Essays on information technology access and health outcomes

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経済学専攻

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(情報技術アクセスと健康アウトカムに関する研究)

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Chapter 1

General Introduction

Access to information enables individuals to make informed decisions. Information and communication technologies contribute significantly to improving access to information by providing the infrastructure and tools for individuals to obtain, process and share information. Communication devices and services are now accessible even in remote areas where basic necessities such as clean water and improved sanitation are often lacking. To improve health outcomes, authorities around the world leverage this opportunity to disseminate health information (Haenssgen and Ariana, 2017).

The improvement in access to communication services in developing countries has been most remarkable in recent decades. Particularly, Sub-Saharan Africa has experienced the most rapid growth, both in terms of mobile phone and internet penetration (International Telecommunication Union, 2018; GSMA, 2019). As a result, an increasing number of individuals can now access various sources of information that would have been either inaccessible or costly. The majority of individuals in Sub-Saharan Africa access the internet via mobile phones, and approximately 41% of these users utilize it to obtain health information (Pew Research Center, 2018). The significant utilization of information technologies to obtain medical information has the potential to greatly impact health outcomes.

The aim of this thesis is to provide insight on how access to information technologies impacts health outcomes. First, we start by a cross-country analysis involving Sub-Saharan African countries, and explore whether an increasing search for immunization information on the Internet has an impact on vaccines uptake. Although a significant proportion of Internet users access health information, there is a lack of empirical evidence on its impact on health outcomes. By investigating this relationship, we enrich the literature on the impact of access to health information. The increase in Internet access in the region is mainly due to improved telecommunications infrastructure that has led to the massive adoption of mobile devices. We therefore proceed to examining the impact of access to mobile communication infrastructure on vaccination coverage. We particularly focus on Côte d'Ivoire, a Sub-Saharan African country that has experienced rapid growth in its telecommunications services and has taken the opportunity to raise awareness about the importance of vaccination. Moreover, to address the low rate of HIV testing, the country takes advantage of high mobile phone penetration by using mobile technology to disseminate HIV-related information. Finally, we explore the impact of access to mobile phones on HIV testing while taking into account potential complementarity with earlier information devices such as TV and radio. The remainder of this dissertation is organized as follows.

Chapter 2 explores the impact that searching the Internet for immunization information has on vaccination coverage. By using Google search trends to measure vaccination information seeking behavior in Sub-Saharan African countries, we found an overall positive impact on vaccine uptake. We also found that the effects are heterogeneous among vaccines.

The effect is statistically significant for the vaccine related to high-risk disease, but not significant for the controversial vaccine and the vaccine related to low-risk disease.

Chapter 3 investigates the impact of mobile communication infrastructure on vaccination coverage in Côte d'Ivoire. By combining geocoded cell tower information with data from a nationally representative household survey, we found a positive association between proximity to cell towers and vaccine uptake. Our findings suggest that access to cell towers helps bridge the vaccination coverage gap resulting from lack of education.

Chapter 4 examines potential complementarity between mobile phone and earlier information devices regarding their impact on health outcomes. We found that not controlling for TV/radio access leads to an overvaluation of the impact of mobile phone by about 20%. Moreover, the impact of accessing mobile phone on HIV testing is significantly greater when used in conjunction with TV/radio. A greater complementarity between phone and TV/radio is found among the socio-economically disadvantaged groups.

Chapter 5 concludes our dissertation.

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Chapter 2

Does searching online for vaccination information affect vaccination coverage? Evidence from Sub-Saharan African Countries

2.1 Introduction

The Internet is transforming the way people obtain information. The United Nations specialized agency for information and communication technologies (ICT) estimates that 51.2% of the world's population, or 3.9 billion people, have used the Internet at the end of 2018. The growth in the share of internet users in developing countries has been the most remarkable over the past decades. Particularly, the African continent has recorded the highest growth between 2005 and 2018, with an increase from 2.1% to 24.4% in the average share of people using the Internet (International Telecommunication Union, 2018). The Internet is a vehicle for educational opportunities, access to social and government services, and health information in developing countries (Madon, 2000). According to the Pew Research Center (2018), about 41% of internet users in Sub-Saharan Africa use the Internet to access health and medical information.

While the Internet is empowering people with various kinds of knowledge, it can also be a channel through which people spread biased or misleading information. Scholars have raised concerns that the Internet may negatively impact people's perceptions of vaccines.

Zimmerman et al. (2005) report that several websites make strong affirmations that vaccination causes adverse reactions such as sclerosis, autism, and diabetes.

Some studies suggest that the Internet contains an overall higher amount of pro-vaccination content. Wolfe and Sharp (2005) find that the use of the keyword "immunization" on search engines yields 98% pro-vaccination sites and only 2% anti-vaccination sites, but for the keyword "vaccination," these are 40% and 60%, respectively. Using individual-level web browsing data coupled with US sample survey responses, Guess et al. (2020) find that encounters with vaccine-critical content are less frequent. They represent only 7.5% of the vaccine-related views on the Internet and are seen by only 18.5% of people each year. Further, provided that the Internet consists of both public health communicators and anti-vaccination activists (Betsch and Sachse, 2012), it is worth exploring whether the net impact of searching for immunization information is positive or not.

The objective of this study is to investigate the impact Internet searches for vaccine-related information have on vaccination coverage. This study contributes to the literature on the impact of health information in two ways. First, it uses Google search trends to measure vaccination information seeking behavior and investigates its effect on immunization coverage. By using panel data from sub-Saharan African countries between 2004 and 2017, we empirically analyze whether an increasing search for immunization information has a positive impact on vaccines uptake. Particularly, we explore the heterogeneity of impact among the major vaccines recommended by the World Health Organization (WHO) since 1974. An important strand of the extant literature has paid attention to the impact of media coverage of misinformation regarding measles vaccine on its vaccination rates (Chang, 2018; Smith et al., 2008; Tangvatcharapong, 2020).

Second, this study complements the literature on the use of the Internet to search for vaccination information. Most empirical studies build on an experimental framework to assess the impact of the Internet on attitude toward immunization (Allam et al., 2014; Betsch et al., 2017; Tustin et al., 2018) or analyze the global search trends on vaccine-related information (Rampally et al., 2020). Our study utilizes actual data on vaccination rates and searches for immunization information over a long period to explore their relationship. Moreover, there is a lack of empirical studies investigating this relationship for developing countries, particularly for Sub Saharan African countries. Although a significant proportion of Internet users in the region access health and medical information (Pew Research Center, 2018), no attempt has been made to assess the potential influence of seeking vaccination information on vaccine uptake. By examining the impact of access to online immunization information, this study empirically ascertains whether Internet information can be beneficial in improving the vaccination rates.

The remainder of this chapter is organized as follows. Section 2 gives overviews on the use of the Internet for health information in Sub-Saharan Africa and the different vaccines investigated in this study. Data and descriptive statistics are presented in Section 3. In Section 4, we provide the econometric model employed. Section 5 presents the results of the empirical analysis. Section 6 discusses the findings and Section 7 concludes the chapter.

2.2 Background

2.2.1 Use of the Internet for health information

The Internet arrived in sub-Saharan Africa in the early 1990s. By the end of the 20th century, the penetration in the region was still very insignificant and stood at 0.5% in 2000, while the world average was about 7% (World Bank, 2020). However, according to International Telecommunication Union (2018), the growth in the share of Internet users in developing countries has been more sustained, rising from 7.7% to 45.3% over the period 2005 to 2018. During the same period, among all ITU regions, the highest growth was recorded in Africa, where the average share of people using the Internet increased from 2.1% to 24.4%. According to Frankfurter et al. (2020), most people in sub-Saharan Africa access the Internet via mobile phones rather than personal computers. At the end of 2020, 28% of Sub-Saharan Africans were connected to the internet through mobile phones, continuing the positive trend observed since 2014.

Recent studies in some African countries suggest an important use of Internet to access online health information. Osei Asibey et al. (2017) investigate university students' use of the Internet to access health information using a questionnaire. 650 students from three universities participated by answering the questionnaire. Their study reveals that 78.3% (509/650) of university students in Ghana use the Internet daily and about 68% (440/650) use it for health purposes. Borzekowski et al. (2006) provide evidence of adolescents' use of the Internet to access health information. They survey a representative sample of 778 in and out of school adolescents. They find that 66% of those in school and 54% of those out-of-school use the Internet. Among them, 53% use the Internet to search for health information, and the share does not differ significantly according to the gender, age, or even school status. In Nigeria, a survey among patients on Internet usage for health information shows that a substantial proportion of patients use the Internet to search medical information (Yusuf, 2015). The study reveals that almost 76% of respondents use Google as their primary search engine, 40% of searches are for disease status and 16% for drug treatment, and 64% of respondents found the information useful. Although there is evidence of increased use of the Internet for health information seeking, little is known about its impact on health outcomes in Sub Saharan Africa.

The internet is one of the main sources of health information and consists of a significant number of pro and anti-vaccination sites (Sak et al., 2016), this might have significant implications for vaccine uptake. According to WHO (2019), vaccination coverage in Sub-Saharan Africa has stagnated at 72% over the past five years, exposing populations to vaccine preventable diseases and epidemics.

2.2.2 Overview on Vaccines and related diseases

The WHO launched the Expanded Program on Immunization (EPI) in 1974 with the goal of immunizing children worldwide. At that time, less than 5% of children in developing countries were vaccinated (Miller and Sentz, 2006). In 1984, WHO issued a standardized immunization schedule for the four original EPI vaccines against six diseases which are: Tuberculosis (BCG), diphtheria-tetanus-pertussis (DTP), poliomyelitis, and measles (Halsey and Galazka, 1985). These vaccines were provided in most countries in Africa by the mid-eighties, in contrast to vaccines like Hepatitis B and Haemophilus influenzae type b introduced from 2000 by at most two African countries (Kamadjeu, 2017).

The BCG vaccine protects against tuberculosis which is a highly contagious disease spreading through respiratory droplets (WHO, 2020). In 2019, despite having the highest vaccination coverage (about 80%) among the four original EPI vaccines, the disease incidence of tuberculosis is surprisingly the highest in Africa. The number of reported cases stood at about 2.5 million. Although the Tuberculosis vaccine protects against disseminated tuberculosis, it does not prevent primary infection and reactivation of a latent pulmonary infection. The impact of BCG vaccination on the transmission of tuberculosis is limited compared to others (WHO, 2021).

The DTP vaccine is designed to deal with three diseases among which, tetanus is the only non-communicable disease that registered about 3,600 cases in 2019. However, both diphtheria and pertussis can be transmitted from person to person through respiratory excretions. Yet, in 2019, the burden of the disease was 4,121 cases for pertussis, while the disease incidence for diphtheria was about 11,400 cases across all of Africa.

The polio vaccine is against poliomyelitis which is also a highly infectious viral disease. The virus is transmitted from person to person, primarily through the fecal-oral route or, unusually through contaminated food or water. The number of reported cases in Africa were about 5 and 65, respectively, in 2016 and 2018, which are the lowest numbers of cases among the EPI target diseases. Polio cases decreased by 99.9% in Africa region between

1988 and 2021. The region became eligible to be certified free of wild polio in 2019, and subsequently has been certified in 2020 (UNICEF, 2021)

The measles vaccine protects against measles. It is the most highly communicable disease, requiring a higher proportion of immune persons to achieve herd immunity. Indeed, herd immunity against measles requires about 95% of the population to be vaccinated, while 86% is needed against tuberculosis (Chang et al., 2020; Chow and Leo, 2017). Unlike tuberculosis, natural infection generates a lifelong immunity and the measles vaccine provides long-run and probably lifelong immunity in most people. According to Rothman et al. (2006), the measles vaccine is one of the safest and most effective of all vaccines, and is mostly given in combination with the rubella vaccine (as MR vaccine) or with the rubella and mumps vaccine (as MMR vaccine). However, in 2019, with the lowest vaccination rate of 69%, the number of reported cases of measles in Africa was about 620,000. Indeed, the MMR vaccine is a highly controversial vaccine. In 1998, a scientific study published by Wakefield et al. (1998) suggested a causal link between the MMR vaccine and autism. Although the study was discredited and retracted later in 2010, claims that the vaccine causes autism continued to circulate on the Internet, resulting in a decline in vaccination rates and multiple measles outbreaks throughout the world (Hussain et al., 2018).

Although not available at the regional level, Google allows us to obtain the global popularity of a given search term. We capture the extent to which people searched on the relationship between each vaccine and autism over our study period. For measles, we collect google trends data on all search queries that included measles, vaccine, and autism simultaneously. We repeat the same procedure for each of the other vaccines. Figure 2.1

presents global google search trends on the relationship between each vaccine and autism. We observe that the search interest on the relationship between measles vaccine and autism was fairly high throughout our study period. However, the search interest on the relationship between autism and each of the other vaccines stagnated at zero. Figure 2.2 depicts the vaccination coverage of the four original EPI vaccines in Africa from 1980 to 2019. From 1980 until before MMR controversy in 1998, the coverage for the measles vaccination was higher than those of polio and DTP. From 1998, it decreased before increasing from 2000, but remained lower than the others over nearly the rest of the period. Figure 2.3 shows the incidence rates of each disease in Africa from 2000 to 2019. Tuberculosis and measles have the highest incidence rates over the whole period. In 2000, the incidence rates were 3360 and 842 per 1,000,000 total population for tuberculosis and measles, respectively. In 2019, the rates were still high and stood at 2260 and 567. The incidence rates for Diphtheria, Pertussis and Tetanus were comparatively low, stood at 18, 9 and 4 in 2019, respectively. Poliomyelitis has the lowest rates over the entire period. The incidence rate was 0.7 in 2019, and almost zero in the previous five years.

2.2.3 Literature on the impact of access to information on health outcomes

The impact of access to information on health outcomes, specifically on vaccination, has received increasing attention over the past decade. While one strand of the literature has paid attention to the use of the Internet for health information, another has focused on the media coverage of false information. According to Allcott and Gentzkow (2017), fake news comes with private and social costs by making it harder for consumers to infer the true state of the world. Therefore, the consumption of misinformation can lead people to make different choices than they would have made otherwise.

Several empirical studies have paid attention to the impact on vaccine uptake from media coverage of the claim that the MMR vaccine causes autism. Chang (2018) counts the number of articles in which the words "vaccine" and "autism" were mentioned to investigate the impact of media coverage. He finds that the controversy resulted in lower vaccination rates, suggesting that parents reacted to the controversy by either not vaccinating their children, or by delaying vaccination. Tangvatcharapong (2020) investigates the effect of the surge in media coverage of the MMR controversy in the US. Using a difference in differences analysis, the study suggests that parents who are ex-ante most sensitive to the false news about the MMR vaccine were 3.3% less likely to have their children vaccinated. On the other hand, Smith et al. (2008) concluded that the impact of media coverage on MMR vaccination was limited.

Other studies explore the relationship between internet use for vaccination information and vaccination decisions in a broader context. Allam et al. (2014) conducted experiments that manipulate the selection and sorting criteria of the google search engine and evaluated their influence on users' knowledge and attitude toward vaccination. The result suggests that the lesser the exposure participants had to anti-vaccination websites, the more their attitudes toward vaccination changed positively. Tustin et al. (2018) investigated the relationship between Canadian parents' search for vaccine information on the Internet and their risk perception of childhood vaccination. They concluded that the likelihood of perceiving vaccines as less safe was 1.6 to 2 times higher for parents who used the Internet to search for vaccination information. Betsch et al. (2017) conducted an online experiment involving Western and Eastern countries and collected vaccination decisions from more than 2,000 participants. The study reveals that online communication about herd immunity can increase vaccine uptake in the population. Furthermore, the findings suggest a significantly higher intention to be vaccinated against a high-risk disease than against a low-risk disease. According to Kessler and Zillich (2019), Internet users mostly use neutral search terms and rarely see additional descriptions below the headlines of search results. Moreover, they browse balanced amounts of pro-and anti-vaccination sites. Their study suggests no evidence that users mainly encounter vaccine-critical websites that might raise concerns about vaccine safety and influence users' behavior. In summary, previous studies suggest that the impact of internet use on vaccination might be influenced by the information people mainly encounter on the Internet, the risk of the disease and the controversy associated to each vaccine.

2.3 Data and descriptive statistics

2.3.1 Outcome and independent variables

This study uses data from several sources. First, data on vaccination coverage are taken from the World Health Organization (2020). We use data on the four major vaccines of the WHO EPI, for which we have long time series for all countries. These data represent the percentage of the target population that has been vaccinated against tuberculosis (Bacille

Calmette Guérin or BCG vaccine); diphtheria, tetanus, and pertussis (DTP); measles; and polio.

Second, we rely on Google trends data to capture the extent to which people search for vaccine-related information and assess its impact on vaccination coverage. With a market share of about 96% in 2022, Google has remained the most used search engine in Africa (GlobalStats, 2022). Google trends data have been available since 2004 and show the evolution of search interest for a given keyword over time in a given region. Previous studies suggested that search queries and the search volume derived from google are language-dependent as people use different search terms depending on the official language of their country (Jun et al., 2017; Vaughan and Romero-Frías, 2014). Shee and Louis (2022), in their study on COVID-19 search interest, translate English keywords into various non-English language equivalents for each country. We focus on English and French speaking countries in sub-Saharan which represent more than two-thirds of all countries in the region. Our final sample consists of a panel of 33 English-French speaking countries from 2004 to 2017. Figure 2.4 gives the geographical distribution of countries included in this study. Google trends allows the use of a connector to combine many search terms. For instance, results from using “vaccin + vaccination + immunisation” include all searches containing at least one of these keywords. This combination consists of words related to immunization for French speaking countries (Ward et al., 2015), and is used to capture the interest in vaccination-related information. The corresponding combination “vaccine + vaccination + immunization + immunisation” is used for English speaking countries (Kata, 2010). While immunization and immunisation are used in English, immunization is not used in French. For countries where both English and French are official languages, we combine search terms of both languages. Figure 2.5 depicts the relationship between vaccination rates and google searches for immunization information for each of the four vaccines. It shows a general pattern that higher vaccination rates are associated with higher search rates for immunization information. This is more apparent for BCG, DTP and Polio, for search rates above 13, vaccination rates are generally over 80%.

Lastly, we controlled for socio-economic and demographic variables that can potentially influence vaccination rates and internet use. The data on GDP per capita, the share of urban population, the share of population with access to electricity and health expenditure per capita are extracted from the World Development Indicators (2020). The health expenditure per capita identifies key issues such as areas that need investment, for instance additional health facilities, better health information systems, or better trained human resources. Education, measured as the average number of years of education received by people aged 25 and older, is converted from education attainment levels by using official durations of each level (UNESCO, 2020). The annual growth in the value added of the transport and communications sector from the African Development Bank's socio-economic database is used to approximate improvements in the transport and communication systems. Government effectiveness captures perceptions of the quality of public services, the quality of policy formulation and implementation, and the credibility of the government's commitment to such policies (World Governance Indicators, 2020).

2.3.3 Descriptive statistics

Table 2.1 shows the summary statistics for the dependent and explanatory variables. From 2004 to 2017, the lowest vaccination rate is that recorded for DTP and polio (12%), and the highest for each vaccine is 99%. On average, BCG has the highest vaccination rate (89%) and the measles vaccine has the lowest (83%). People's interest in online vaccination information varies between 0 and 24. With an average of USD 4,486, the GDP per capita varies from USD 489 to 27,000. The average number of years of schooling ranges between 1.3 and 10.2, and the share of urban population is between 9% and 89%. The government effectiveness indicator is bounded between -1.74 and 1.06. With an average of USD 482, the health expenditure per capita varies between USD 22 and 11,884. On average, about 39% of people have access to electricity, and the annual growth in the value added of the transport sector is 7%.

2.3.2 How are Google trends data computed?

Google trends gives the search interest of a keyword in relation to the highest point for a given region and time. To avoid that the regions with the most search volume (for a given search term) are always ranked highest, each data point is divided by the total searches of the geography to compare relative popularity. This corresponds to the probability that a given individual searches for a certain search term in a specific period of time in a particular region. The resulting numbers are then scaled on a range of 0 to 100 based on a search term proportion to all searches. A value of 100 corresponds to the peak popularity of a term. A value of 50 means that a term is half as popular. Trends only shows data for popular terms, so search terms with very low volume within a specific time period appear as zero.

For the keyword "vaccine," the search interest (SI) in a region *i* for time *t*, is the ratio of the number of searches for "vaccine" to the total number of searches, adjusted by dividing by the maximum search interest of "vaccine" over all regions and multiplied by 100, as followings:

$$SI_{i,t}(\text{vaccine}) = \frac{NV_{i,t}}{NT_{i,t}} * \frac{100}{\text{Max}} \quad \text{with} \quad \text{Max} = \max_j \left(\frac{NV_{j,t}}{NT_{j,t}}\right)$$

where, $NV_{i,t}$ is the search volume for "vaccine" in region *i* at time *t* and $NT_{i,t}$ is the total number of searches.

2.4. Econometric models

We evaluate the impact of access to online vaccination information on immunization coverage. For this purpose, we use the Google trends data to capture the extent to which people access vaccination-related information over time. The regression model is given as the following:

$$Y_{it} = gs_{it} + X_{it}\boldsymbol{\beta} + \eta_i + t_i + \alpha_t + \mu_{it} \tag{1}$$

where the dependent variable Y_{it} is the vaccination rate in country *i* at time *t*. gs_{it} represents the Google search on immunization information. X_{it} is a vector of socio-economic and demographic controls that allows us to mitigate omitted variable bias. We include the GDP per capita, the average number of years of schooling, and the share of urban population which are likely to impact both the use of internet and vaccine uptake. We also control for improvements in transport and communication systems which influence access to health facilities, and electricity since it is necessary to power vaccine storage appliances as well as to access information. To take differences in health-related investments into account, we add the health expenditure per capita. Furthermore, we include government effectiveness, a useful indicator for broad cross-country comparisons and for evaluating broad trends over time (World Governance Indicators, 2020). η_i and α_t represent country and year fixed effects, respectively. The country fixed effects control for unobserved and time-invariant differences across countries that may influence vaccination rates. The year-fixed effects deal with any time-varying unobserved factors. However, fixed effects do not account for unobserved factors that are different across countries and vary over time. Each country might implement various health related policies over time that affect vaccine uptake. If such policies exist and are correlated with both our dependent and key independent variables, our coefficient estimates might be biased. To mitigate this concern equation (1) includes country specific time trends (t_i).

2.5 Results and discussion

2.5.1 Results

We use OLS to estimate the impact of Google search for immunization information on vaccine uptake. Our baseline results are reported in Table 2.2. Column 1 of Table 2.2 uses the full sample that includes all vaccines. The result suggests that for a unit increase in searching for vaccination information, vaccination rates increase by 0.18%. As discussed earlier, all vaccines do not have the same features and the measles vaccine, particularly, is known to be controversial. Hence, by removing the measles vaccine from the full sample, we reexamine the effect of vaccine-related searches on immunization rates, and present the results in column 2 of Table 2.2. Compared to the result using the full sample, the coefficient of the result without the controversial vaccine is larger. One unit increase in accessing online information enhances vaccination rates by about 0.2%. This suggests that the impact of accessing online vaccine knowledge is likely to differ according to the features of each vaccine. Particularly, higher coefficient for search on immunization information in column 2 suggests that the impact of the Internet search might be lower for the controversial vaccine.

We further investigate the heterogeneity of impact among the vaccines. Columns 1 – 4 of Table 2.3 show the results for BCG, DTP, polio, and measles vaccines, respectively. Only the coefficient for BCG, the vaccine related to high-risk disease, is statistically significant. A unit increase in online searches increases BCG uptake by about 0.2%. For the other vaccines, although the estimated coefficients are all non-significant, the coefficient size for the measles vaccine is the smallest, as expected. In summary, the results suggest that the impact of online searches on vaccination is influenced by the risk of disease and the controversy associated with each vaccine.

There is a possibility that reverse causality biases our OLS estimates on the impact of online searches downward. It is possible that higher vaccination rates reduce people's concern for disease risk, thus leading to fewer Google searches about vaccination. To further investigate the extent to which our estimates might be downward biased, we rely on the herd immunity threshold. It is defined as proportion of people who need to be vaccinated to prevent the transmission of a given disease. Beyond this threshold, disease transmission is lower, which could result in fewer searches for vaccination information and lower immunization rates. If this is the case, the downward bias arising from the reverse causality should be smaller when vaccination rates are below the herd immunity threshold. According to Chang et al. (2020) the threshold for the disease related to BCG is 86 %. They found that there are fewer disease cases and deaths after crossing this threshold. The immunity threshold for measles is 95% (Chow and Leo, 2017), while it is 85% for polio (Frederiksen et al., 2020; Lippi and Henry, 2021). The DTP vaccine is designed to deal with three diseases of which pertussis is the most contagious, with an immunity threshold of 94% (Kovitwanichkanont, 2017; Perry et al., 2020). As such, we use the threshold for pertussis in our analysis. Using OLS, we re-estimate the impact of vaccination information seeking on vaccine uptake for subsamples with vaccination rates below and above the herd immunity thresholds. The results are shown in Table 2.4. The top panel (a) of the table presents the results for subsamples with vaccination rates below the thresholds, while the bottom panel (b) is for those above the thresholds. For each of the vaccines, the estimated coefficient size of the impact of search on immunization is much bigger for the below-threshold subsample. Still, for both subsamples, the results show a statistically significant impact only for BCG. Below the threshold, a unit increase in search for immunization information increases BCG vaccine uptake by about 0.47%. This is about twice as high as the estimated coefficient for the above-threshold subsample (Table 2.4, column 1) as well as that for the full sample (Table 2.3, column 1). This result suggests that reverse causality may have halved the estimated impact.

2.5.2 Discussion

The obtained results have revealed that the use of the Internet for searching vaccine-related information has an overall positive impact on vaccine uptake. Despite the existence of vaccine-critical content on the Internet, our main finding suggests that access to online vaccination information improves immunization coverage. This is consistent with several studies in the literature. Kessler and Zillich (2019) showed that Internet users mostly use neutral search terms and rarely see additional descriptions below the headline of search results. Their study suggested no evidence that users mainly encounter vaccine-critical websites that might raise concerns about vaccine safety. In addition, vaccine-critical content represented only 7.5% of vaccine-related pageviews, was seen by only 18.5% of people each year (Guess et al., 2020), and users reported being careful about the credibility of the websites (Powell et al., 2003). Most importantly, Rampally et al. (2020) analyzed global search trends on common vaccine-related information and concluded that information on "schedule" and "when" to get vaccines are the most common keyword searched with "side effect" being the lowest.

Our investigation suggests differences in impact according to the features of the vaccines. The impacts are not significant for the controversial vaccine (measles) and the vaccines related to diseases with low incidence rates. The results suggest statistically significant impact only for the vaccine (BCG) related to high-risk disease. These are in line with Betsch et al. (2017) who found a significantly higher intention to be vaccinated against a high-risk disease than against a low-risk disease. On the other hand, we did not observe the same pattern for the controversial vaccine. Indeed, the results do not show any benefit for the measles vaccine, which is related to the most contagious disease with high incidence rates. This suggests that the positive impact for vaccines related to high-risk disease could be offset by controversy. Tangvatcharapong (2020) investigated the effect of the surge in media coverage of the MMR controversy and suggested a decline in the MMR vaccine uptake. Moreover, several studies point out that attempts to correct misinformation about vaccines are mostly likely to be counterproductive and not effective to promote immunization (Nyhan et al., 2014; Nyhan and Reifler, 2015).

2.6. Conclusion

This study investigated the impact that access to the Internet for vaccine-related information has on vaccination coverage in Sub-Saharan Africa. The results suggest an overall positive impact on vaccination coverage. In addition, the effects are heterogeneous among vaccines. The results indicate a statistically significant impact for the vaccine related to high-risk disease. However, the effect is insignificant for the controversial vaccine which is also related to high-risk disease.

These findings suggest that the Internet can empower people with health knowledge, but can also be a catalyst for the spread of misinformation. As the internet is a fast-growing source of information, public health authorities should communicate more on the Internet, such as making available and publicizing official websites for health/vaccine-related information. In addition, this study recommends that policymakers keep an eye on trends in health-threatening information and work on improving official websites' ranking in google search results.

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Figures

Figure 2.1: Global search trends on the relationship between vaccines and autism 2004-2017
Source: Google

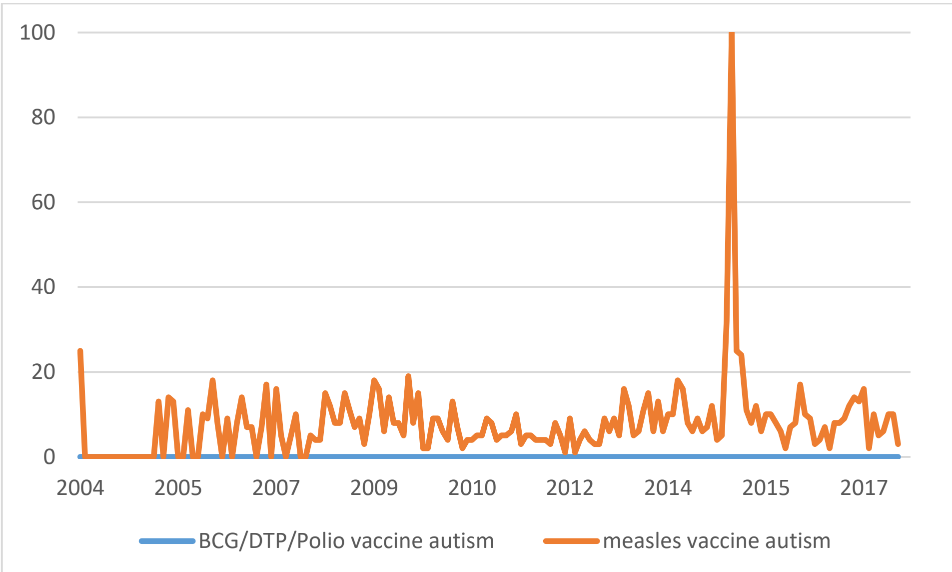


Figure 2.2: Vaccination coverage of the four EPI vaccines in Africa from 1980 to 2019
Source: WHO

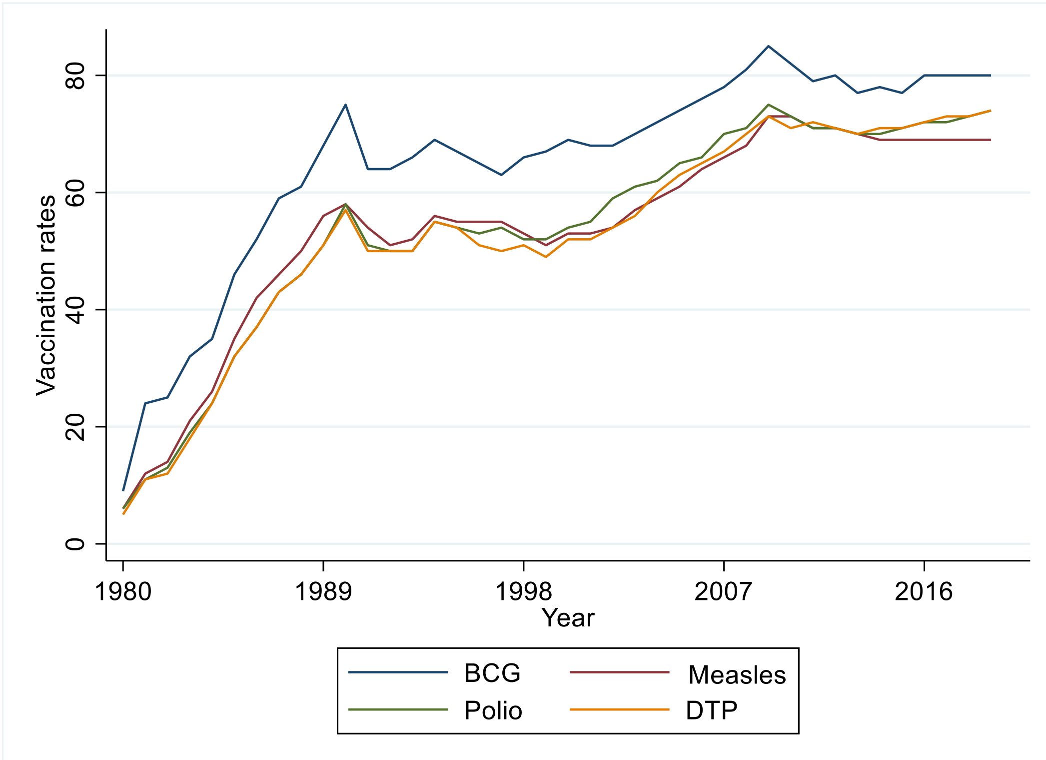


Figure 2.3: Incidence rates of each disease in Africa from 2000 to 2019.
Source: WHO

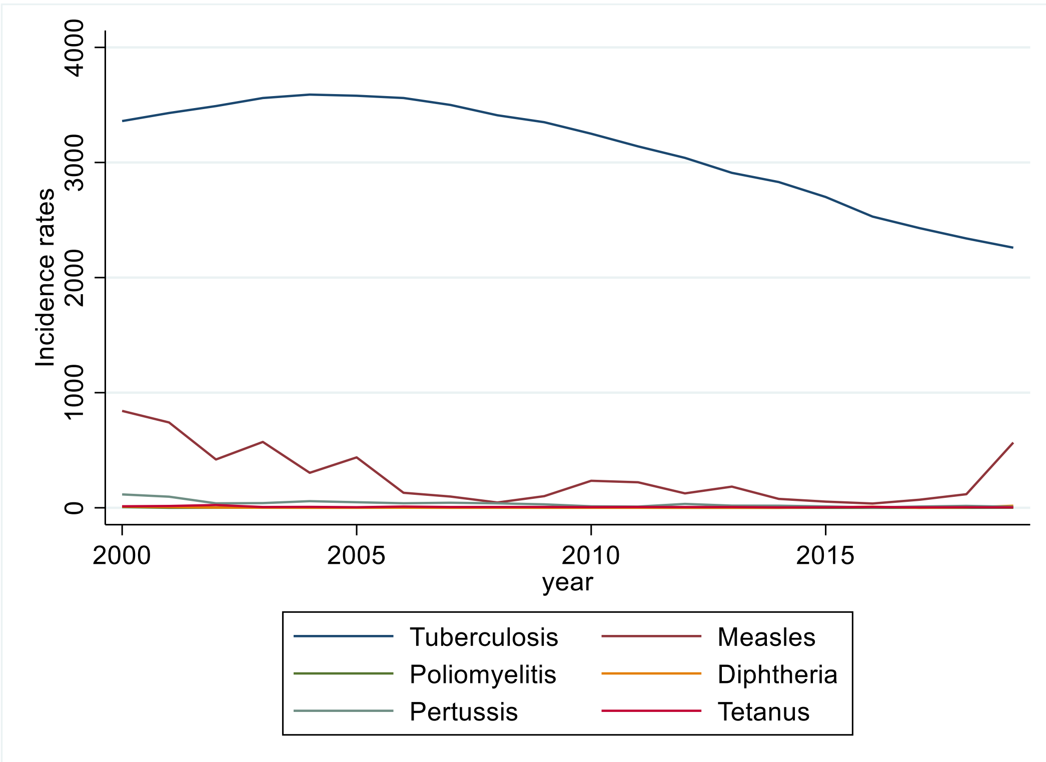


Figure 2.4: Study area

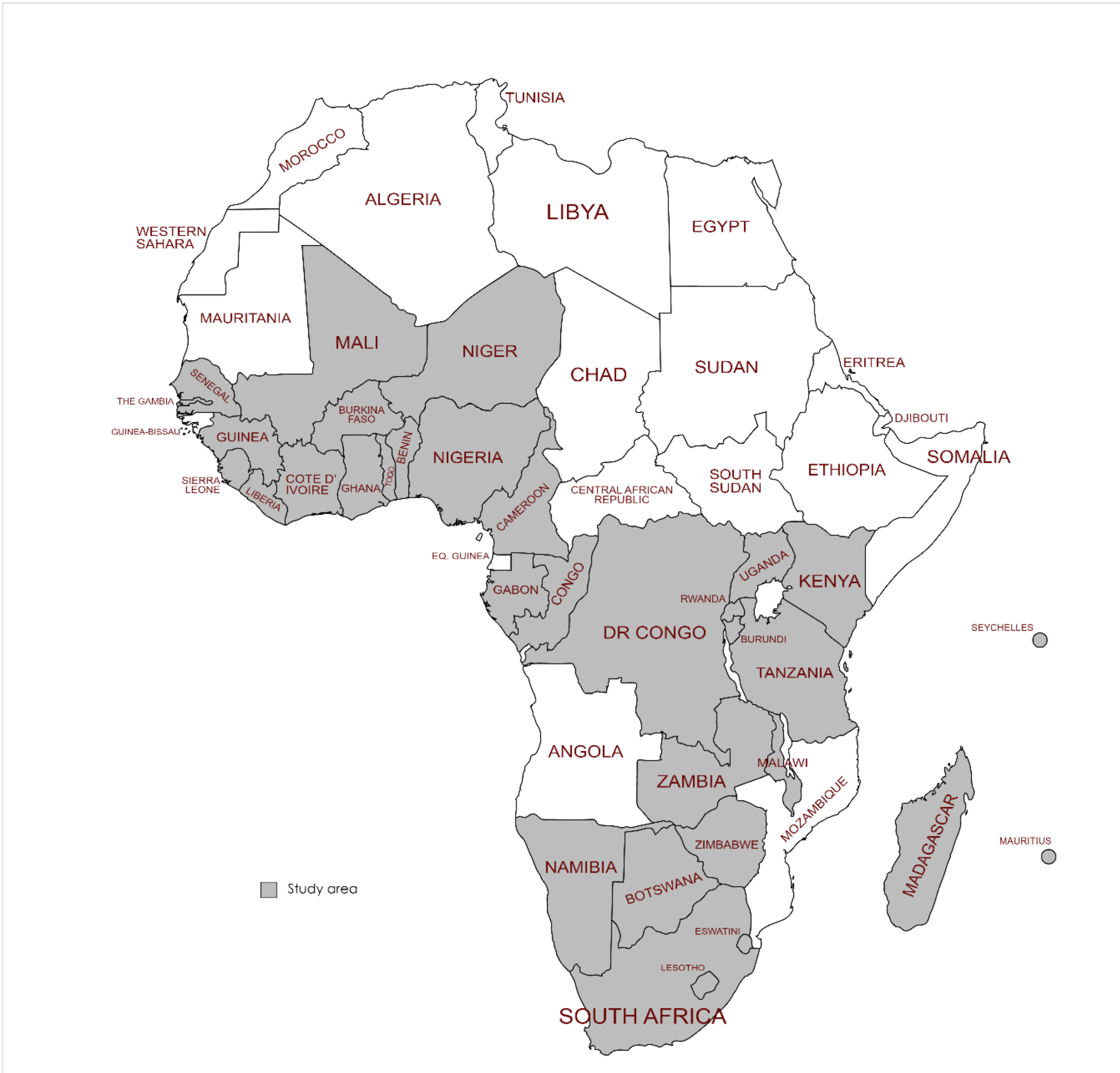
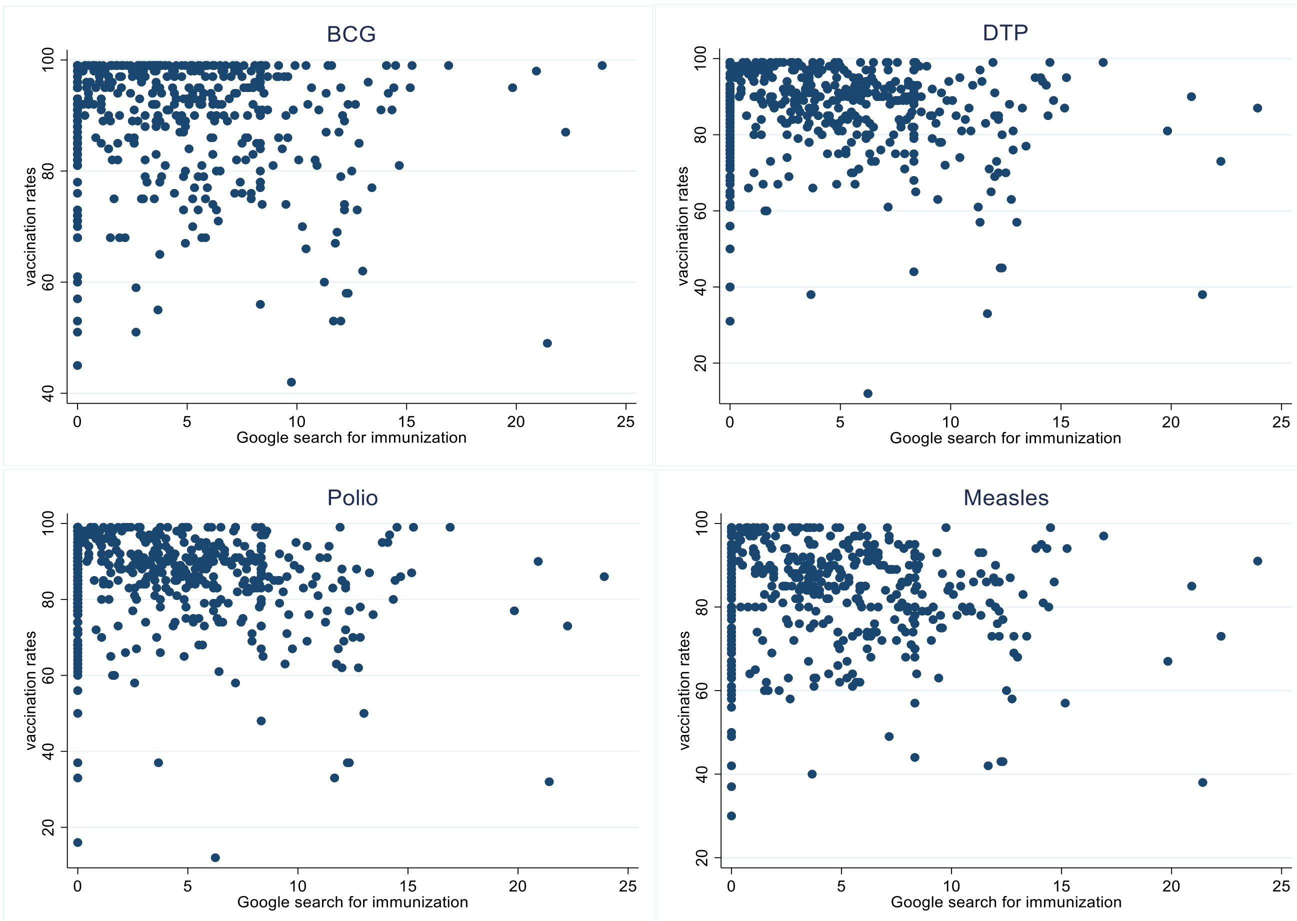


Figure 2.5: Vaccination rates and google searches for immunization information
Source: WHO, Google



Tables

Table 2.1 Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Vaccination rates					
BCG	462	89.327	11.034	42	99
DTP	462	86.054	12.174	12	99
Polio	462	85.177	12.777	12	99
Measles	462	83.136	12.633	30	99
Search on immunization	462	4.663	4.301	0	23.917
GDP per capita	462	4486.137	5170.479	489.42	27242.66
Education years	462	5.130	2.242	1.3	10.2
Gov effectiveness	462	-0.629	0.586	-1.746	1.057
Urban population	462	39.211	16.455	9.139	88.976
Health expenditure	456	481.669	1377.864	21.571	11884.35
Electricity	459	38.720	26.163	1.279	100
Transport	462	7.352	8.034	-36.333	53.147

Table 2.2: Impact of search for immunization information on vaccination coverage

VARIABLES	(1) Full sample OLS	(2) Without Measles OLS
Search on immunization	0.180**	0.201**
	(0.075)	(0.079)
GDP per capita	0.001**	0.001
	(0.001)	(0.001)
Education years	-8.347***	-8.890**
	(2.759)	(3.484)
Gov effectiveness	-1.957	-2.049
	(2.155)	(2.370)
Urban population	9.311***	9.121***
	(1.362)	(1.496)
Electricity	0.051	0.045
	(0.080)	(0.087)
Health expenditure	-0.006***	-0.007***
	(0.002)	(0.002)
Transport	-0.012	0.006
	(0.027)	(0.027)
Observations	1,812	1,359
R-squared	0.606	0.629

Fixed effects and country-specific linear time trends are included.
Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 2.3: Heterogeneity among vaccines

VARIABLES	(3) BCG	(4) DTP	(5) Polio	(6) Measles
Search on immunization	0.199*	0.202	0.200	0.119
	(0.120)	(0.134)	(0.149)	(0.169)
GDP per capita	0.001	0.001	0.001	0.002*
	(0.001)	(0.001)	(0.001)	(0.001)
Education years	-3.264	-11.883	-11.523	-6.716**
	(2.182)	(7.359)	(7.643)	(3.239)
Gov effectiveness	-0.362	-2.492	-3.294	-1.681
	(3.530)	(4.139)	(4.412)	(4.171)
Urban population	11.212***	6.986***	9.165***	9.882***
	(2.663)	(2.408)	(2.927)	(2.973)
Electricity	-0.031	0.069	0.096	0.068
	(0.136)	(0.138)	(0.152)	(0.150)
Health expenditure	-0.003	-0.009**	-0.009*	-0.003
	(0.003)	(0.004)	(0.004)	(0.004)
Transport	0.069	-0.018	-0.033	-0.066
	(0.047)	(0.045)	(0.048)	(0.071)
Observations	453	453	453	453
R-squared	0.725	0.674	0.656	0.710

Fixed effects and country-specific linear time trends are included.

Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table 2.4: Subsample analysis with respect to herd immunity threshold

VARIABLES	(1) BCG	(2) DTP	(3) Polio	(4) Measles
(a) Below threshold				
Search on immunization	0.468*	0.187	0.093	0.076
	(0.271)	(0.177)	(0.258)	(0.159)
Observations	123	326	163	364
(b) Above threshold				
Search on immunization	0.250***	-0.043	0.074	-0.122
	(0.062)	(0.068)	(0.111)	(0.102)
Observations	330	127	290	89
Thresholds	**86%**	**94%**	**85%**	**95%**

All control variables, fixed effects and country-specific linear time trends are included.
Robust standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Chapter 3

Do Cell Towers Help Increase Vaccine Uptake? Evidence from Côte d'Ivoire

3.1 Introduction

Vaccination is an effective public health intervention to prevent disease and death. In Africa, approximately 20% of children fail to receive all basic vaccines, resulting in more than 30 million children under five suffering from vaccine-preventable diseases annually (WHO, 2018). One of the principal obstacles to vaccination is the difficulty in providing information to parents, especially in rural areas where access to education is limited (UNICEF, 2018). According to Obi-Jeff et al. (2021), the most common reason for non-vaccination is lack of knowledge about where, when, and why to vaccinate.

The rapid increase in mobile technology usage in recent decades has increased the potential to overcome obstacles to knowledge access. (Aker et al., 2012; Asongu et al., 2016; Asongu & Nwachukwu, 2016). Mobile technology reduces information sharing time and facilitates knowledge transfer to less educated populations (Islam et al., 2020; Chib, 2010). Past research has shown that mobile technology enhances the efficiency and use of healthcare services (Agarwal et al., 2015). Moreover, it creates economic opportunities and enables access to credit markets, which can lead to better health outcomes (Aker & Mbiti, 2010).

While the effect of mobile technology on health outcomes has gained increasing attention, the existing literature has mainly focused on SMS reminders and mobile phone ownership

(Akamike et al., 2021; Amankwaa et al., 2018; Bangure et al., 2015; Brown et al., 2016; Greenleaf et al., 2019; Jadhav & Weis, 2020; LeFevre et al., 2020; Uddin et al., 2016; van Heerden et al., 2017). Nonetheless, a systematic review and meta-analysis by Yunusa et al., (2021) indicates that the evidence supporting the positive effect of mobile phone interventions on health outcomes is limited. In addition, studies linking mobile phone usage with socio-economic outcomes are susceptible to bias because of the existence of unobserved confounders (Flückiger & Ludwig, 2023). Indeed, the literature documented that sharing phones is common in developing countries, and SMS outreach also propagates to community members at gatherings (Obi-Jeff et al., 2021; Pierskalla & Hollenbach, 2013).

Cell towers are the prerequisite for mobile communication that improve access to information within communities. Previous studies have documented that these communication infrastructures facilitate the use of GPS to track vaccinators, which helps reduce the number of missed settlements during vaccination campaigns (Chandir et al., 2017; Touray et al., 2016). However, the extent to which they impact vaccination coverage is not well understood.

This study evaluates the impact of mobile communication infrastructure on vaccine uptake. Notably, it examines whether households in areas with cell towers are more likely to have their children vaccinated. We posit that knowledge flows in these areas are higher and benefit non-mobile phone owners through social interaction. Moreover, vaccinators may achieve better coverage in areas with access to cell towers, which also affects vaccine uptake of all individuals. We further analyze heterogeneity in the impact among different types of vaccines.

Vaccines protect against various diseases, some of which have a very low incidence, which may have implications for vaccination.

Using nationally representative data on vaccine uptake, we found that proximity to cell towers was associated with higher vaccine uptake. Every unit increase in distance from cell towers was associated with a decrease of around 0.4% in the likelihood of a child being vaccinated. The results also indicate that the benefits of improved communication infrastructure accrue mainly to rural populations. Furthermore, the impact was heterogeneous among vaccines, with a substantial effect found for the vaccine related to the disease with high incidence. Lastly, our results suggest that access to cell towers can help close the vaccination gap between children whose parents have no formal education and those whose parents do.

This study contributes to the literature in several ways. First, it complements the literature exploring the socio-economic benefits and detriments of communication infrastructures. Studies show that mobile network coverage fosters growth in the retail sector, increases employment and decreases the prevalence of gender-biased social norms and early marriage (Aldashev & Batkeyev, 2021; Klonner & Nolen, 2010; Viollaz & Winkler, 2020). Previous studies have further documented the negative effects of communication infrastructures on property values, suggesting that an increase in distance to cell towers rises property prices (Acharya et al., 2022; Locke & Blomquist, 2016; Rajapaksa et al., 2018). Other researchers suggest that communication infrastructures facilitate the dissemination of information about ongoing conflicts to remote areas, thereby influencing the diffusion of conflicts (Ackermann et al., 2021; Pierskalla & Hollenbach, 2013).

Second, we add new insight to the literature specific to the impact of communication infrastructures on health outcomes. Although there are many compelling pathways through which access to cell towers could help increase vaccination coverage, there is a lack of studies analyzing this relationship (see section 2.1). An important body of literature has focused on the adverse health effects of communication infrastructures, suggesting that proximity to cell towers increases the likelihood of serious health problems such as cancer and muscular pain (Ali et al., 2021; Hamza et al., 2023; Subhan et al., 2018). The strand of the literature exploring the positive effects on health outcomes has focused on HIV testing and infant mortality. Flückiger & Ludwig, (2023) find that the availability of mobile phone signal reduces the likelihood of infant mortality within the first year after birth by 0.9 percentage points. Iacoella & Tirivayi, (2021) show that for every unit increase in distance from the closest cell tower, the probability of women ever being tested for HIV decreases by 0.5 percentage points.

The rest of this paper is organized as follows. Section 2 provides background information on the distribution of cell towers and vaccine uptake in Côte d'Ivoire. Section 3 presents the data and methodology used in this study. Section 4 presents the empirical results, and Section 5 concludes the paper.

3.2 Background

3.2.1 How could cell towers help improve vaccination coverage

There is anecdotal evidence on the various ways by which cell towers can help increase vaccination coverage. However, the literature lacks empirical studies that focus on the impact of cell towers on immunization coverage. Due to the lack of data, this study does not examine these pathways, but rather provides an overview of these potential avenues through which cell towers affect vaccination coverage.

Vaccines necessitate a "cold chain", a transportation and storage system that maintains the recommended temperature for vaccines, which can make it challenging to distribute vaccines to remote areas where electricity is often scarce. According to Energize the Chain (EtC)[1], each cell tower generates excess electricity, sufficient to sustain a refrigeration unit for storing vaccines. In 2013, refrigeration units powered by cell towers were used to preserve "cold chain" conditions for vaccines sent to rural areas, enabling the vaccination of 250,000 children in Zimbabwe (State Department, 2014).

Vaccination campaigns are known to be effective in increasing the number of people getting vaccinated. However, reaching optimum vaccination coverage in certain regions is hindered by issues such as imprecise hand-drawn maps and the inability to track field teams in real-time. Evidence from Pakistan and Nigeria shows that GSM-based tracking system helps mitigate these issues (Chandir et al., 2017; Touray et al., 2016). The system allows managers to track employee attendance and performance, and to determine whether all target areas have been covered. In Côte d'Ivoire, the transparency of the measles vaccination campaign was improved through a mobile communication platform (UNICEF, 2018). The

[1] EtC is an organization that collaborates with cell tower companies and health authorities to provide access to the energy, connectivity, and data required to extend the vaccine cold chain into developing countries.

platform provides a two-way communication channel for volunteers and families to report problems, obtain information and ask questions.

In many developing countries, awareness is an important obstacle to childhood immunization, particularly in rural areas where the literacy rate is low. The improvement in cell tower coverage has enhanced mobile communication which improves vaccination knowledge sharing (Jama et al., 2020). In addition, health officials take advantage of increased network coverage to raise awareness and encourage more people to get vaccinated. In 2011, the Ivorian health ministry authorized the introduction of the country's first vaccination reminder service, which consists of sending messages to remind the dates and importance of vaccination.

3.2.2 Overview on cell tower distribution in Côte d'Ivoire

Mobile telephony was introduced in most African countries during the early 1990s. Prior to 1995, fixed-line telephony was the only available form of telecommunication in Côte d'Ivoire. In order to stimulate the communication sector, the Ivorian government embarked on a liberalization process to attract private investment. The first company providing mobile services was established in the country in 1996, followed by two others later that same year (Laffont & N'Guessan, 2002). Until the early 2000s, only a few cities outside the economic capital could access to mobile telephone services.

During the second decade of the 2000s, the country witnessed an expansion of network coverage, but many households remained in areas with limited or no access to mobile services. Figure 1 illustrates the distribution of cell towers across the country in 2015. While some areas have dense coverage, others have poor or no coverage. Numerous factors, including infrastructural needs such as roads and electricity, influence the roll-out of cell towers. Private companies that finance the deployment of communication infrastructure seek to minimize costs and maximize profits, so cell towers are primarily located in areas with high population density, where the demand is expected to be high. Terrain topography also affects the cost of installing a cell tower and its range; steeper terrains increase the cost of cable routing (Dinkelman, 2011; Klonner & Nolen, 2010).

3.2.3 Vaccine uptake and disease incidence in Côte d'Ivoire

The incidence of vaccine-preventable diseases remains alarmingly high in Côte d'Ivoire, despite a gradual decline. Tuberculosis, in particular, continues to be highly endemic and is one of the leading causes of death among communicable, maternal, and neonatal diseases. In 2021, an estimated 35,000 individuals contracted tuberculosis, of whom 6,000 succumbed (WHO, 2022). Although not as severe as tuberculosis, measles is the second most common vaccine-preventable disease. Over the past few decades, fluctuations in the number of reported measles cases have been observed. Measles-related incidents declined from around 600 in 2011 to 48 in 2013, remained below 100 until 2016, and then rose to 1,800 in 2021. The incidence of poliomyelitis has stagnated at 0 since 2013. As of 2021, the incidence of diphtheria, tetanus, and pertussis were 0, 29, and 10, respectively.

The country recommends that all children receive the four major vaccines recommended by the World Health Organization (WHO): BCG, measles, polio, and DTP. Of these vaccines, only DTP protects against three diseases, namely diphtheria, tetanus, and pertussis. However, vaccination rates are lower than the targets set by WHO, especially in rural areas. The vaccination rate for BCG was highest in rural areas, at 70.3%, while the rate for measles was lowest, at approximately 56%. The vaccination rates for the third dose of DTP and polio were about 59% and 64%, respectively. It is worth noting that the measles vaccine was associated with a controversial claim that it causes autism, which has adversely impacted its uptake, resulting in multiple measles outbreaks worldwide (Hussain et al., 2018).

3.3 Empirical analysis

3.3.1 Data

We obtained data from multiple sources, the summary statistics are presented in Table 3.1. First, data on cell towers were drawn from OpencellID, the world's largest open database providing comprehensive information on the global distribution of cell towers. Unfortunately, the database does not report the date of construction for each tower but instead provides the date on which each tower's information was added. As such, there may be a time lag between constructing a new tower and registering it into the database. However, we expect this lag to gradually diminish over the years following the commencement of the database. As the database entry for Côte d'Ivoire began in 2008, we postulate that towers registered in the database up to 2016 are a suitable proxy for towers constructed up to 2015. For robustness check, we restricted our sample to cell towers available in database up to 2015.

The second data source was the 2015 Côte d'Ivoire Living Standards Survey (CILSS), a nationwide household survey that collects socio-demographic data. CILSS is the most recent household survey providing exhaustive information on the vaccination status of children. The sampling frame is based on a two-stage draw to ensure national representativeness. The first stage involves drawing Enumeration Areas (EAs) within the study strata, and the second stage entails selecting households in each EA. Approximately 12,900 households were surveyed across the country, with the dataset providing the administrative unit where households are located. As shown in Figure 1, households are clustered in prefectures across different regions.

Third, we included data on health facilities, electricity, and road infrastructure to control for factors that can affect the use of mobile technology and access to vaccination. We utilized the spatial database of health facilities released by the World Health Organization (WHO) in 2019 to determine the number of health facilities per capita. We calculated the electricity grid per capita using data from Meta's Electrical Distribution Grid Maps. Population data were sourced from the 2014 General Census of Population and Housing. Additionally, we computed the distance from each cluster centroid to the closest main road using data extracted from OpenStreetMap, released by the World Food Programme in 2017.

3.3.2 Econometric specification

To examine the impact of cell towers on vaccine uptake, we specify our empirical model as follows:

$$Y_{icr} = \beta_0 + \beta_1 tower_{cr} + \beta_2 X_{icr} + \beta_3 Z_r + \varepsilon_{icr} \quad (1)$$

where Y_{icr} is a dummy variable indicating if child i in cluster c within region r is fully vaccinated. *tower* is our key explanatory variable and represents the distance from a household location to the nearest cell tower. X_{icr} is a vector of control variables, and Z_r is a vector of region fixed effects.

While the inclusion of region fixed effects controls for unobserved factors that may differentially impact vaccine uptake across regions, it may not fully address endogeneity concern arising from the placement of cell towers. If the choice of cell tower location is correlated with unobserved factors that affect vaccine uptake, our estimates could be biased. To mitigate this problem, we use instrumental variables technique. As previously mentioned, terrain topography influences the cost of installing a cell tower and its range. In addition, cell towers are more likely to be placed in areas with high population density, where the demand is expected to be high. Once a cell tower is installed in a particular area, it becomes less costly for the provider to extend coverage to neighboring locations. Therefore, we use terrain slope[2] and distance to the closest dense area as instrumental variables. The key identification assumption is that our instruments affect the roll out of cell towers but have no direct effect on vaccine uptake. We test this assumption using the Sargan–Hansen test for over-identification.

3.4 Results

[2] Data on terrain slope come from NASA, calculated at 90 meters resolution level.

Table 3.2 presents our OLS estimates from baseline specifications. The results of the robustness check using an alternative sample are presented in Table A of the appendix. Column 1 shows the result from our full sample while Columns 2 and 3 relate to urban and rural households, respectively. Overall, the results suggest a negative association between distance to communication facilities and vaccine uptake. Column 1 shows that one unit increase in the distance to towers lowers the probability of a child being vaccinated by 0.36%. Furthermore, the results suggest that benefits from cell towers accrue mainly to rural populations. In Column 2, the estimated coefficient is not statistically significant, while Column 3 indicates that every unit increase in the distance to towers decreases the probability of a child being vaccinated by 0.37%. We continue our analysis by focusing on rural households.

These results align with those of other studies exploring the impact of communication facilities on health outcomes. Flückiger & Ludwig, (2023) found that access to mobile phone coverage reduces childhood mortality risk by 0.9% and that the impact is more pronounced in rural area. According to Iacoella & Tirivayi, (2021), a unit increase in distance from the closest cell tower is associated with 0.5% decrease in the probability that women test for HIV. The coefficient size in our study is smaller than that found in previous studies. The difference may arise from the fact that these studies employ different outcome variables and focus on sub-Saharan Africa.

Diseases have different incidence rates, which may affect their vaccine uptake. We explore the heterogeneity of impact and present the results in Table 3.3. The estimated coefficients are statistically significant for all the vaccines except for polio, possibly due to the zero incidence of the related disease. In absolute value, the coefficient size for BCG is the highest, supporting our hypothesis that disease risk may influence vaccine uptake. This suggest that access to communication network may improve knowledge about vaccines and related diseases. This finding is consistent with previous research suggesting a higher willingness to vaccinate against high-risk diseases (Betsch et al., 2017). While measles incidence rates are generally higher than those of diphtheria, tetanus, and pertussis, the estimated coefficient for DTP is about twice that for measles vaccine. One possible explanation is that improved knowledge about vaccines does not fully increase measles vaccine uptake due to the controversial claim associating the vaccine with autism. Nyhan et al. (2014) suggested that access to information about the controversy negatively impacted the measles vaccine uptake. Another reason may be that the disease incidence was low, only 65 measles cases were reported in 2015 (WHO, 2022).

As discussed earlier, we are unable to thoroughly explore the mechanisms through which mobile network coverage affects vaccine uptake due to lack of data. As documented by Jama et al., (2020), these pathways include the improved vaccination knowledge sharing. If this is the case, one would expect the impact of network coverage to be substantial for those with limited knowledge. We further investigate the impact of cell towers with respect to education level and report the results in Table 3.4. The results show that access to cell towers does not affect vaccine uptake for those with at least a primary education level. However, a unit increase in the distance to cell towers reduces vaccine uptake by 0.45% among those with no education. This supports our hypothesis that improved vaccination knowledge is a plausible explanation for the impact of communication infrastructure. Vaccine uptake is generally higher for those with education (Table 3.2), therefore access to cell towers may help bridge vaccination gap arising from lack of education, as it only increases vaccine uptake among those with no education.

Although including spatial fixed effects may help mitigate biases arising from unobserved factors that affect vaccine uptake differently across regions, it may not appropriately address endogeneity concerns. The choice of where to place cell towers is not random; it depends on various factors, some of which may be correlated with unobserved factors that impact vaccine uptake. If so, our OLS estimates may be biased and should be interpreted as associations. We use the instrumental variables technique to identify the causal effect of access to cell towers on vaccine uptake. Using terrain slope and distance to the closest dense area as instrumental variables, we re-estimate our baseline models in Table 3.2 and present the results in Table 3.5. The F-statistics and Hansen statistics suggest that our instruments are valid. The estimates align with those obtained from the OLS models, but they increase in magnitude.

3.5 Conclusion

This study examined the impact of access to cell towers on vaccine uptake. We found a negative association between distance from cell towers and vaccine uptake, suggesting that access to mobile network may help increase vaccination coverage. Further investigations suggest that the associations are heterogeneous among vaccines. Notably, the association is strong for the vaccine-related to the disease with high incidence.

The key identification challenge stems from the non-random placement choice of cell towers, which may be correlated with unobserved factors that affect vaccine uptake.

Therefore, OLS estimates might be biased and should be interpreted as an association. To mitigate these issues, we employ the instrumental variables technique. Our estimates remain positive and significant but increase in size. These results suggest that the instrumental variable have helped alleviate the bias.

Additional findings of interest were that the benefits of cell towers only accrued to people living in rural areas and to the uneducated. This implies that increasing mobile phone coverage in areas where people lack access to education can help bridge the vaccination coverage gap.

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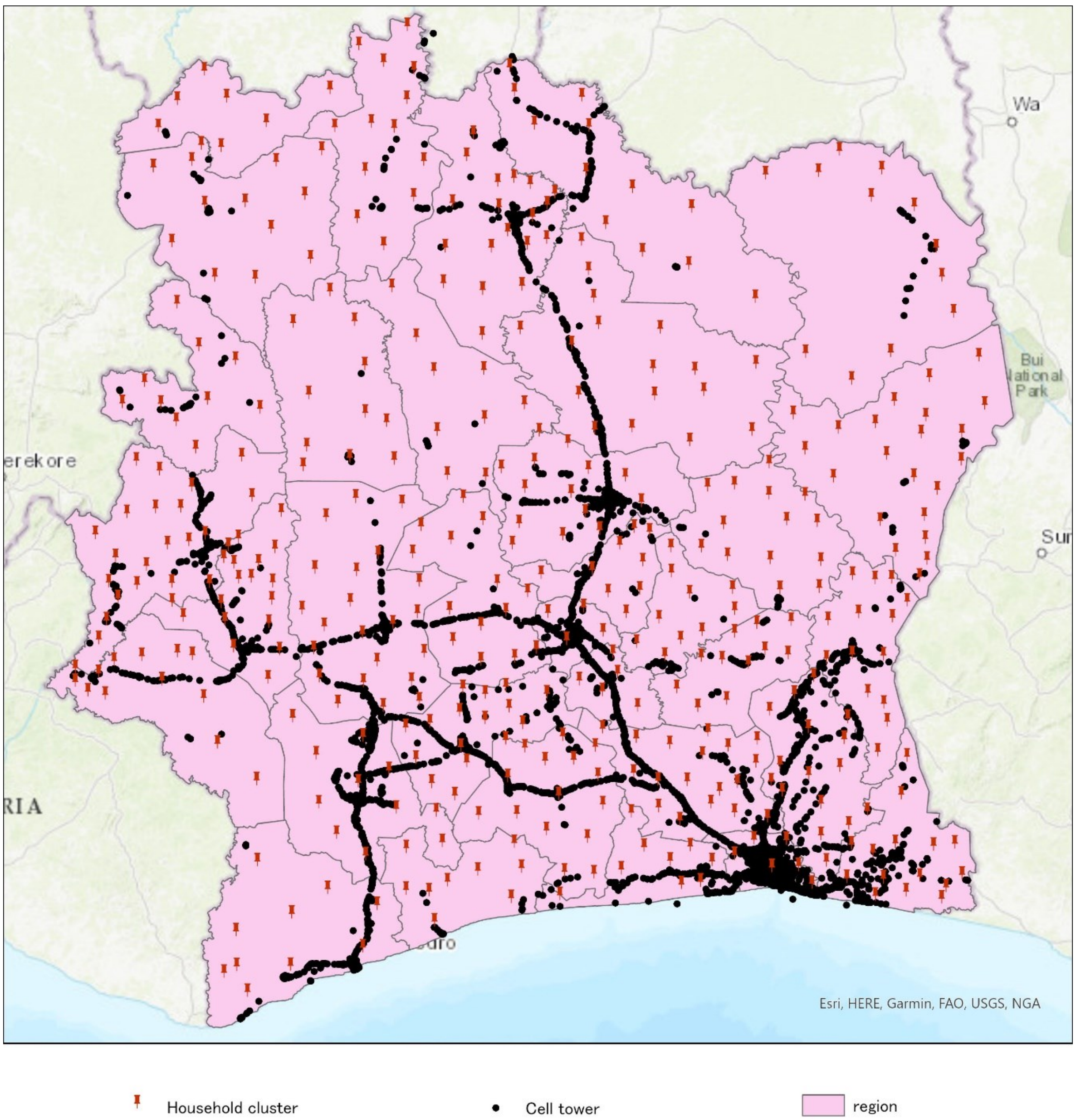
Figure

Figure 3.1 Distribution of cell towers in the Côte d'Ivoire in 2015



Tables

Table 3.1 Descriptive statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
Vaccine uptake					
full vaccination	7,630	0.68	0.47	0	1
BCG	8,124	0.85	0.36	0	1
DTP	7,954	0.80	0.40	0	1
Polio	8,237	0.87	0.33	0	1
Measles	7,978	0.77	0.42	0	1
Distance to cell tower (km)	9,170	14.11	16.13	0.01	89.58
Population density	9,170	637.51	1991.33	5	7948
Hospital per 10 thousand	9,170	0.93	0.73	0	7.01
Distance to nearest road (km)	9,170	7.05	8.22	0.01	44.21
Electricity grid per 10 thousand	9,170	14.22	12.77	0	93.42
Gender of household head	9,170	0.84	0.36	0	1
Income (tertile)					
Middle	9,170	0.33	0.47	0	1
High	9,170	0.33	0.47	0	1
parents living together	9,170	0.91	0.29	0	1
Household head age	9,170	40.46	11.90	16	102
Household head education					
Primary	9,094	0.16	0.37	0	1
Secondary and up	9,094	0.17	0.38	0	1

Table 3.2. Access to cell tower and vaccine uptake

VARIABLES	(1) Full sample	(2) Urban	(3) Rural
Distance to cell tower	-0.0036***	-0.0016	-0.0037***
	(0.0005)	(0.0010)	(0.0005)
Hospital per capita	0.0013	-0.0248	0.0173*
	(0.0090)	(0.0221)	(0.0103)
Population density	-0.0000	-0.0000	0.0004**
	(0.0000)	(0.0000)	(0.0001)
Distance to road	0.0011	-0.0008	0.0025**
	(0.0008)	(0.0016)	(0.0010)
Electricity	0.0010*	-0.0025*	0.0021***
	(0.0006)	(0.0015)	(0.0007)
Gender of household head	-0.0214	-0.0331	-0.0107
	(0.0170)	(0.0245)	(0.0245)
Middle income	0.0626***	0.0275	0.0760***
	(0.0132)	(0.0236)	(0.0162)
High income	0.1026***	0.0699***	0.1091***
	(0.0133)	(0.0220)	(0.0176)
Parents living together	-0.0046	0.0170	-0.0046
	(0.0213)	(0.0310)	(0.0298)
Age of household head	0.0024***	0.0024***	0.0025***
	(0.0004)	(0.0007)	(0.0006)
Head education (primary)	0.0307**	-0.0029	0.0386**
	(0.0148)	(0.0241)	(0.0191)
Head education (secondary up)	0.0785***	0.0747***	0.0574***
	(0.0141)	(0.0192)	(0.0217)
Region fixed effects	YES	YES	YES
Observations	7,565	2,888	4,677

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.3. Heterogeneity among vaccines

VARIABLES	(1) BCG	(2) DTP	(3) Polio	(4) Measles
Distance to cell tower	-0.0033***	-0.0024***	-0.0006	-0.0015***
	(0.0005)	(0.0005)	(0.0004)	(0.0005)
Hospital per capita	0.0168**	0.0082	0.0202***	0.0075
	(0.0077)	(0.0089)	(0.0075)	(0.0095)
Population density	0.0002**	0.0003***	0.0001	0.0003**
	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Distance to road	0.0023***	0.0019**	-0.0017**	0.0000
	(0.0008)	(0.0009)	(0.0008)	(0.0009)
Electricity	0.0025***	0.0012*	-0.0006	0.0012*
	(0.0006)	(0.0007)	(0.0005)	(0.0007)
Gender of household head	-0.0257	-0.0423**	-0.0602***	-0.0243
	(0.0182)	(0.0205)	(0.0161)	(0.0227)
Middle income	0.0879***	0.1076***	0.0430***	0.0721***
	(0.0125)	(0.0140)	(0.0119)	(0.0147)
High income	0.0888***	0.1152***	0.0705***	0.0899***
	(0.0136)	(0.0152)	(0.0123)	(0.0159)
Parents living together	0.0254	0.0242	0.0461**	0.0088
	(0.0222)	(0.0254)	(0.0206)	(0.0273)
Age of household head	0.0008*	0.0019***	0.0017***	0.0021***
	(0.0004)	(0.0005)	(0.0004)	(0.0005)
Head education (primary)	0.0430***	0.0526***	0.0224*	0.0375**
	(0.0135)	(0.0156)	(0.0133)	(0.0169)
Head education (secondary up)	0.0769***	0.0898***	0.0446***	0.0472**
	(0.0133)	(0.0163)	(0.0139)	(0.0192)
Region fixed effects	YES	YES	YES	YES
Observations	5,008	4,894	5,067	4,927

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.4. Impact of cell towers by education level

VARIABLES	(1) No education	(2) Primary	(3) Secondary up
Distance to cell tower	-0.0045***	-0.0014	-0.0034
	(0.0006)	(0.0016)	(0.0021)
Hospital per capita	0.0197	0.0008	0.0227
	(0.0121)	(0.0278)	(0.0362)
Population density	0.0007***	0.0000	-0.0002
	(0.0002)	(0.0003)	(0.0004)
Distance to road	0.0050***	-0.0047*	-0.0020
	(0.0012)	(0.0027)	(0.0031)
Electricity	0.0030***	0.0011	-0.0014
	(0.0008)	(0.0022)	(0.0029)
Gender of household head	-0.0219	-0.0028	0.0345
	(0.0287)	(0.0598)	(0.0829)
Middle income	0.1031***	-0.0114	0.0513
	(0.0195)	(0.0423)	(0.0488)
High income	0.1392***	-0.0128	0.0702
	(0.0211)	(0.0463)	(0.0453)
Parents living together	0.0018	-0.0019	-0.0294
	(0.0362)	(0.0666)	(0.0840)
Age of household head	0.0022***	0.0044***	0.0031
	(0.0007)	(0.0015)	(0.0020)
Region fixed effects	YES	YES	YES
Observations	3,332	774	571

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3.5. Instrumental variables regression

VARIABLES	(1) Full sample	(2) Urban	(3) Rural
Distance to cell tower	-0.0041***	0.0037	-0.0050***
	(0.0012)	(0.0029)	(0.0014)
Hospital per capita	0.0011	-0.0189	0.0159
	(0.0090)	(0.0221)	(0.0104)
Population density	-0.0000	-0.0000*	0.0003**
	(0.0000)	(0.0000)	(0.0002)
Distance to road	0.0015	-0.0043*	0.0033**
	(0.0012)	(0.0023)	(0.0014)
Electricity	0.0012*	-0.0049**	0.0023***
	(0.0007)	(0.0019)	(0.0008)
Gender of household head	-0.0220	-0.0347	-0.0142
	(0.0171)	(0.0246)	(0.0246)
Middle income	0.0623***	0.0329	0.0758***
	(0.0132)	(0.0237)	(0.0162)
High income	0.1021***	0.0785***	0.1087***
	(0.0133)	(0.0224)	(0.0175)
Parents living together	-0.0036	0.0166	-0.0008
	(0.0214)	(0.0309)	(0.0302)
Age of household head	0.0025***	0.0025***	0.0025***
	(0.0004)	(0.0007)	(0.0006)
Head education (primary)	0.0305**	-0.0007	0.0383**
	(0.0148)	(0.0242)	(0.0190)
Head education (secondary up)	0.0779***	0.0760***	0.0552**
	(0.0141)	(0.0192)	(0.0217)
Region fixed effects	YES	YES	YES
Kleibergen-Paap F statistic	380.76	72.03	303.02
Hansen statistic	1.31	0.11	0.369
Observations	7,565	2,888	4,677

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix

Table 3.A. Robustness check with alternative sample

VARIABLES	(4) Full sample	(5) Urban	(6) Rural
Distance to cell tower	-0.0020***	0.0006	-0.0021***
	(0.0004)	(0.0008)	(0.0004)
Hospital per capita	0.0003	-0.0234	0.0155
	(0.0089)	(0.0221)	(0.0104)
Population density	-0.0000	-0.0000	0.0004**
	(0.0000)	(0.0000)	(0.0001)
Distance to road	-0.0002	-0.0022	0.0011
	(0.0008)	(0.0015)	(0.0010)
Electricity	0.0005	-0.0034**	0.0016**
	(0.0006)	(0.0014)	(0.0007)
Gender of household head	-0.0184	-0.0331	-0.0022
	(0.0172)	(0.0246)	(0.0247)
Middle income	0.0634***	0.0305	0.0773***
	(0.0133)	(0.0236)	(0.0163)
High income	0.1041***	0.0739***	0.1102***
	(0.0133)	(0.0220)	(0.0176)
Parents living together	-0.0067	0.0158	-0.0110
	(0.0213)	(0.0310)	(0.0297)
Age of household head	0.0024***	0.0024***	0.0024***
	(0.0004)	(0.0007)	(0.0006)
Head education (primary)	0.0298**	-0.0018	0.0379**
	(0.0149)	(0.0242)	(0.0191)
Head education (secondary up)	0.0784***	0.0759***	0.0597***
	(0.0141)	(0.0192)	(0.0216)
Region fixed effects	YES	YES	YES
Observations	7,565	2,888	4,677

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Chapter 4

How does access to multiple information devices affect HIV testing? Empirical study in Côte d'Ivoire

4.1 Introduction

Television and radio have conventionally been the primary means by which individuals access information. Prior research has suggested that access to television and radio can impact health outcomes by increasing exposure to new knowledge (Stone, 2018; Tasciotti et al., 2022). According to Burzyńska et al., (2015), television is a key medium for improving health literacy, as it provides ample opportunities for viewers to encounter health-related content. Oh et al. (2002) further documented the effectiveness of television campaigns in disseminating information on sexually transmitted diseases (STDs) and increasing testing uptake. Exposure to television and radio has been linked to improvements in reproductive behavior and HIV knowledge (Agegnehu and Tesema, 2020; Westoff et al., 2011; Westoff and Koffman, 2011).

Over the past few decades, the number of mobile phone users has increased dramatically, especially in developing countries. Sub-Saharan Africa has experienced the most rapid growth, with a 44% penetration rate in 2018 and annual growth of 4.6% (GSMA, 2019). Mobile technology has become accessible even in remote areas where basic necessities such as clean water and medical personnel are often lacking. Consequently, it has become a popular means of disseminating health information. Health authorities around the world have implemented thousands of mobile phone-based health projects, while hundreds of thousands of health-related smartphone applications have emerged (Haenssgen and Ariana, 2017). Empirical researchers have shifted their focus to exploring the impact of mobile phone ownership on health outcomes (LeFevre et al., 2020; Greenleaf et al., 2019; Rajkhowa and Qaim, 2022; Billari et al., 2020; Jadhav and Weis, 2020). However, there is a lack of studies examining possible complementarity between mobile phone and earlier information devices.

Albouy et al. (2020) documented that goods may exhibit complementarities that are essential in determining their individual value. Neglecting complementarity may lead to an inadequate assessment of the impact of information device access. In developing countries, income and education limitations often prevent individuals from fully utilizing mobile technology capabilities. In Côte d'Ivoire, despite high mobile phone penetration, less than half of users own a smartphone (Digital Business Africa, 2020). In addition, the costs of using most services and the low literacy rate, particularly in rural areas, may prevent effective use of phone phones. In contrast, accessing information through television and radio is relatively more affordable, and familiar, as it necessitates no active input to obtain information (Shaikh, 2017). Nonetheless, the main advantage of mobile phone over television and radio is that it enables direct connection with health professionals. Overall, the use of mobile phone together with earlier devices may help overcome some limitations to accessing information, particularly for the most disadvantaged groups.

This study examines the existence of complementarity between new and earlier information devices with regard to their impact on health outcomes. We posit that individuals with access to both types of devices face fewer limitations in accessing health information, leading to better health outcomes. To test our hypothesis, we utilize data on HIV testing among individuals with access to different information devices. We further explore the implications of socio-economic heterogeneity by examining which groups exhibit greater complementarity between phone and TV/radio. Building upon prior research, this study adopts the direct approach to investigate complementarity, which consists of directly testing the impact of joint access to mobile phone and TV/radio on health outcomes (see sub-section 2.2).

Prior to conducting the complementarity analysis, we carried out two benchmark estimations and found that the omission of control for TV/radio access resulted in an overestimation of the impact of mobile phone by about 20%. Further results revealed that overlooking complementarity obscures the importance of accessing multiple types of devices, thereby biasing individual valuation. Indeed, after accounting for complementarity, the impact of TV/radio alone was no longer statistically significant but it was substantial in conjunction with mobile phone. We also found that the most socio-economically disadvantaged group exhibits greater complementarity between mobile phone and TV/radio.

The remainder of this chapter is organized as follows. Section 2 provides an overview on the use of information technology for HIV information dissemination, as well as the theoretical and empirical backgrounds on complementary. Data and econometric model are presented in Section 3. Section 4 presents the results of the empirical analysis. Section 5 concludes the chapter.

4.2 Background

4.2.1 Use of information technology for HIV information dissemination

Côte d'Ivoire is amongst the West African countries most affected by HIV/AIDS (Lasry et al., 2021). In 2017, the prevalence rate among adults aged 15 to 49 stood at 2.5%, more than three times the global average (PHIA, 2018; World Bank, 2023). The disease constitutes the second leading cause of death in the country (EGPAF, 2023). Nevertheless, only a meager proportion of infected individuals aged 15-64 are aware of their status, which hinders efforts to curb the spread of the disease (Lasry et al., 2021). Jean et al. (2012) documented that lack of HIV knowledge is a major barrier to testing. With low literacy rates, only around 20% of individuals have comprehensive knowledge of HIV in rural areas, which may explain the low testing rate, about half that of urban areas (MICS, 2016). However, leveraging information technology can help alleviate this issue.

In order to promote HIV testing and raise public awareness, numerous campaigns have been undertaken. Initial campaigns were broadcast on radio and television. In 1991, a weekly soap opera called "AIDS in the city" gained considerable viewership, with around two-thirds of television owners having viewed at least one episode (Dodd, 1995). Exposure to the soap opera has had a positive impact on sexual behavior, particularly condom use in the country (Shapiro et al., 2003). Subsequently, in 2012, a public awareness campaign was launched to encourage HIV testing, broadcast on radio in different local languages (USAID, 2023).

The sharp increase in mobile phone penetration offers a novel means of transmitting health information. Both national and international health organizations collaborate with telecommunications service providers to implement mobile-health applications. The Joint United Nations Program on HIV/AIDS (UNAIDS) and the Ministry of Health have introduced different applications that deliver text messages on reproductive health and HIV. Nevertheless, using these services often incurs a weekly fee and subscribers are restricted to receiving a limited number of messages (ODESS, 2023).

There is some evidence that individuals with access to both mobile phone and TV/radio have greater potential to enhance their health literacy. They can seek out more knowledgeable sources or healthcare professionals for further information or clarification regarding topics encountered on TV/radio. For instance, on a radio show aired in 2014, an HIV/AIDS doctor and a psychologist answered listeners' queries during the show (Johns Hopkins Center for Communication Programs, 2014).

In summary, the sources of health information, including content, format and language, can differ considerably depending on the medium used. In addition, discrepancies exist in the cost and level of education necessary to obtain and comprehend information. It is therefore imperative to determine whether emerging technologies complement or replace existing ones, as they transform the way health information is obtained.

4.2.2 Theoretical and empirical overview on complementarity

The economic literature distinguishes between perfect and imperfect complements. However, in the real world, most goods are not perfect complements (Mankiw, 2018). Imperfect complements are characterized by a lower degree of complementarity, i.e. they yield a higher effect when consumed together but a lower effect when consumed separately. According to Serrano-Bedia et al. (2018), complementarity implies that the adoption of one knowledge source yields higher benefits when the complementary source is also present. Analogously, a complementary relationship between mobile phone and TV/radio arises when the adoption of mobile phone provides greater benefits in the presence of TV/radio. The complementary relationship between goods is not immediately evident but necessitates empirical investigation (Xu et al., 2014).

The literature also distinguishes between two types of complementarities: complementarities-in-use and complementarities-in-outcome (Ballot et al., 2015). While the former implies that the use of mobile phone requires the use of TV/radio, the latter suggests that simultaneous use of the set leads to better outcomes. However, it is worth mentioning that complementarities-in-use do not necessarily imply complementarities-in-outcome. The direct approach that tests the benefit of combining different practices, is used in studies that investigate complementarities-in-outcome. To demonstrate complementarity, the output measure is regressed on the entire set of the potential complementarity sources and their interactions. The presence of complementarity is indicated by positive and significant coefficients of the interaction terms (Catozzella and Vivarelli, 2014). However, to avoid biased estimates of pair-wise interaction effects due to multicollinearity, researchers use discrete variables to indicate the exclusive implementation of one or more practices (Carree et al., 2011; Schmiedeberg, 2008).

4.3 Data and econometric model

4.3.1 Data

This study utilizes two cross-sectional datasets from different sources. Specifically, we draw upon data from the 2011 Demographic and Health Surveys (DHS-2011) and the 2017 population-based HIV impact assessment (PHIA-2017). Both sources provide comprehensive information on HIV testing, access to information technology (household ownership of mobile phone and TV/radio), and relevant socio-economic variables. The sampling procedure is based on a two-stage random draw, where the first stage involves selecting the Enumeration Areas (EAs), which can be considered neighborhood clusters. In the second stage, households are chosen within each cluster. Approximately 10,000 and 12,000 households were selected for DHS-2011 and PHIA-2017, respectively, with interviews conducted for individuals aged 15 years and older. To protect respondent privacy, the geo-locations of the EAs were displaced. However, during the displacement procedure, the locations were compelled to remain within their original district, thereby enabling us to control for unobserved factors that are constant over time within districts. This study focuses exclusively on rural households, as we expect improvement in knowledge resulting from information technology use to be particularly important in areas where individuals have limited access to education.

Table 4.1 presents a descriptive summary of the sample distribution for the variables under consideration. Approximately 14% of individuals have tested for HIV in the preceding 12 months, while the rest have never tested. The prevalence of mobile phone is much higher than that of TV/radio, about 84% of individuals have access to a mobile phone while only 47% have access to either a TV or radio (TV/radio). Table 4.2 provides information on the prevalence of mobile phone use in conjunction with TV/radio. Roughly 39% of individuals have access only to a mobile phone, while 5% have access exclusively to TV/radio. On the other hand, 42% have access to both a mobile phone and TV/radio. The remaining 14% do not have access to any of these information devices.

4.3.2 Econometric model

We investigate complementarity-in-outcome between mobile phone and TV/radio. Due to data constraints, we are unable to assess complementarity for each pair-wise combination (phone-TV and phone-radio) separately. Instead, we create *TV/radio*, a composite variable that encompasses individuals with access to either only TV or only radio. Our econometric model is specified as follows:

$$Y_{idt} = \beta_0 + \beta_1 phone_{idt} + \beta_2 TV/radio_{idt} + \beta_3 phone\&TV/radio_{idt} + \beta_4 Z_{idt} + \alpha_d + \alpha_t + \mu_{idt} \quad (1)$$

where the outcome variable Y_{idt} is the HIV testing status of individual *i* in district *d* at time *t*. $phone_{idt}$ takes 1 if the individual has access to only mobile phone, 0 otherwise. $TV/radio_{idt}$

takes 1 if the individual has access to only television or only radio, 0 otherwise. $phone\&TV/radio_{idt}$ is a dummy that equals 1 if individuals have access to either phone and TV or phone and radio. Z_{idt} is a vector of control variables. α_d and α_t represent district and time fixed effects, respectively. While the former controls for unobserved and time-invariant factors that differ across districts and may influence HIV testing uptake, the latter deals with any time-varying unobserved factors.

4.4 Results

4.4.1 Baseline analysis

The results from probit estimations are shown in Table 4.3 while the OLS estimates are presented in Table 4.A in the Appendix. The first two columns report estimates from specifications benchmark estimations that ignore complementarity. Column 1 suggests that access to mobile phone is associated with approximately 3% higher likelihood of testing for HIV. After accounting for access to TV/radio in Column 2, the association between phone access and HIV testing falls to 2.4%, which corresponds to a decrease of 20%. Moreover, the results indicate a positive and statistically significant association between access to TV/radio and HIV testing. Column 3 reports the main finding in this chapter, relating to the complementarity analysis. It differs from the previous specifications in that it distinguishes between individuals who have access to either phone or TV/radio exclusively and those who access both. The result suggests existence of complementarity between phone and TV/radio, as the coefficient of phone&TV/radio is positive and statistically significant. Notably, the coefficient is approximately twice as large as the coefficient of phone. The statistical significance of mobile phone effect becomes weaker, while the estimate for TV/radio is no more significant.

In summary, these findings suggest the impact of mobile phone on health outcomes is substantial in presence of TV/radio. Previous studies (Greenleaf et al., 2019; LeFevre et al., 2020; Quail, 2012) that do not account for TV/radio may overestimate the impact of mobile phone. Most importantly, ignoring complementarity obscures the benefits of accessing multiple information devices, leading to a biased estimate of the individual value of each device.

4.4.2 Heterogeneous effects

We further explore the implications of socio-economic heterogeneity for the complementarity between phone and TV/radio. The results are presented in Table 4.4, where the top panel (a) relates to education and the bottom panel (b) to income heterogeneity. None of the estimated coefficients were statistically significant for the most advantaged groups (highest education and income groups). Among the non-educated group, those with access to both phone and TV/radio are about twice as likely to be tested for HIV as those with only access to phone. Regarding the group with elementary education, although the estimates are larger, the difference between the coefficients of phone and phone&TV/radio is relatively smaller. This suggests that the additional benefit from accessing TV/radio in presence of phone is smaller. With respect to income, the estimated coefficient for phone is not significant for the group with low income. Nevertheless, the joint access to mobile phone and TV/radio is associated with a 3% higher likelihood of HIV testing. As for the group with middle income, the difference in coefficient size is less pronounced, using mobile phone in conjunction with TV/radio is associated with an approximately 1% higher likelihood of being tested for HIV.

In summary, we found that the most socially disadvantaged group exhibits a greater complementarity between phone and TV/radio. This may be because they face more barriers to improving their knowledge by using only mobile phone, due to insufficient education and income. Therefore, the additional benefit from accessing mobile phone along with TV/radio is more important. As discuss earlier, the use of most mobile phone services requires some level of education and is associated with variable costs that can be prohibitive, while TV/radio use incurs lower costs and requires no active input except for changing channels (Shaikh, 2017). This may also explain why the impact of access to mobile phone is more considerable for those with primary education and the middle income group. Lastly, our results indicate no benefits for most advantaged groups, suggesting that knowledge improvement through accessing information technology is less important for the highly educated, who are mostly the wealthiest.

4.4.3 Instrumental variables

We examine the robustness of our main findings by using instrumental variables to deal with potential endogeneity. Previous studies documented that social networks influence technology adoption (Bonan et al., 2021; Maertens and Barrett, 2013). According to Manski (2000), the spread of technology via social interaction results from social learning or imitation. Bandiera and Rasul (2006) suggested that technology adoption decision is influenced by the adoption among the network of friends. In line with Miyajima (2022), we use the share of individuals with access to each information device in each neighborhood as instrument variable. The estimation results are presented in Table 4.5. Column 1 uses only the share of individuals with mobile phone access as instrument, while in Column 2 the share of those with TV/radio access is also included. The results indicate that access to mobile phone increases the likelihood of testing for HIV by 8.5%-9%. Column 3 relates to our complementarity analysis and uses a set of three instruments: the share of individuals with only phone access, the share of those with only TV/radio access and the share of those with access to both devices. The results suggest that accessing mobile phone alone increases HIV testing by 5.6%, while the increase is 6.2% when used in conjunction with TV/radio.

Overall, these findings are consistent with those in Table 4.3, suggesting that disregarding complementarity may obscure the benefits of accessing multiple information devices, resulting in a biased estimate of the individual value of each device.

4.5 Conclusion

This study investigated the possibility of complementarity-in-outcome between mobile phone and TV/radio and found that there is indeed complementarity. Specifically, we found that accessing mobile phone in conjunction with TV/radio has a greater impact on HIV testing. Our results also reveal that neglecting complementarity may lead to an overestimation of the individual value of each device. Further investigations suggest that the most socio-economically disadvantaged group exhibits higher complementarity, as the additional benefits from accessing mobile phone in conjunction with TV/radio is more substantial.

In light of these findings, we conclude that access to information devices helps bridge health knowledge gap between lower and upper social classes, thereby improving health outcomes. The impact of accessing mobile phone alone among the most disadvantaged group could be greater if education levels improve and the costs of access to mobile phone services decrease. These could be achieved by improving infrastructure that facilitates access to education, as well as by reducing installation costs incurred by telephone companies. We also recommend that health authorities continue to disseminate health information on television and radio, in addition to mobile platforms.

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Tables

Table 4.1. Descriptive statistics

Variable		Obs	Mean	Std. Dev.	Min	Max
HIV testing		14,022	0.14	0.34	0	1
Access to technology						
	Phone	19,218	0.84	0.36	0	1
	TV/radio	15,686	0.48	0.50	0	1
Gender		19,222	0.43	0.50	0	1
Relashionship to household head						
	Spouse	19,218	0.33	0.47	0	1
	Child	19,218	0.15	0.36	0	1
	Other	19,218	0.19	0.40	0	1
education						
	Primary	17,396	0.28	0.45	0	1
	Secondary and up	17,396	0.14	0.34	0	1
income						
	Middle	19,222	0.33	0.47	0	1
	High	19,222	0.34	0.47	0	1
Age		19,222	32.42	11.83	15	64
Number sex partner past 12 months		16,686	1.07	0.99	0	25
Access to electricity		19,213	0.38	0.49	0	1

Table 4.2. Summary statistics on the use of multiple devices

	TV/radio	No TV/radio
Phone	0.42	0.39
No Phone	0.05	0.14[a]

a baseline for the estimations in complementarity analysis.

Table 4.3. Information technology and HIV testing

VARIABLES	(1) Benchmark estimation	(2)	(3) Complementarity
Phone	0.030***	0.024***	0.024**
	(0.009)	(0.009)	(0.011)
TV/radio		0.018***	0.018
		(0.006)	(0.017)
Phone&TV/radio			0.042***
			(0.010)
gender	-0.134***	-0.131***	-0.131***
	(0.009)	(0.009)	(0.009)
Relationship: Spouse	-0.036***	-0.042***	-0.042***
	(0.010)	(0.011)	(0.011)
Relationship: child	-0.053***	-0.048***	-0.048***
	(0.011)	(0.012)	(0.012)
Relationship: other	-0.025**	-0.016	-0.016
	(0.011)	(0.011)	(0.011)
Education: primary	0.055***	0.050***	0.050***
	(0.007)	(0.008)	(0.008)
Education: secondary	0.166***	0.147***	0.147***
	(0.012)	(0.014)	(0.014)
Income: middle	-0.012*	-0.008	-0.008
	(0.007)	(0.008)	(0.008)
Income: high	-0.010	-0.008	-0.008
	(0.007)	(0.008)	(0.008)
Age	0.017***	0.016***	0.016***
	(0.002)	(0.002)	(0.002)
Agesq	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
Number of sex partner	0.013***	0.013***	0.013***
	(0.003)	(0.003)	(0.003)
Access to electricity	0.034***	0.024***	0.024***
	(0.006)	(0.007)	(0.007)
Observations	12,922	10,673	10,673

Coefficients are marginal effects. District and year fixed effects are included.
Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4.4. Heterogeneity analysis

VARIABLES	(1)	(2)	(3)
(a) Education	No education	Primary	Secondary up
Phone	0.023*	0.037*	-0.047
	(0.012)	(0.022)	(0.046)
TV/radio	0.023	-0.004	-0.024
	(0.018)	(0.041)	(0.073)
Phone&TV/radio	0.040***	0.044**	0.002
	(0.012)	(0.022)	(0.044)
Observations	6,679	2,866	1,128
(b) Income	Low	Middle	High
Phone	0.025	0.038**	0.001
	(0.016)	(0.019)	(0.022)
TV/radio	0.028	-0.001	0.015
	(0.023)	(0.030)	(0.041)
Phone&TV/radio	0.030*	0.049***	0.033
	(0.016)	(0.019)	(0.022)
Observations	3,709	3,823	3,141

Coefficients are marginal effects. District and year fixed effects are included.

Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 4.5. Instrumental variables

VARIABLES	(1)	(2)	(3)
	Benchmark estimation		Complementarity
Phone	0.091***	0.085***	0.056*
	(0.024)	(0.025)	(0.033)
TV/radio		-0.005	-0.042
		(0.020)	(0.063)
Phone&TV/radio			0.062**
			(0.030)
gender	-0.138***	-0.134***	-0.133***
	(0.009)	(0.010)	(0.010)
Relashionship: Spouse	-0.045***	-0.050***	-0.049***
	(0.011)	(0.012)	(0.012)
Relashionship: child	-0.051***	-0.046***	-0.047***
	(0.011)	(0.012)	(0.012)
Relashionship: other	-0.030***	-0.019	-0.018
	(0.011)	(0.012)	(0.012)
Education: primary	0.056***	0.049***	0.049***
	(0.007)	(0.008)	(0.008)
Education: secondary	0.160***	0.142***	0.143***
	(0.012)	(0.013)	(0.013)
Income: middle	-0.019**	-0.014*	-0.012
	(0.008)	(0.008)	(0.008)
Income: high	-0.018**	-0.015*	-0.014
	(0.008)	(0.009)	(0.009)
Age	0.014***	0.012***	0.012***
	(0.001)	(0.002)	(0.002)
Agesq	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
Number of sex partner	0.013***	0.013***	0.013***
	(0.003)	(0.004)	(0.004)
Access to electricity	0.031***	0.027***	0.028***
	(0.008)	(0.009)	(0.009)
F- statistic	1310.61	624.55	120.56
Partial Rsq (*phone*)	0.112	0.113	0.092
Partial Rsq (*TV/radio*)		0.105	0.056
Partial Rsq (*Phone&TV/radio*)			0.107
Observations	12,922	10,673	10,673

District and year fixed effects are included.

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Appendix

Table 4.A. Information technology and HIV testing (OLS)

VARIABLES	(1)	(2)	(3)
	Benchmark estimation		Complementarity
Phone	0.026***	0.021***	0.020**
	(0.008)	(0.008)	(0.009)
TV/radio		0.018***	0.015
		(0.007)	(0.014)
Phone&TV/radio			0.038***
			(0.009)
gender	-0.134***	-0.132***	-0.132***
	(0.009)	(0.010)	(0.010)
Relashionship: Spouse	-0.041***	-0.048***	-0.048***
	(0.011)	(0.012)	(0.012)
Relashionship: child	-0.050***	-0.047***	-0.047***
	(0.011)	(0.012)	(0.012)
Relashionship: other	-0.024**	-0.015	-0.015
	(0.010)	(0.011)	(0.011)
Education: primary	0.057***	0.051***	0.051***
	(0.007)	(0.008)	(0.008)
Education: secondary	0.163***	0.144***	0.144***
	(0.012)	(0.013)	(0.013)
Income: middle	-0.013*	-0.008	-0.008
	(0.007)	(0.008)	(0.008)
Income: high	-0.011	-0.009	-0.009
	(0.008)	(0.009)	(0.009)
Age	0.014***	0.012***	0.012***
	(0.001)	(0.002)	(0.002)
Agesq	-0.000***	-0.000***	-0.000***
	(0.000)	(0.000)	(0.000)
Number of sex partner	0.014***	0.013***	0.013***
	(0.003)	(0.004)	(0.004)
Access to electricity	0.041***	0.032***	0.032***
	(0.007)	(0.008)	(0.008)
Observations	12,922	10,673	10,673

Robust standard errors in parentheses. District and year fixed effects are included.
*** p<0.01, ** p<0.05, * p<0.1

Chapter 5

General conclusion

Information and communication technologies play a crucial role in developing countries by improving access to health information. This dissertation examined the impact of access to information technologies on health outcomes. We investigated the impact of Internet searches for vaccine information on immunization coverage. Furthermore, the impact on vaccination coverage of access to mobile communication infrastructure that enables access to the Internet and call/SMS services was explored. Finally, we analyzed potential complementarity between mobile phone and earlier information devices regarding their impact on health outcomes.

In Chapter 2, the results from our cross-country analysis indicate an overall positive impact of access to immunization information on vaccines uptake. Further investigations suggest differences in impact according to the features of the vaccines. The impact is substantial for the vaccine related to high-risk disease, while the estimates are not significant for the controversial vaccine and the vaccines related to diseases with low incidence rates.

In Chapter 3, we found a household closer to access to cell towers where more likely to have their children vaccinated. The impact was salient for rural households, especially for those with no education. The results also reveal substantial effect for the vaccine related to the disease with high incidence. Overall, our findings suggest that access to cell towers helps bridge the vaccination coverage gap resulting from lack of education.

In Chapter 4, we found existence of complementarity between phone and TV/radio regarding their impact on health outcomes. Specifically, our results suggest that the impact of accessing mobile phone on HIV testing is significantly greater when used in conjunction with TV/radio. We also found that the degree of complementarity varies across socio-economic groups. The most socio-economically disadvantaged group exhibits higher complementarity compared to the middle class. However, accessing information devices does not impact HIV testing among those from the most advantaged group.

In light of these findings, we conclude that improvements in mobile communication facilities in Sub-Saharan Africa, especially in Côte d'Ivoire have greatly facilitated access to and dissemination of health information, thereby improving health outcomes. However, there are also potential downsides to consider, as access to information technology can contribute to the spread of misinformation. Effective solutions to these problems are urgently needed, as they tend to negate the benefits of access to health information technology.