note: Cluster-robust standard errors in brackets. *** p<0.01, ** p<0.05, * p<0.1. Underidentification and weak-instrument (Kleibergen-Paap rk Wald F statistic) tests reported at bottom of the table for IV regressions.

Figure A1. Differences between DCW and gROADS datasets



Note: Comparisons between the two road networks show minimum differences between the two datasets, which could be driven by the fact that in gROADS dataset the authors could not exclude trails from the list of roadways.

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