Impact of Broadband Internet on Preventive Healthcare Behaviors in Senegal

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Abstract – In Sub-Saharan African (SSA) countries the main channels of morbidity and mortality are preventable and treatable diseases. Yet, SSA countries invest little in preventive healthcare. Literature has shown that providing health information can have an impact on health behaviors. The arrival of optic fiber submarine cables in 2010 brought broadband connectivity to Senegal, allowing access to healthcare information online. Using the Demographic and Health Surveys datasets combined with the Afterfibre database, and a difference-in-differences methodology, this study aims to assess the impact of the arrival of broadband internet on preventive health behaviors in Senegal. Broadband access is found to be positively associated with the use of bed-net, mixed results are found regarding the use of antenatal care and child immunization. If the positive impacts of internet access are confirmed, the expansion of broadband internet could be important to improve health.

JEL: I12, I15, L86, O33
Keywords: preventive healthcare, broadband internet, Senegal, difference-in-differences

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Preventive healthcare is of the utmost importance for developing countries. Since the Alma-Ata Declaration in 1978, primary health care,[1] in which preventive healthcare plays an important role, has been considered a necessary step towards achieving universal health coverage (UHC) and the Sustainable Development Goals (SDGs). Nonetheless, households in Low and Middle-Income Countries (LMICs) invest little in preventive care but rather face high levels of curative health expenditures (Dupas, 2011a). This low level of investment is even more problematic for LMICs given the multiple health challenges they face. Indeed, disease burden affects people at a younger age than in developed countries and the main channels of morbidity and mortality are infectious and parasitic diseases. The great majority of diseases encountered in those countries (e.g. malaria, respiratory infections, diarrhea, AIDS) can be prevented or treated, highlighting the crucial role of primary and preventive care. In sub-Saharan Africa, communicable, maternal, neonatal, and nutritional diseases accounted for two third of mortality in 2010, according to the Institute for Health Metrics and Evaluation (IHME).

Low-level of investments in preventive healthcare is sometimes linked to individuals' present bias (Kremer & Glennerster, 2011). In the absence of budget constraints, under-optimal adoption of high-return health products or behaviors can also be explained by a lack of information on the health costs or benefits of different products or behaviors (Dupas & Miguel, 2017). Literature available on developing countries has shown that providing health information can have an important impact on health behaviors such as a change in sexual behaviors in response to information on the risk of contracting HIV (Dupas, 2011b) or improvements in good hygiene practices after promotion campaigns for hand-washing to reduce diarrhea (Cairncross *et al.*, 2005; Luby *et al.*, 2004). Another example is the change in household behaviors toward water storage to limit dengue contamination after repeated exposure to information in Peru (Dammert *et al.*, 2014). However, the impact of information provision on health behaviors is not always so clear. Indeed, other studies have found little effect of information on health behaviors. For example, Meredith *et al.* (2013) found that health information did not impact healthcare demand for preventive healthcare products (rubber shoes for children as prevention against hookworm infection in Kenya, hand soap as prevention against diarrhea or multivitamin supplements as prevention against nutritional deficiencies in Guatemala, Uganda, and India). These results are consistent with the study of Iajya *et al.* (2013) highlighting that blood donations were not impacted by information on their importance in Argentina.

Internet is an established effective way of data and knowledge transmission that can provide health information as well as constitute a new mode of connection to the healthcare environment (Lewis & Behana, 2001). Information and communication technologies can help improve access for geographically isolated communities, provide support for healthcare workers, or even inform the population regarding outbreaks of diseases (Majeed & Khan, 2019). In America, Rains (2008) highlighted that broadband users were more likely than those with dial-up access[2] to internet to perform health-related communication and information-seeking behaviors online. As submarine cables giving access to broadband connectivity are fairly recent in sub-Saharan Africa, very few studies regarding the impact of high-speed internet on health outcomes have been conducted in this region. Most of the available studies on LMICs focus on cell phone access only and do not address the specific effect of broadband internet, such as Gonzalez & Maffioli (2020) who studied the impact of mobile phone access on the spread of Ebola during the 2014 epidemic in Liberia. Their results pointed to a reduction in the likelihood of Ebola cases in villages with access to mobile phone coverage.

Outside of the health area, the literature on the various impacts of high-speed internet in LMICs is growing. Bahia *et al.*, (2020) found that mobile broadband internet boosted household consumption and contributed to a reduction in moderate and extreme poverty in Nigeria. In Senegal, a World Bank report on the impact of digital technologies on household welfare (Rodriguez-Castelan *et al.*, 2021) confirmed this result. Hjort & Poulsen (2019) also found that broadband internet enabled more rapid job creation and economic activity in 12 sub-Saharan countries. Farrell (2012) and Campante *et al.* (2018) investigated the relationship between internet and political participation finding a negative impact on election turnout.

Within the health domain, studies on the effect of internet connectivity on health mainly focused

1. Primary care corresponds to first-line or local healthcare. It differs from specialized (secondary) or hyperspecialized (tertiary) care.

2. Dial-up internet users must establish a connection each time they desire to use the Internet and are subject to substantially longer wait-time for Web pages to properly load and files to be transmitted than broadband users.

on developed countries. Amaral-Garcia *et al.* (2020) studied the effect of internet diffusion on childbirth procedures in England. Evidence of the growing importance of the internet as a source of health-related information was provided by the authors and reflected by the C-section ‘gap’ between high-income and low-income mothers that closed after the diffusion of broadband internet. Studies also investigated how 5G internet could improve medical practices with the help of virtual reality of artificial intelligence (Latif *et al.*, 2017; Dananjayan & Raj, 2021). However, as for the relationship between information and health behaviors, a positive relationship between internet use and health outcome is not systematic. Indeed, in a survey of the literature investigating internet use and well-being mixed results were found (Castellacci & Tveito, 2018). These discrepancies might be explained by the health indicators used and specific behaviors associated with them, but also due to differences in individuals’ use of internet. Nonetheless, most of those studies conducted in developed countries focused on concerns that are not the ones that matter to developing countries. Indeed, these studies did not focus on primary care, including preventive healthcare, which is of the utmost importance in LMICs. Moreover, the development of broadband internet and the utilization of the internet differ between developed and developing countries (improvement of internet speed was more gradual over time in developed countries), thus calling for specific analyses regarding the impact of broadband internet on health behaviors in LMICs.

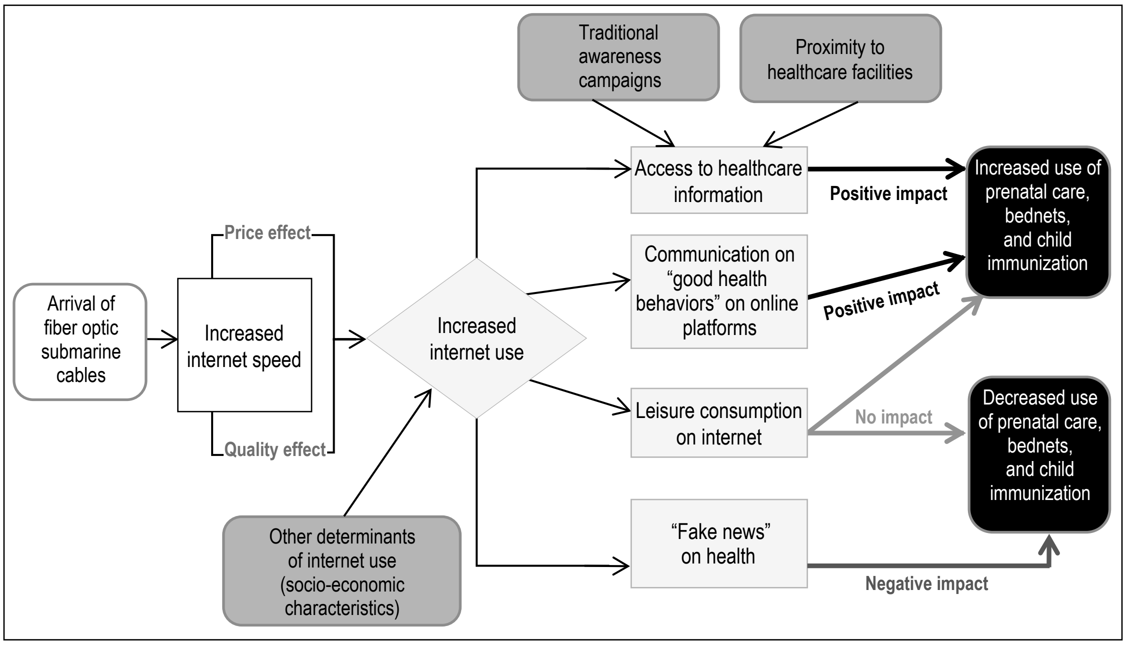
In LMICs, a notable exception in the lack of literature is a study by the World Bank assessing the effect of mobile phone access (2G, 3G, and 4G) on health outcomes in 25 African countries (Mensah *et al.*, 2022). This study found that a 10% increase in mobile phone coverage was associated with a 0.45% reduction in infant mortality. We aim to extend the analysis offered in this paper by broadening the scope of health preventive behaviors studied. Moreover, the study of the World Bank included the effect of 2G coverage, which corresponds only to voice calls and text messaging, that largely drove the main results obtained, while we aim to study the impact of broadband internet which is supported by 3G and 4G coverage only. Finally, our study also differs from that of the World Bank by the econometric techniques used to identify the effect of broadband internet on preventive healthcare behaviors.

Other studies have recently emerged such as Byaro *et al.* (2023) who studied the impact of internet use on infant mortality, under-five mortality, and life expectancy in 48 sub-Saharan countries. They found that internet use has a positive effect on health outcomes. A recent Demographic and Health Surveys (DHS) analytical study investigated, at macro-level, the relationship between three types of access to or use of digital resources (ownership of a mobile phone, use of a mobile phone for financial transactions, and frequent use of the internet) and several health outcomes, namely correct knowledge of the fertility cycle, current use of modern contraception, use of a condom at last sexual intercourse, use of antenatal care, iron supplementation during pregnancy, medical treatment of child illness, and health-seeking for experience with physical or sexual violence (Edmeades *et al.*, 2022). Their results suggested that the strength of the relationship between health and digital resources access varies depending on the health outcome examined and between men and women, even though digital resources access and use were generally associated with better health outcomes.

The objective of this study is to assess the impact of the arrival of broadband internet on preventive health behaviors in Senegal. Since access to the internet might allow individuals to gather information regarding good health practices, but also to benefit from information on the behaviors of others (*via* access to social networks for example), we formulate the hypothesis that the availability of broadband internet (both fixed and mobile) has positive effects on the use of preventive health care in connected areas, and more specifically on the use of antenatal care, bednet and child immunization.

Figure I summarizes the framework and hypotheses of the study. The arrival of fiber optic submarine cables increased internet speed (Akamai, 2012; Hjort & Poulsen, 2019). This increased speed of the internet led to an increase in internet utilization. Access to internet does not guarantee internet use as many socio-economic characteristics matter for internet adoption. However, it has been shown that the arrival of broadband internet led to an increase in internet use in SSA, thanks to both a price reduction and quality improvement effect (Cariolle, 2021; Hjort & Poulsen, 2019). This increase in internet use can have consequences on healthcare utilization and healthcare behaviors through many channels. In this study, the main channel we are interested in is access to information. Thanks to internet use, people can easily access

Figure I – **Diagram summarizing the study hypotheses and illustrating the potential transmission channels between the arrival of the submarine cables and preventive healthcare**



Note: This diagram summarizes the hypotheses used in the study. The black boxes represent the main variables analyzed, namely the arrival of fiber optic submarine cables and the preventive healthcare use. The other boxes represent the potential effects and mechanisms underlying the main link studied. To signify the hypothetical relationships between these variables, arrows connect each box, indicating the assumed direction of the link between two variables. A dark, grey and light grey arrow represents a positive, negative and null impact, respectively.

health information leading to a positive effect on preventive healthcare behaviors (Dupas, 2011b; Cairncross *et al*., 2005). Another channel through which the adoption of preventive healthcare behaviors can increase with internet use is the communication on "good health behaviors" on online platforms such as social media (Willis, 2016). In addition, increased internet use can translate into an increase in leisure consumption online (Bryce, 2001; Falck *et al*., 2014), without influencing healthcare behaviors. Some studies have shown that intensive internet use can lead to depression, anxiety, and poor sleep quality, but most of the studies on the subject focus on teenagers in developed countries (Morrison & Gore, 2010; Weinstein & Lejoyeux, 2010). Additionally, the increased use of internet can also lead to an increased exposition to fake news (Del Vicario *et al*., 2016), which in turn can modify healthcare behaviors and reduce some preventive healthcare use such as vaccinations (Wilson & Wiysonge, 2020). Internet use can also affect other aspects of health not studied here, for example, the use of social networks allows communication with distant relatives and friends which can lead to a positive effect on mental health, or internet use can increase healthy behaviors such as engaging in physical activity (Li *et al*., 2020). Nevertheless, as those pathways are out of the scope of our study, they do not appear in Figure I. It is also important to keep in mind that access to healthcare information does not occur exclusively thanks to the internet, but that traditional awareness campaigns or proximity to healthcare facilities are also important transmission vectors of health-related information. Indeed, the transmission of preventive health information can occur thanks to community health workers or peers. In addition, the channels presented in Figure I might not be effective right after individuals gain access to internet, as a "learning phase" might be necessary to identify appropriate health information online.

Access to information (thanks to internet or via other means) does not solve all the issues of healthcare access and healthcare utilization. Indeed, for healthcare services to be used, they must be accessible both economically and geographically. The Senegalese health system is organized following the standard 3-level pyramid. Achievement of universal health coverage is one strategic priority for the country, however, improvements on the subject are still needed despite progress over the last decades. Communicable, maternal, neonatal, and nutritional diseases were responsible for 87% of deaths in under-5 children in 2010, according to the IHME. Insurance coverage was quite low (Daff *et al*., 2020) but healthcare services, especially for women and children such as vaccination included in the WHO

Extended Program on Immunization (EPI), were provided free of charge. The ESPCC/SPA survey of 2014 in Senegal showed that 91% and 84% of health structures offered prenatal healthcare services and children immunization respectively (ANSD & ICF International, 2015). Regarding the availability of bednet, nearly 80% of surveyed households possessed a bednet over the period studied, yet their actual utilization lagged significantly behind ownership rates. Indeed, several national and regional campaigns were conducted in the country over the years to distribute bednets free of charge. Thus, the main concerns seemed to be the actual utilization of bednet rather than having access to it, even though, for the poorest households, financial barriers to accessing bednets could still be a reality.

The paper is organized as follows. Section 1 provides information on internet infrastructure in Senegal, the data and methodology used. Section 2 presents the results which are further discussed in section 3.

1. Material and Methods

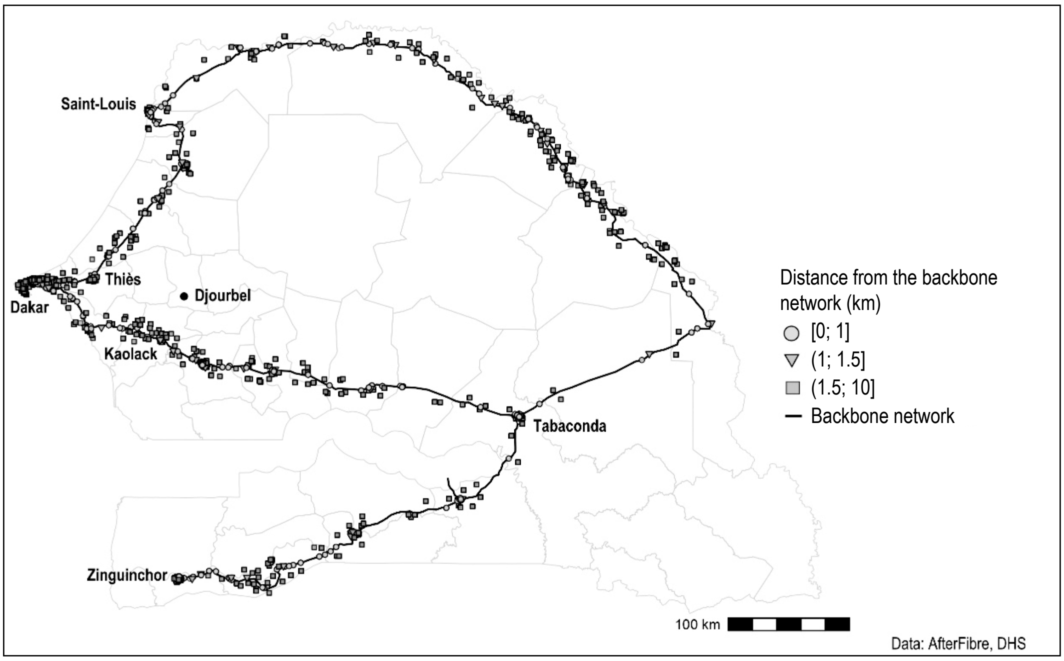
1.1. Background on Internet Infrastructure

In sub-Saharan Africa, most of the internet traffic (fixed and mobile) goes through backbone networks. The backbone network, also called the core network, is partly the legacy of the fixed telephone network and of the first mobile telephone antennas and provides low internet connectivity. As shown in Figure II, in Senegal, the backbone network (represented by the black line) mostly follows the borders of the country, both in rural and urban areas, leaving the central and south-eastern parts of the country uncovered. Each observation in our database is associated with GPS coordinates represented by dots (the shape depending on the distance to the network), allowing to see differences in the density of the population. Fiber-optic submarine cables can carry a huge amount of data from one remote location to another (e.g. from Europe to Southern Africa). The arrival of optic-fiber submarine cables in 2010 brought international broadband connectivity in Senegal which highly increased the availability of high-speed internet in areas near the already existing backbone networks.

It is globally recognized that you need to be no more than 1,000 m to 1,500 m from the backbone to benefit from broadband. Indeed, the quality of bandwidth, and thus access to the internet, decreases very quickly as the distance to the main network increases in the absence secondary network or antenna as it is the case in Senegal.[3]

3. For fixed network (copper network) the attenuation decreases very quickly 1.5 km after the splitter, depending on the technology (ADSL, VDSL, ADSL2...). For mobile network (cell phone antennas), the signal quality decreases rapidly after 1 km distance.

Figure II – **Backbone network in Senegal**



Note: This map provides a comprehensive overview of Senegal, displaying geolocated observations (the dots) from the DHS databases. The black lines represent the projection of pre-existing backbone cables, which were in place prior to the introduction of submarine cables. The shape of the dots on the map indicates the distance of each observation from the backbone infrastructure.

As our study focuses on internet access rather than internet use, it is crucial to establish a relationship between the two. This has been done by Hjort & Poulsen (2019) who highlighted a clear link between submarine cable arrival and internet speed and use in SSA. Indeed, based on the Akamai's data,[4] they found that cable arrival increased measured speed by around 35 to 38% in connected locations compared to unconnected locations (these coefficients being likely underestimated). Regarding internet use, and based on data provided by the Afrobarometer, the authors found that daily and weekly internet use among connected individuals increased by 12 and 14% respectively after the arrival of submarine cables arrival compared to unconnected individuals.

1.2. Data

Data on health behaviors were extracted from the Demographic and Health Surveys datasets which are nationally representative population-based surveys with large sample sizes (see Box). Our database included Standard DHS from the years 1997, and 2005 as well as Continuous DHS from 2012, 2014, and 2016 with geolocation of participating households for all surveys. In addition to the DHS datasets, the Malaria Indicators Survey (MIS) of 2008 was included in our database for regressions regarding the use of bednet.

We considered three preventive health indicators: use of antenatal care, use of bednet for children, and child immunization.

Use of antenatal care was measured as a dummy variable equal to 1 if the mother had at least 4 antenatal care visits during her last pregnancy. The threshold of 4 visits was used as the World Health Organization (WHO) considered a minimum of 4 visits to have complete antenatal care before 2016 – since then this number has been increased to 8 visits. Indeed, in 2002 the WHO recommended a focused or goal-orientated approach to antenatal care (ANC) to improve the quality of care and increase ANC coverage, particularly in LMICs. The focused ANC (FANC) model, also known as the basic ANC model, includes four ANC visits occurring between 8 and 12 weeks of gestation, between 24 and 26 weeks, at 32 weeks, and between 36 and 38 weeks.

Use of bednet was measured as a dummy variable equal to 1 if the child (under the age of 5) or some or all children under the age of 5 in the household slept under a bed net the previous night.

Child immunization was measured as a dummy variable equal to 1 if children from 1 to 5 years old received all vaccination from the Extended Program on Immunization. This EPI includes 4 vaccines: BCG vaccine, DPT/pentavalent vaccine, OPV vaccine, and measles vaccine, and should be completed by the time the children are

4. Akamai Technologies, Inc. is a content delivery network which owns servers around the world. Akamai's data provides average internet speeds recorded for different users (residential, educational, government and business) in a given area for each quarter, excluding mobile network connections.

Box – **Insights on DHS Datasets**

The Demographic and Health Surveys (DHS) program is responsible for collecting nationally representative data on health and population in developing countries (over 90 countries since 1984). The project is funded by the United States Agency for International Development (USAID) with contributions from other donors such as UNICEF, UNFPA, WHO, and UNAIDS. Several data collections are available among which we can find:

The Demographic and Health Surveys (DHS). Those surveys are nationally-representative household surveys that provide data for a wide range of monitoring and impact evaluation indicators in the areas of population, health, and nutrition. The samples are stratified, weighted, and representative at national, regional, and residence levels (urban-rural). We used women's questionnaire targeting women age 15-49. We used Standard DHS for the years 1997 as well as 2005 and Continuous DHS for the years 2012, 2014 and 2016. Standard DHS surveys are typically conducted every few years, with a gap of several years between each survey round whereas continuous DHS surveys are conducted continuously throughout the year, enabling more frequent data collection. Croft *et al.* (2018) provide more details about DHS surveys.

The Malaria Indicators Surveys (MIS) are surveys nationally representative focusing on malaria. The methodology is similar to standard or continuous DHS. We also used the women's questionnaire. More details about MIS 2008 can be found in Ndiaye & Ayad (2009).

The Service Provision Assessment (SPA) Surveys are surveys of a national sample of formal health facilities. We used SPA Senegal 2012, the sample of surveyed facilities includes 35 hospitals, 64 health centers, 265 health posts, and 74 health huts. More details can be found in the final reports (ANSD & ICF International, 2012).
All of those databases are available upon request on https://dhsprogram.com/, journal articles based on those databases are also available on the website.

9 months old. The BCG vaccine (named after its inventors A. Calmette and C. Guérin) targets tuberculosis and is injected at birth. The DPT vaccine targets diphtheria, pertussis, and tetanus. After 2005, the DPT vaccine has been replaced by the pentavalent vaccine which additionally targets hepatitis B and Haemophilus influenzae type b (Hib) disease. Both vaccines are injected at 6, 10, and 14 weeks. The OPV vaccine targets polio and is also injected at 6, 10, and 14 weeks. The measles vaccine is injected at 9 months. For vaccination requiring three doses, we considered receiving the third dose of vaccine as full vaccination.

These outcomes were chosen according to the availability of data and to account for the main health issues in Senegal. Indeed, maternal care, malaria prevention, and child immunization are well-known preventive healthcare behaviors and are of paramount importance within the Senegalese epidemiological context. In 2010, neonatal disorders, diarrheal diseases, lower respiratory infection, and malaria were indeed the four main causes of death for under-5 children according to the IHME. For this specific year, maternal disorder alone caused 1,705 deaths, while tuberculosis caused 3,700 deaths. Malaria and measles were responsible for 14.5% and 3.8% of under-5 deaths respectively.

Control variables corresponded to socio-economic and demographic variables and included localization of residence (urban or rural), wealth index factor (a composite measure of a household's cumulative living standard), mother's age, highest educational level (no education, primary, secondary, or higher), marital status (married or living together vs single, divorced or widowed), employment status (working or unemployed) and children birth order.[5] These variables were collected from the DHS datasets and MIS datasets. Children's birth order was preferred over the total number of children to account for shifts in parental knowledge and behaviors as they gain more experience with children. DHS datasets include a wealth income indicator (Rutstein & Johnson, 2004) instead of household income which is extremely difficult to measure accurately. DHS surveys collect a number of variables, usually for purposes other than ascertaining economic status which are thought to be correlated with a household's economic status. Almost all household assets and utility services available, such as type of flooring, water supply, type of vehicle, ownership of agricultural land, etc., are included in the construction of the wealth index factor. In addition, an indicator of healthcare centers' density at the regional level was included. This measure was constant throughout the whole study period and was obtained from the Service Provision Assessments (SPA) dataset of 2012. This database contains a representative sample of health facilities (health huts, health centers, hospitals, and health posts) in Senegal, and their GPS coordinates. To construct an indicator of health facility density, we aggregated the number of health facilities per region and divided the resulting value by the surface area in each region. However, only fixed health facilities were included in the indicator; itinerant healthcare services were not included, which may lead to an under-representation of healthcare services in rural areas.

Depending on outcome variables, the availability of data was different. Thus, for each outcome, different datasets were used. Table 1 displays which waves of DHS or MIS were used depending on the outcome considered. More recent surveys were also available but we choose not to include them due to the recent development of new internet infrastructures in Senegal which increases the risk of individuals considered as controls being in reality treated (i.e. having access to the internet).

Access to broadband internet (our treatment variable) was measured by the distance from the backbone network, only backbone cables that have been installed prior to the arrival of broadband were considered. Data on the localization of the backbone network and on the date of the cables' installation was obtained thanks to the Afterfibre database (www.afterfibre.nsrc.org). The date of arrival of the submarine cable, and thus connection, was obtained from www.infrapedia.com.

It is important to note that GPS localization in DHS is not exact. Indeed, to protect the confidentiality of respondents the geo-located data are displaced up to 2 km in urban areas and up to 5 km in rural areas (and even can go up to 10 km for one observation out of 100). The displacement is a random direction/random distance process and the new location is checked to make sure it falls within the designated administrative boundaries, i.e. within the same district in Senegal. Several analyses have been made on the impact of displacement. For example, for the 2010 wave in Senegal (not used in this study as it was the year of optic-fiber cable arrival) the average displacement was 0.92 km in urban

5. *Except in regressions including MIS 2008 database in which employment and marital status of the mother were not available.*

Table 1 – **DHS wave used by outcome**

	Before optic-fiber cable arrival			After optic-fiber cable arrival		
	DHS 1997	DHS 2005	MIS 2008	DHS 2012	DHS 2014	DHS 2016
Use of antenatal care	X	X			X	X
N	7,146	6,604			4,375	4,470
Use of bednet		X	X	X	X	
N		10,202	15,217	6,771	6,629	
Child immunization		X		X	X	
N		7,243		5,154	5,154	

Note: This table indicates the surveys used depending on the outcome considered (one line per outcome). The number of observations (N) in each survey is also included.

areas and 2.36 km in rural areas (Burgert *et al.*, 2013). Despite the inexact localization of our individuals, a household actually living within a 1-kilometer distance from the backbone network has a higher chance to be relocated in the 1-kilometer area around the network than a household located 1.5 kilometers away or more from the backbone network. Then, inexact localization in DHS data does not prevent the creation of the control and treatment groups but only implies interpreting our results as 'intention to treat' estimators.

To ensure the robustness of our analyses, we incorporated additional data sources. Population density information was obtained from the WorldPop hub (https://hub.worldpop.org), which provides highly precise spatial demographic data for countries worldwide. We utilized gridded population counts data with a resolution of 30 arc seconds, available since 2000.[6] This data source enabled us to assess population density at a fine-grained level. For information on the localization of healthcare centers, we referred to the dataset available at https://data.humdata.org/dataset/hotosm_sen_health_facilities. This dataset, derived from OpenStreetMap data, not only provides the location of healthcare facilities but also includes some of their characteristics. To enrich our analysis, we computed the distance between each cluster of surveyed individuals and the nearest healthcare facility. By incorporating these additional datasets, we aimed to capture the influence of healthcare accessibility on our research outcomes, thus enhancing the robustness of our findings. However, this database is not exhaustive and includes currently existing healthcare structures in 2023, while structures might have been created during or after the arrival of broadband internet.

1.3. Data Analysis

Two different empirical strategies, both based on the Difference-in-Differences (DiD) methodology, were used to estimate the impact of broadband internet on the three outcomes considered. DiD relies on several assumptions, the main one being the parallel trend assumption. Indeed, to ensure internal validity, DiD assumes that in the absence of treatment, the difference between the 'treatment' and 'control' groups would be constant over time. DiD also requires the intervention to be unrelated to the outcome at baseline, and the composition of the two groups to be stable over time, in the case of repeated cross-sectional design as it is the case here.

The first methodology follows the work of Hjort & Poulsen (2019), who assessed the impact of the arrival of high-speed internet on employment in Africa, and used a DiD methodology with fixed effects to estimate the causal impact of the arrival of broadband internet on preventive health behaviors in Senegal. Fixed effects based on localization (10 kms x 10 kms cell-level characteristics) were included in regression analysis along the aforementioned control variables. The databases used for this methodology were the ones presented in Table 1.

The model estimated with this first methodology is specified by equation (1):

$$\begin{aligned} Y_{ijt} &= \alpha + \beta * SubCables_t * Connected_i \\ &+ \delta_j * Connected_i + X_{it} + \gamma_t + \epsilon_{ijt} \end{aligned} \quad (1)$$

where Y_{ijt} is one of the three health outcomes (use of antenatal care, use of bednet, child immunization) for individual i in cell j and at time t. $SubCables_t$ is a dummy variable indicating whether the submarine cable was available in the country at time t. $Connected_i$ corresponds to the treatment variable, based on the distance to the backbone cables. The coefficient on the interaction between the arrival of submarine cables and individuals' distance from the network

6. Open data available at this address: https://hub.worldpop.org/project/categories?id=3 – accessed June 2023.

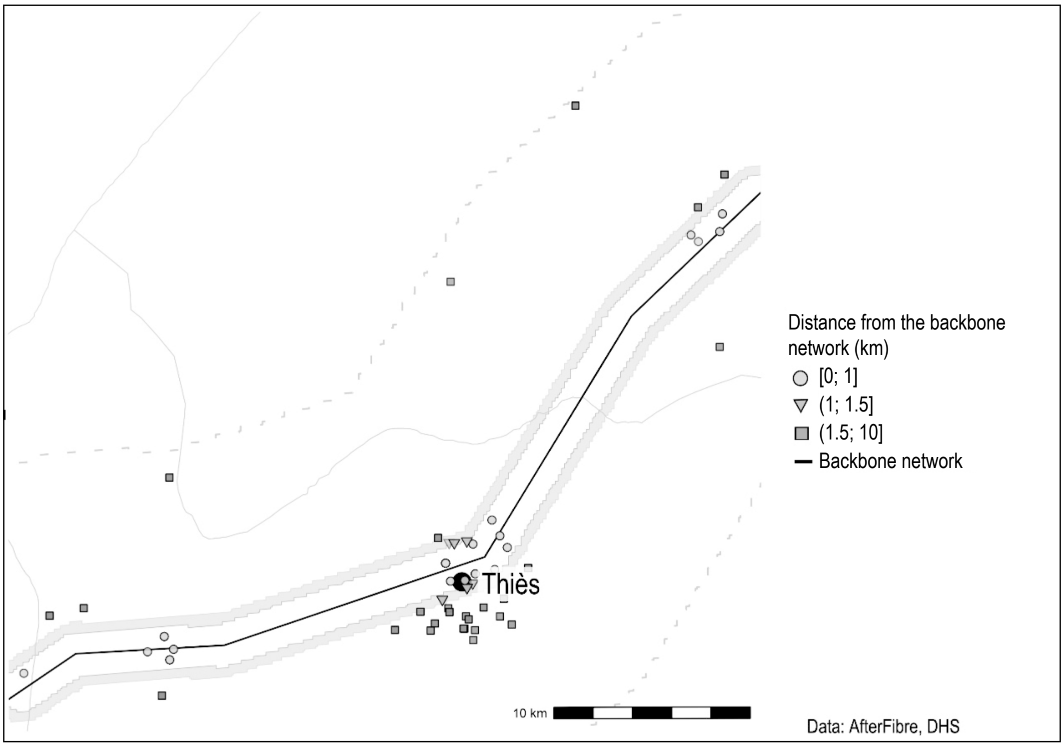
β is our coefficient of interest as it measures the impact of internet access on health behaviors. The δ_j coefficient (10 kms x 10 kms cell-level fixed effects) captures time-invariant differences in health outcomes between treatment and control groups. X_{it} is a vector of control variables for an individual i at time t and γ_t corresponds to time fixed effects.

Figure III provides a zoom of Figure II of the coast of Senegal around the city of Thiès to better illustrate individuals included in our analyses. People living between 0 and 1,000 m of the backbone network were considered connected, as illustrated by the dots, and thus constitute the treatment group, whereas people living between 1,500 m and 10 km were considered unconnected (squares) and constitute the control group. As a result, people living between 1,000 m and 1,500 m (triangles) from the backbone network were excluded. We also excluded individuals living further than 10 km as we considered those individuals to be too different from a socio-economic point of view from those living in connected areas, and we want to avoid including less comparable individuals. We chose this double cut-off of 1,000 m and 1,500 m given the fact that there is no clear consensus on the distance until which the quality of the bandwidth is acceptable. The most conservative definition for the treated group (1,000 m) and the least conservative definition for the control group (1,500 m), based on internet speed attenuation (cf. Section 1.1), was used to limit the risk of an individual being wrongly attributed to a group. This distinction between connected and unconnected areas slightly differed from the one used by Hjort & Poulsen (2019) who defined 500 m as the maximal distance acceptable. However, no clear justification for that very restrictive threshold was given in their paper.

As DHS surveys are not panel data but repeated cross-sectional surveys, the second methodology used in this study was DiD with coarsened exact matching. Exact matching provides perfect balance but produces few matches with continuous variables. Coarsened exact matching temporally coarsen continuous variables into strata to operate the matching.[7] The variables used for matching at baseline were the localization of residence, household wealth index factor, age, highest educational level, working and marital status of the mother, and child birth order. For categorical variables (localization of residence, highest educational level, working

7. The -cem- *Stata® command (Blackwell* et al.*, 2009) was used to perform this matching.*

Figure III – **Connected vs unconnected**



Note: This map zooms in on a specific area near Thiès, Senegal, representing the connectivity status of respondents based on their proximity to a central backbone (represented by a black line). Buffer zones, shown in grey on the map, represent people located between 1 and 1.5 km from the backbone network. They are excluded from the analysis. The shape of the dots indicates the distance from the backbone.

status, and marital status), exact matching was used while for continuous variables, bins were created. The age of the mother was divided into four strata, each covering 8 years (15-23; 24-32; 33-40; 41-49). The household wealth index factor was divided into five strata by quintile while child birth order was divided into 4 strata based on the distribution (1st kid; 2nd or 3rd; 4th or 5th; 6th or above). For the use of antenatal care, out of the 965 strata created, 532 were matched representing 11,847 observations out of 12,693 (93%). For the use of bednet out of the 364 strata created, 277 were matched representing 15,514 observations out of 15,750 (98%). Finally, for child vaccination, out of the 844 strata created, 469 were matched representing 8,897 observations out of 9,625 (92%). Once the weights were obtained from the matching, ordinary least squares regression was used.

In robustness analyses, urban and rural areas were analyzed separately. Then, the cut-offs for treated and controls were modified to limit the bias linked to the displacement of GPS localizations. In the second robustness analysis, we modified the control group to include people living between 3 km and 10 km from the backbone network in urban areas and people living between 6 km and 10 km from the backbone network in rural areas. In a third robustness analysis, the cut-off of 500 m used by Hjort & Poulsen (2019) for the treated group was considered. Finally, alternative coding of the health outcomes was used. Regarding antenatal care, different cut-offs were considered (8 visits as recommended since 2016 or 3 visits as recommended before 2002). Regarding the use of bednet, we considered a dummy variable equal to 1 only if all under-5 children slept under a bednet during the previous night and we restricted to household with bednets. Regarding vaccination, analyses were disaggregated by vaccines. In addition, robustness analysis performed heterogeneity analyses by wealth quintile and educational level. As the methodology with cells fixed effects relies on the hypothesis of no migration over time some robustness analyses with a measure of population density were performed. Lastly, since our proxy for healthcare offer (density of healthcare structures) extracted from the SPA database is not perfect, the main regressions were conducted with an alternative measure, the distance to the closest healthcare facility.

Geographical data were dealt with using R while regression analyses were run using Stata® version 17. With both methodologies, the same datasets were used.

2. Results

Table 2 displays the descriptive statistics before and after treatment. As the years considered varied from one outcome to another given data availability, the table is split into panel A for the use of antenatal care, panel B for the use of bednet, and panel C for child immunization. At baseline there was a higher utilization of antennal care from respondents living connected in areas, this difference was still significant after treatment following progress in both treatment and control groups. In detail, before treatment, only 29% of respondents were using antenatal care in the control group, whereas this percentage was up to 35% in the treated group. After treatment, the use of antenatal care was around 52% and 58% in the control and treatment groups, respectively. The use of bednet was significantly higher for the treated group both before (45% vs 41%) and after treatment (73% vs 57%). This difference between the two groups increased over time. Child immunization was equal to 59% at baseline for the two groups. After treatment, the mean vaccination score was 73% and 72% for unconnected and connected respondents, respectively. In all cases (panels A, B, and C) respondents living in connected areas were on average more urban, wealthier, and more educated than unconnected respondents, both before and after treatment.

In addition, the variable "density of healthcare structures", used as a proxy of the healthcare supply at the regional level in 2012, varied from 0.001 to 0.131 per km^2 with an average of 0.012. As part of the robustness analyses, the distance from the closest healthcare facility was used. The distance varied from 0.1 km to 45 km with an average of 6.4 km. We looked at the distance for connected and unconnected respondents separately. For connected respondents, the average distance was 4.8 km whereas for unconnected respondents the average distance was 7.1 km, this difference being significant ($t=22$, $p<0.01$).

Before conducting the regression analyses, the parallel trend assumption (i.e. the stability in the difference in the outcome variable between the 'treatment' and 'control' group over time in the absence of treatment) was checked as illustrated by Figure IV. For the use of antenatal care and bednet, the years displayed in Figure IV were the ones used for regression analyses. For child immunization, the 1992 wave (the most recent wave available before 2005) was added to the graphical representation but was not used in regression analysis as it was judged too old. Graphically, the parallel trend assumption seems

Table 2 – **Descriptive statistics**

Variables	Before [(a)]			After [(b)]		
	Treated (0-1 km)	Control (1.5-10 km)	Difference	Treated (0-1 km)	Control (1.5-10 km)	Difference
Panel A: Use of antenatal care						
Use of antenatal care	**0.35 (0.48)**	**0.30 (0.46)**	**0.05*** (0.01)**	**0.58 (0.49)**	**0.52 (0.50)**	**0.06*** (0.02)**
Controls						
Urban	0.65 (0.48)	0.45 (0.50)	0.20*** (0.01)	0.75 (0.43)	0.38 (0.48)	0.36*** (0.02)
Age	29.58 (7.35)	29.77 (7.20)	−0.18 (0.20)	30.05 (7.10)	29.83 (7.29)	0.26 (0.24)
Wealth index	0.33 (0.93)	0.21 (1.15)	0.12*** (0.03)	5.10 (8.49)	0.39 (10.17)	4.89*** (0.33)
Education level						
No education	0.61 (0.49)	0.69 (0.46)	−0.07*** (0.01)	0.49 (0.50)	0.64 (0.48)	−0.14*** (0.02)
Primary	0.29 (0.45)	0.21 (0.41)	0.08*** (0.01)	0.30 (0.46)	0.22 (0.42)	0.07*** (0.01)
Secondary or higher	0.10 (0.29)	0.10 (0.30)	0.00 (0.01)	0.20 (0.40)	0.13 (0.34)	0.07*** (0.01)
Married or living together	0.92 (0.27)	0.92 (0.27)	0.00 (0.01)	0.88 (0.33)	0.94 (0.24)	−0.06*** (0.01)
Currently working	0.48 (0.50)	0.48 (0.50)	0.00 (0.01)	0.43 (0.50)	0.41 (0.49)	0.02 (0.02)
Child birth order	3.93 (2.66)	4.05 (2.67)	−0.12* (0.07)	3.43 (2.27)	3.68 (2.40)	−0.21*** (0.08)
N	2,003	4,010		986	2,347	
Panel B: Use of bednet						
Use of bednet	**0.45 (0.50)**	**0.41 (0.49)**	**0.05*** (0.01)**	**0.73 (0.44)**	**0.57 (0.50)**	**0.17*** (0.01)**
Controls						
Urban	0.59 (0.49)	0.38 (0.49)	0.21*** (0.01)	0.76 (0.43)	0.39 (0.49)	0.36*** (0.01)
Age	28.85 (7.02)	29.27 (7.02)	−0.42*** (0.15)	29.79 (6.87)	29.67 (6.87)	0.12 (0.21)
Wealth index	1.88 (5.97)	0.70 (8.10)	1.19*** (0.16)	3.71 (8.68)	0.92 (9.78)	2.80*** (0.30)
Education level						
No education	0.62 (0.49)	0.71 (0.45)	−0.09*** (0.01)	0.51 (0.50)	0.65 (0.48)	−0.14*** (0.02)
Primary	0.28 (0.45)	0.22 (0.41)	0.06*** (0.01)	0.32 (0.47)	0.24 (0.43)	0.08*** (0.01)
Secondary or higher	0.09 (0.29)	0.07 (0.26)	0.02*** (0.01)	0.17 (0.37)	0.11 (0.31)	0.06*** (0.01)
Child birth order	3.51 (2.40)	3.75 (2.52)	−0.24*** (0.05)	3.43 (2.36)	3.53 (2.35)	−0.10 (0.07)
N	3,333	7,328		1,477	3,350	
Panel C: Child immunization						
Child immunization	**0.59 (0.49)**	**0.59 (0.49)**	**0.00 (0.02)**	**0.72 (0.45)**	**0.73 (0.44)**	**−0.01 (0.02)**
Controls						
Urban	0.67 (0.47)	0.43 (0.49)	0.25*** (0.02)	0.76 (0.43)	0.40 (0.49)	0.36*** (0.02)
Age	29.53 (6.90)	29.68 (6.84)	−0.16 (0.25)	30.35 (6.76)	30.11 (6.89)	0.24 (0.24)
Wealth index	0.33 (0.87)	0.05 (1.06)	0.28*** (0.04)	3.88 (8.70)	1.00 (9.73)	2.88*** (0.33)
Education level						
No education	0.60 (0.49)	0.72 (0.45)	−0.12*** (0.02)	0.52 (0.50)	0.66 (0.48)	−0.14*** (0.02)
Primary	0.30 (0.46)	0.21 (0.41)	0.09*** (0.02)	0.33 (0.47)	0.24 (0.43)	0.08*** (0.02)
Secondary or higher	0.10 (0.30)	0.07 (0.26)	0.03*** (0.01)	0.16 (0.37)	0.11 (0.30)	0.06*** (0.01)
Married or living together	0.95 (0.22)	0.94 (0.23)	0.01 (0.01)	0.88 (0.32)	0.94 (0.23)	−0.06*** (0.01)
Currently working	0.42 (0.49)	0.33 (0.47)	0.09*** (0.02)	0.51 (0.50)	0.42 (0.49)	0.09*** (0.02)
Child birth order	3.55 (2.42)	3.67 (2.52)	−0.12 (0.09)	3.46 (2.38)	3.50 (2.35)	−0.04 (0.08)
N	1,255	2,077		1,153	2,603	

[(a)] for Panel A: 1997 & 2005; for Panel B: 2005 & 2008; for Panel C: 2005.
[(b)] for Panel A: 2014 & 2016; for Panel B and C: 2012 & 2014.
Note: The first three columns "Before" refer to the period before arrival of broadband connection in Senegal while the last three columns "After" refer to the period of the arrival of broadband connection. The treatment group is composed of all individuals located between 0 and 1,000 meters from the closest backbone. The control group is made up of individual who are located between 1,500 meters and 10 kms from the blackbone. Means with standard errors in parentheses. ***p<0.01; **p<0.05; *p<0.1.

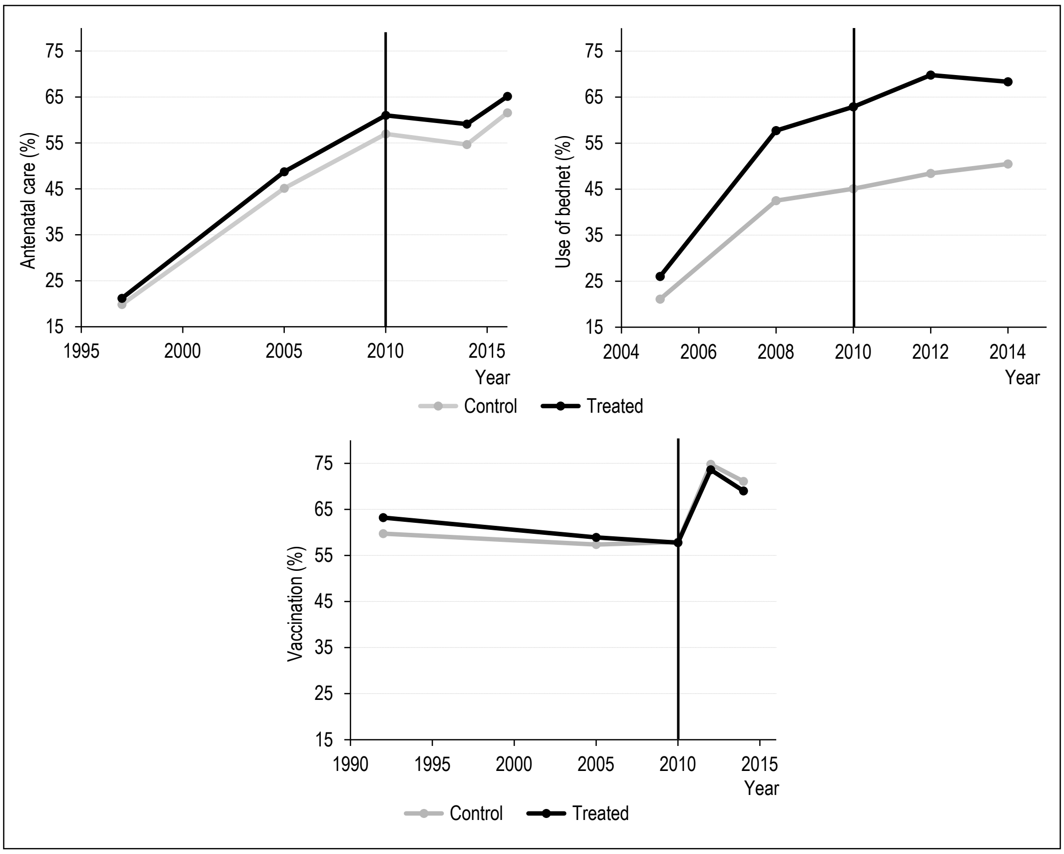
to hold for all three outcomes. Indeed, before the arrival of submarine optic-fiber cables in 2010, represented by the vertical line, outcome variables appeared to evolve in parallel. In addition, placebo tests with an earlier treatment date were performed for all the three outcomes. Placebo tests consist of running the regression with a fake treatment date prior to actual treatment, then necessitating at least two periods before treatment. No impact was found for our three outcomes confirming our visual impression that before actual treatment our two groups had similar evolution. Results of these tests are available in Appendix A1.

The results of the regression analyses are presented in Table 3. Mixed results were found regarding the utilization of antenatal care. While the first methodology using fixed effects highlighted a positive and significant association between broadband internet access and the use of antenatal care, the second methodology pointed to no impact. Regarding the utilization of bednet, our results pointed out a positive effect of the arrival of broadband internet with both methodologies. As could be expected from the descriptive statistics, broadband internet access did not seem to impact child immunization. Results of regression analyses including all control variables are available in Appendix A2. To ensure that the suppression of households between 1 km and 1.5 km from the backbone network does not create a selection bias, complementary analyses have been performed and results are available in Appendix A3.

Several robustness analyses were conducted to confirm the main findings. First, the main analysis was performed for urban and rural areas separately. Results are displayed in Table 4. Our main finding regarding the positive impact of internet access on the use of bednet was confirmed. Use of antenatal care also seemed to increase for connected respondents in urban areas, but not in rural areas. On the contrary, internet access was found to decrease child vaccination in rural areas.

Secondly, the cut-offs used to classify connected and unconnected respondents were modified as explained in the material and methods section. Results are displayed in Table 5. The positive association between internet access and the use of bednet was confirmed in the first two

Figure IV – **Parallel trend assumption**



Note: In this figure, each point represents the share of individual having used antenatal care, bednet, and child immunization for the specified group and for each available wave. The treatment group consists of individuals located within 1,000 meters of the nearest backbone. The control group consists of those located between 1,500 meters and 10 kms.

Table 3 – **Results of regressions analyses**

Outcome	Fixed effects	Matching	Impact of broadband
Use of antenatal care	0.057* (p=0.058)	−0.030 (p=0.240)	Positive / Not significant
N	9,346	8,703	
Use of bednet	0.143* (p=0.056)	0.078*** (p<0.001)	Positive
N	15,488	15,254	
Child immunization	−0.060 (p=0.460)	−0.007 (p=0.822)	Not significant
N	7,088	6,551	

Note: The "Fixed effects" column displays the reported estimates of the β coefficient on the $Subcables_t*Connected_i$ variable in model (1). Time fixed effects correspond to years, while Location fixed effects represent grid-cells of 0.1 x 0.1 decimal degrees, approximately equivalent to 10 kms x 10 kms. Individuals within a 1 km proximity to the backbone network are classified as connected, while those located between 1.5 km and 10 km from the backbone are considered controls. Robust standard errors are clustered at the level of Location fixed effects. The regressions include control variables such as urban or rural classification, age, wealth index, education level, marital status and employment status of the mother, and child birth order. The "Matching" column presents the estimation results of the Difference-in-Differences (DiD) analysis with coarsened exact matching, based on the localization of residence, household wealth index factor, age, highest educational level, working status and marital status of the mother, and child birth order variables. Each row reports the results for a distinct outcome variable. ***p<0.01; **p<0.05; *p<0.1.

specifications. A positive impact of internet access on antenatal care utilization was found when the distance to the backbone used to identify connected respondent is reduced, supporting the mixed results found in the main specification. However, given the displacement of the data and the lack of support for the 500 m limit from a technical point of view, results with this cut-off should be treated with caution. Lastly, child immunization did not seem to be impacted on average by internet access in robustness checks.

Alternative coding of the outcomes was also tested with Table 6 displaying the results. Once again, the main findings were confirmed. Mixed results were found regarding the use of antenatal care while a positive effect of broadband internet on bednet use was evidenced and no effect on child immunization was found.

In addition, as our outcomes, and especially child vaccination, could have been affected by disinformation spread on the internet some heterogeneity analyses were conducted. As income or education levels were found to be linked with the probability to holds such beliefs (Douglas *et al.*, 2019), analyses based on the quintile of wealth and educational level were performed to identify a potential differentiated effect of internet access. Results are available in Appendix A4. The main findings were confirmed, no matter the level of wealth or education internet access did not impact children's vaccination except for those with a secondary or higher education level for which a positive impact was found. The use of bednet increased for respondents with lower levels of wealth (poorest, poorer, intermediate) or education (no education, primary) and the effect on the use of antenatal care remained uncertain.

Robustness analyses conducted with the variation of population density over time showed no major migration of individuals from unconnected areas to connected areas. More details are available in Appendix A5.

Table 4 – **Results of robustness analyses for urban and rural areas**

	Urban areas		Rural areas	
Outcome	Fixed effects	Matching	Fixed effects	Matching
Use of antenatal care	**0.087*****	−0.016	0.062	−0.047
	(p=0.009)	(p=0.632)	(p=0.536)	(p=0.259)
N	4,769	4,506	4,577	4,197
Use of bednet	0.118	**0.095*****	**0.279*****	**0.057***
	(p=0.149)	(p<0.001)	(p<0.001)	(p=0.078)
N	7,200	7,130	8,288	8,124
Child immunization	−0.057	−0.001	**−0.338*****	−0.018
	(p=0.574)	(p=0.973)	(p=0.001)	(p=0.686)
N	3,637	3,441	3,451	3,110

Note: The same models (Fixed effects and Matching) are estimated by subgroups of individuals (urban areas vs rural areas).
***p<0.01; **p<0.05; *p<0.1.

Table 5 – **Results of robustness analyses with different cut-offs for treated and control group**

	Control group >3 km (urban area) or >6 km (rural area) from backbone		Analysis of urban areas only and control group >3 km from backbone		Treatment group <=500 m and control group >500 m from backbone		Treatment group <=500 m and control group >3 km (urban area) or >6 km (rural area) from backbone	
Outcome	Fixed effects	Matching	Fixed effects	Matching	Fixed effects	Matching	Fixed effects	Matching
Use of antenatal care	0.073 (p=0.145)	−0.009 (p=0.789)	0.086 (p=0.150)	0.020 (p=0.645)	**0.091***** (p=0.002)	**0.049*** (p=0.094)	**0.112**** (p=0.040)	0.053 (p=0.163)
N	5,926	5,609	3,360	3,201	10,375	8,703	4,657	4,394
Use of bednet	**0.172**** (p=0.015)	**0.077***** (p=0.001)	**0.161**** (p=0.042)	**0.073**** (p=0.022)	0.068 (p=0.581)	0.016 (p=0.493)	0.141 (p=0.272)	0.023 (p=0.433)
N	9,464	9,343	4,936	4,790	17,491	14,905	7,205	6,979
Child immunization	−0.035 (p=0.712)	0.008 (p=0.844)	−0.050 (p=0.666)	−0.001 (p=0.978)	−0.069 (p=0.205)	−0.052 (p=0.118)	−0.008 (p=0.926)	−0.033 (p=0.444)
N	4,642	4,360	2,679	2,545	7,901	6,551	3,429	3,218

Note: The same models (Fixed effects and Matching) are estimated by varying the connection radius and the distances to determine the control group. ***p<0.01; **p<0.05; *p<0.1.

Table 6 – **Results of robustness analyses with different outcomes**

Outcome		Fixed effects	Matching
Use of antenatal care	*At least 4 visits*	***0.057**** *(p=0.058)*	*−0.030 (p=0.240)*
	N	9,346	8,703
	At least 3 visits	−0.019 (p=0.680)	−0.017 (p=0.403)
	N	9,346	8,703
	At least 8 visits	0.010 (p=0.196)	**0.012**** (p=0.049)
	N	9,346	8,703
Use of bednet	*Some children*	***0.143**** *(p=0.056)*	***0.078****** *(p<0.001)*
	N	15,488	15,254
	All children	**0.121*** (p=0.062)	**0.071***** (p=0.001)
	N	15,488	14,905
	Some children with a restriction to households with bednet	**0.123*** (p=0.070)	**0.080***** (p<0.001)
	N	15,152	14,558
Child immunization	*Complete EPI*	*−0.060 (p=0.460)*	*−0.007 (p=0.822)*
	N	7,088	6,551
	BCG vaccination	−0.039 (p=0.214)	−0.014 (p=0.305)
	N	9,071	8,399
	DPT/Pentavalent vaccination	−0.030 (p=0.455)	−0.005 (p=0.812)
	N	9,052	8,381
	OPV vaccination	−0.017 (p=0.781)	0.005 (p=0.827)
	N	9,055	8,384
	Measles vaccination	0.003 (p=0.964)	0.007 (p=0.785)
	N	9,017	8,346

Note: The same models (Fixed effects and Matching) are estimated by changing the outcomes used. Original outcomes are in italics. ***p<0.01; **p<0.05; *p<0.1.

Lastly, as controlling for healthcare supply is important but our indicator of healthcare centers' density has some limits (available only at the regional level and constant throughout the period studied) supplementary analyses were conducted using the distance to the closest healthcare facility. However, this alternative measure also bears some limits as we do not have information on the date of creation of the healthcare facilities, thus this variable is constant throughout the period studied. Using this alternative variable, our results still hold and no difference is observed as shown in Appendix A6.

3. Discussion

According to our initial hypothesis, the arrival of broadband internet, and thus of increased information flows, combined with exposure to a larger variety of information sources was expected to increase knowledge in the healthcare domain translating into higher preventive healthcare demand. However, we found mixed results regarding the impact of broadband internet on various preventive health behaviors. Confirming our initial hypothesis, access to the internet was associated with an increase of bednet utilization for under 5 children. Heterogeneity analyses highlighted this positive impact for respondents with lower levels of wealth or education. Results regarding the impact of internet access on the utilization of antenatal care remained unclear, since there seemed to be a positive impact in some of our specifications, especially in urban areas, but not in others. Finally, no significant result was found in regression analyses regarding child vaccination, meaning that internet access did not seem to influence child immunization.

The positive association between internet access and some preventive health indicators (use of bednet in particular) is a positive finding for public authorities. Indeed, once broadband internet access is established, communication campaigns, which are among the most cost-effective interventions in the health domain, can easily be set up. As a result, the health of the population could be improved at low costs. Such campaigns have proven to be effective (Wakefield *et al.*, 2010). Still, an important challenge remains for public authorities in order to make sure that information of quality is easily accessible on official websites and in all the languages needed.

The mixed or non-significant results for some of the outcomes studied (use of antenatal care and child immunization) seem in line with recent literature on the subject (Edmeades *et al.*, 2022). It could be explained by the fact that people may use the internet rather for entertainment purposes than for informative purposes (Falck *et al.*, 2014). Indeed, online care-seeking behaviors might be uncommon at first and public authorities may need to launch official platforms and online health promotion campaigns to provide trusted health information and build e-health literacy capacity among the population. Moreover, as evidenced by the literature presented in the introduction section, information provision can have a heterogeneous effect on different types of behaviors. Thus, it is also possible that access to broadband does not impact all preventive health behaviors, and therefore more research is needed to understand why internet access has a heterogeneous impact on various health behaviors. One explanation could be linked to the results of Jalan & Somanathan (2008) who found that giving specific information on contamination of water sources (i.e. telling each household the actual level of fecal contamination) led to deeper changes in healthcare behaviors (i.e. purifying their water) compared to the households that were only informed about the general importance of treating water. Our mixed results might then be explained by the lack of specific and targeted information online. In addition, it is also possible that the length of exposure to information matters regarding its effect on healthcare behaviors. Indeed, in the studies of Cairncross *et al.* (2005) and Luby *et al.* (2004) educational interventions were conducted over months and a positive effect was found whereas in the studies reviewed by Meredith *et al.* (2013) one-time-only visit did not have any effect. Although in our case the potential length of exposition to information is important, but we do not know how frequently respondents looked for information and a one-time visit to a webpage might not be enough to modify behaviors.

It is also important to keep in mind that access to internet can also increase exposition to health misinformation. As the recent COVID-19 pandemic has illustrated, such misinformation can have dramatic consequences on health behaviors (Baranes *et al.*, 2022). In our case, the use of antenatal care and bednet are less likely to be sensitive to disinformation while vaccination is very often affected by fake news that fuel vaccine hesitancy which remains an important issue in Africa (Cooper *et al.*, 2018). This could explain the negative association found between internet access and child immunization in rural areas, combined with difficulties in healthcare access. Indeed, if someone fears vaccination, they will make less effort to go to healthcare centers. However, the heterogeneity analyses conducted highlighted no clear differentiated effect for the poorest or less educated respondents, which are more susceptible to adhere to by conspiracy beliefs (Douglas *et al.*, 2019), pointing to the relatively low influence of such phenomenon in our study. More globally, the quality of the information found on the internet is a real concern. Eysenbach *et al.* (2002) conducted a systematic review of studies assessing the quality of health information online and found that 70% of included studies concluded that quality is an issue. More recently, while analyzing prostate cancer information online, Moolla *et al*. (2020) highlighted that the majority of websites are unreliable as a source of information by themselves for patients. Even though those studies looked at information available online worldwide, and mostly consulted by people leaving in developed countries, there is no reason to think that the quality of information online is not a matter in SSA also.

Some limitations of this study can be underlined. First, we only measured internet access and not internet use. As some households located in the treatment area are not internet users for financial or other reasons, our analysis tends to underestimate the effect of information provided through internet on health behaviors. However, even if we could not measure actual internet use, according to the International Telecommunication Union, the percentage of individuals using internet was more than multiplied by 3 between 2009 and 2016 (from 7.5% to 25.6%) in Senegal.[8] Second, while our outcome variables were more likely to be influenced by mothers, we did not know among households with internet connection which members can decide to buy internet access or use it. Third, we do not have information on possible obstacles to healthcare centers' access, thus mothers might have been informed about the four antenatal care visits recommended thanks to internet but not able to consult. This could explain why we found a positive effect of internet access in urban areas but not in rural areas where geographical constraints to access are higher. Additionally, traditional awareness campaigns were likely conducted during the period studied, potentially trageting areas not broadband connected in the first instance, allowing respondents from unconnected areas to have access to information they would not have had otherwise, leading to an underestimation of the effect of internet access on health behaviors. Broadband internet access could also possibly affect the healthcare supply and introduce some bias in our results. Indeed, doctors and other skilled medical staff might also benefit from easier access to information to improve their medical practice. However, as our outcome variables fall under primary care and only require basic medical knowledge, it is unlikely that such issues affected our results. Indeed, medical workers should already know the importance of antenatal consultations, child vaccination, and bednet utilization without broadband internet. Moreover, vaccination or prenatal monitoring require in person-consultation and cannot be done via tele-consultation since physical acts are needed. However, broadband internet access can influence the management of vaccine stocks and allow easier access to bednet purchase. Moreover, as mentioned in the data section, GPS localization is not exact in DHS data. As a result, some individuals might have been wrongly assigned to treatment and control groups, especially in rural areas where displacements for anonymity reasons can be made further away. However, to tackle this issue, we conducted different robustness analyses using different backbone distance cut-offs for treatment and control groups and a sub-analysis on urban areas only. All these robustness analyses confirmed the results of the main analysis then pointing to no or a low bias introduced by this issue. At last, we did not consider the migration of individuals over time, as DHS data does not allow it. This could be a problem with the first methodology if some respondents, with specific characteristics, decided to move from unconnected to connected areas because of internet access. However, our robustness analyses using change in population density seem to rule out a major impact of this issue. Moreover, the matching performed in the second methodology allowed us to make sure that differences in observable characteristics among respondents remained constant, then limiting this issue. Lastly, as there may be an omitted variable, the causal impact of our results must be used with caution while discussing the results.

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In the future, investigations on other sub-Saharan countries could be conducted to confirm our results and to test whether geographical disparities exist. Indeed, the timing of connection to sub-marine cables differed from one country to another in sub-Saharan Africa. The first African submarine internet cables arrived in 2009 and covered the east coast of Africa, while the western part of Africa was connected in 2010-2011 and the southeast part of Africa in 2012. These differences in the timing of optic-fiber submarine cables connection between African countries could be exploited to produce more robust results and to assess whether internet access had a differentiated effect on health behaviors depending on countries. The

8. *https://www.itu.int/en/ITU-D/Statistics/Pages/stat/default.aspx – accessed June 2023.*

first studies on the topic seem to point out that relationship between digital resources use and health outcomes are linked to the country's context (Edmeades, 2022), reinforcing the need for further studies to better understand those mechanisms.

If the positive impact of internet access on some health outcomes, such as bednet use, are further confirmed, expansion of broadband internet could have important positive spillover effects to improve health through increased access to information. Prevention and promotion health campaigns would have to integer online campaigns as complementary to in-person actions to improve their efficacy and efficiency. On the other hand, equal access to the internet across a territory, especially between rural and urban areas, would be extremely important not to exacerbate already existing geographical health inequalities. ☐

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APPENDIX A1

RESULTS OF PLACEBO TESTS

Table A1 – **Results of placebo tests with the first methodology**

	Use of antenatal care		Use of bednet		Child immunization	
Treatment	0.027	(p=0.46)	0.127	(p=0.11)	−0.032	(p=0.84)
Urban	0.044	(p=0.32)	−0.103*	(p=0.05)	0.185**	(p=0.02)
Age	0.004***	(p=0.01)	0.003**	(p=0.03)	0.006***	(p=0.00)
Wealth index	0.077***	(p=0.00)	−0.001	(p=0.913)		
Education level	0.019*	(p=0.07)	0.007	(p=0.64)	0.105***	(p=0.00)
Married or living together	−0.079***	(p=0.00)			−0.079**	(p=0.04)
Currently working	−0.030*	(p=0.06)			−0.021	(p=0.18)
Kid birth order	−0.023***	(p=0.00)	−0.008**	(p=0.04)	−0.021***	(p=0.00)
Density of healthcare center					−1.070***	(p=0.00)
Constant	0.164*	(p=0.05)	0.322***	(p=0.00)	0.539***	(p=0.00)
2005	0.267***	(p=0.00)			−0.057	(p=0.70)
2008			0.206***	(p=0.00)		
N	9,346		10,661		4,770	

***p<0.01; **p<0.05; *p<0.1.

Placebo tests with an earlier treatment date were performed for all three outcomes with the first methodology. Placebo tests consist of running the regression with a fake treatment date prior to actual treatment (between 1997 and 2005 for antenatal care, between 2005 and 2008 for use of bednet, and between 1992 and 2005 for child immunization). The wave 1992 DHS wave for Senegal was added in order to perform the placebo test for child immunization as at least two periods before treatment are needed. No impact was found for our three outcomes confirming (first line), confirming that before actual treatment our two groups had similar evolutions).

APPENDIX A2

FULL RESULTS OR REGRESSIONS ANALYSES

Table A2-1 – **Full results of regressions analyses with the first methodology**

	Use of antenatal care	Use of bednet	Child immunization
Treatment	0.058* (p=0.06)	0.143* (p=0.06)	−0.060 (p=0.46)
Urban	0.022 (p=0.59)	−0.116* (p=0.07)	0.069 (p=0.16)
Age	0.006*** (p=0.00)	0.003** (p=0.02)	0.006*** (p=0.00)
Wealth index	0.012*** (p=0.00)	−0.002 (p=0.21)	0.001 (p=0.82)
Education level	0.043*** (p=0.00)	0.024 (p=0.11)	0.059*** (p=0.00)
Married or living together	−0.089*** (p=0.00)		−0.115** (p=0.02)
Currently working	−0.023 (p=0.14)		−0.010 (p=0.59)
Child birth order	−0.029*** (p=0.00)	−0.007** (p=0.01)	−0.022*** (p=0.00)
Density of healthcare center	−1.718*** (p=0.00)	−22.667** (p=0.03)	−65.248*** (p=0.00)
2005	0.273*** (p=0.00)		
2008		0.267*** (p=0.00)	
2012		0.265*** (p=0.00)	0.136** (p=0.04)
2014	0.210*** (p=0.00)	0.323*** (p=0.00)	0.086* (p=0.06)
2016	0.313*** (p=0.00)		
Constant	0.287*** (p=0.00)	1.589*** (p=0.01)	4.110*** (p=0.00)
N	9,346	15,488	7,088

***p<0.01; **p<0.05; *p<0.1.

Table A2-2 – **Full results of regressions analyses with the second methodology**

	Use of antenatal care	Use of bednet	Child immunization
Treatment	−0.030 (p=0.240)	0.078*** (p=0.000)	−0.007 (p=0.822)
Connected	0.035** (p=0.017)	−0.044*** (p=0.000)	−0.013 (p=0.582)
Submarine	0.176*** (p=0.000)	0.181*** (p=0.000)	0.125*** (p=0.000)
Urban	−0.042*** (p=0.003)	−0.023** (p=0.035)	0.044*** (p=0.009)
Age	0.008*** (p=0.000)	0.001 (p=0.382)	0.008*** (p=0.000)
Wealth index	0.011*** (p=0.000)	0.002*** (p=0.009)	0.001 (p=0.581)
Education level	0.053*** (p=0.000)	0.019*** (p=0.009)	0.084*** (p=0.000)
Married or living together	−0.136*** (p=0.000)		−0.109*** (p=0.003)
Currently working	−0.042*** (p=0.001)		−0.014 (p=0.350)
Child birth order	−0.031*** (p=0.000)	−0.000 (p=0.982)	−0.022*** (p=0.000)
Density of healthcare center	−0.144 (p=0.296)	−2.586*** (p=0.000)	−0.557*** (p=0.003)
Constant	0.406*** (p=0.000)	0.517*** (p=0.000)	0.485*** (p=0.000)
N	8,703	15,254	6,551

***p<0.01; **p<0.05; *p<0.1.

APPENDIX A3

RESULTS OF COMPLEMENTARY ANALYSES ON POTENTIAL SELECTION BIAS

Table A3 – **Results of complementary analyses on potential selection bias**

	Treated group <1.2 km & Control group >1.4 km from backbone		Treated group <1.25 km & Control group >1.25 km from backbone	
Outcome	Fixed effects	Matching	Fixed effects	Matching
Use of antenatal care	0.008	−0.035	0.004	−0.033
	(p=0.855)	(p=0.158)	(p=0.933)	(p=0.167)
N	9,901	9,346	10,375	9,816
Use of bednet	**0.127***	**0.082*****	**0.131****	**0.094*****
	(p=0.074)	(p=0.001)	(p=0.050)	(p=0.001)
N	16,700	16,475	17,491	17,266
Child immunization	−0.043	−0.018	−0.048	−0.035
	(p=0.518)	(p=0.513)	(p=0.445)	(p=0.188)
N	7,584	7,062	7,901	7,384

***p<0.01; **p<0.05; *p<0.1.

APPENDIX A4

RESULTS OF HETEROGENEITY ANALYSES

Table A4-1 – **Heterogeneity analyses on wealth quintile**

	Poorest		Poorer		Intermediate		Richer		Richest	
Outcome	Fixed effects	Matching	Fixed effects	Matching	Fixed effects	Matching	Fixe deffects	Matching	Fixed effects	Matching
Use of ante-natal care	**−0.452****	**−0.181****	0.066	−0.047	−0.002	−0.049	**0.154*****	0.074	0.056	−0.068
	(p=0.001)	(p=0.014)	(p=0.585)	(p=0.495)	(p=0.981)	(p=0.309)	(p<0.001)	(p=0.141)	(p=0.208)	(p=0.232)
N	1,661	1,473	1,819	1,696	2,214	2,112	2,025	1,901	1,627	1,532
Use of bednet	**0.449***	0.055	**0.205***	**0.164*****	0.116	**0.087***	0.099	−0.001	0.132	0.071
	(p=0.052)	(p=0.391)	(p=0.076)	(p=0.001)	(p=0.259)	(p=0.014)	(0.340)	(p=0.986)	(p=0.225)	(p=0.130)
N	2,826	2,697	3,595	3,465	3,819	3,715	3,015	2,910	2,233	2,118
Child immunization	0.268	0.092	−0.039	−0.122	−0.037	0.018	−0.261	−0.006	0.014	0.021
	(p=0.625)	(p=0.388)	(p=0.734)	(p=0.113)	(p=0.685)	(p=0.730)	(p=0.122)	(p=0.915)	(p=0.933)	(p=0.735)
N	1,110	966	1,434	1,636	1,904	1,798	1,483	1,397	1,157	1,068

***p<0.01; **p<0.05; *p<0.1.

Table A4-2 – **Heterogeneity analyses on the educational level**

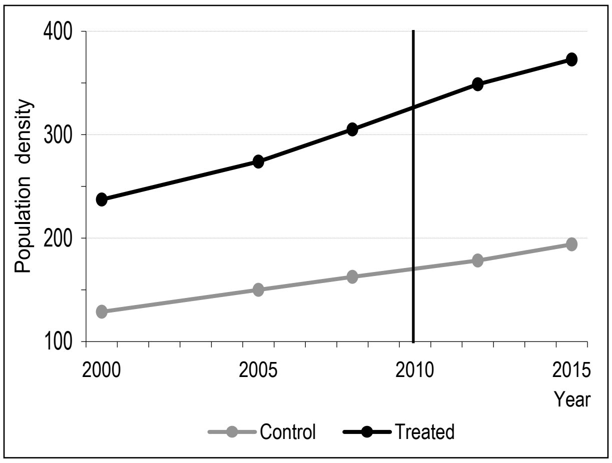
	No education		Primary		Secondary or higher	
Outcome	Fixed effects	Matching	Fixed effects	Matching	Fixed effects	Matching
Use of antenatal care	−0.038	−0.009	**0.171*****	−0.021	0.057	**−0.143****
	(p=0.532)	(p=0.792)	(p=0.001)	(p=0.666)	(p=0.485)	(p=0.035)
N	5,979	5,723	2,263	2,038	1,104	942
Use of bednet	0.122	**0.050***	**0.189****	**0.111*****	0.105	0.088
	(p=0.176)	(p=0.057)	(p=0.047)	(p=0.002)	(p=0.266)	(p=0.120)
N	10,210	10,063	3,836	3,584	1,442	1,258
Child immunization	−0.088	−0.011	−0.133	−0.027	−0.007	**0.129***
	(p=0.379)	(p=0.773)	(p=0.305)	(p=0.603)	(p=0.957)	(p=0.099)
N	4,539	4,324	1,827	1,626	722	601

***p<0.01; **p<0.05; *p<0.1.

APPENDIX A5

RESULTS OF ROBUSTNESS ANALYSES ON THE POPULATION DENSITY

Figure A5 – **Evolution of the density of population in Senegal between 2000 and 2015**



From additional data, we checked if the population density evolved due to internet access. Figure A5 shows that in both connected areas (treated group) and unconnected areas (control group), population density increased over the period. However, the increase in density is higher in connected areas than in unconnected are ($t=3.67$, $p<0.01$). Yet, those results are still reassuring, the growth rate of population density was already higher in connected areas before treatment. The arrival of broadband internet does not seem to have had a huge impact on migrations from unconnected to connected places.

APPENDIX A6

RESULTS OF ROBUSTNESS ANALYSES WITH ALTERNATIVE PROXIES OF HEALTHCARE SUPPLY

Table A6 – **Results of regressions analyses with distance to the closest healthcare facility instead of density of healthcare center**

Outcome	Fixed effects	Matching
Use of antenatal care	0.057* (p=0.064)	−0.029 (p=0.268)
N	9,346	8,703
Use of bednet	0.133* (p=0.070)	0.095*** (p<0.001)
N	15,488	15,254
Child immunization	−0.074 (p=0.356)	0.001 (p=0.998)
N	7,088	6,551

***p<0.01; **p<0.05; *p<0.1.