Social Impacts of New Radio Markets in Ghana: A Dynamic Structural Analysis

Christoph Walsh*

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Abstract

Ghana liberalized its radio broadcasting sector in 1992 to allow the entry of commercial stations, where previously the state had a monopoly. I analyze how the broadcasting regulator affects commercial radio stations' decisions to enter and the resulting effects of coverage spillovers in rural areas. I compute the coverage areas of all radio stations to construct a dataset of which stations are available at every point in the country. I exploit random variation in radio coverage caused by coverage spilling through gaps in mountainous areas. I use this to estimate the effects of coverage on social outcomes, in particular, malaria incidence and night lights growth. I then estimate a dynamic structural entry model for commercial stations where competition is measured by the overlaps of the stations' coverage areas. In counterfactual simulations using the model, I find that allowing higher transmitter strengths to be a particularly effective policy to deliver the social benefits of radio to new communities.

Keywords: Dynamic Games, Spatial Competition, Radio Regulation, Ghana

JEL classification: C73, L13, L51, L82

* Department of Economics, Boston University. Contact: walshcb@bu.edu

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1 Introduction

Exposure to mass media has been found to have effects on a wide range of social and economic outcomes, such as voter turnout, fertility, and education. In many developing countries, radio is the most popular form of mass media, as lower literacy rates and electricity penetration rule out newspapers, television and internet for many individuals. Having access to radio coverage is therefore important to inform listeners of important issues. The radio broadcasting sector is highly regulated since radio makes use of the limited frequency spectrum. These regulations can impact the entry and location decisions of radio stations, which affects which areas receive radio coverage. This can have resulting effects on the social and economic outcomes of communities.

In Ghana, the media was under state control until a new constitution was promulgated in 1992 which allowed the entry of privately-owned radio stations. Since then there has been a large rise in the number of commercial radio stations, with over 300 commercial stations entering in the first twenty years. The entry of commercial radio stations is regulated in a number of dimensions which can affect how many stations enter and whether coverage will spread to rural areas. Licensing fees and restrictions on transmitter strengths may result in radio coverage being underprovided.

In this paper, I use data from Ghana's broadcasting regulator and topographical data to compute the coverage area for each radio station. Using these data, I first estimate the positive effects of radio coverage in reduced form. I then estimate a dynamic structural entry model of radio station competition using the network of overlapping coverage areas. Using this estimated model, I simulate the change in entry patterns under counterfactual regulation schemes and the resulting social and economic effects on the communities receiving radio coverage.

To explore the positive effects of radio coverage, I exploit random variation in coverage caused by coverage spilling through gaps in mountainous areas. Radio stations choose their broadcasting location to broadcast to the population living nearby. The spread of this coverage around the source will eventually be blocked by hilly terrain. However, coverage often manages to spill through gaps in mountainous areas in the form of streaks. If these coverage streaks are sufficiently far away from the source, then the radio station is unlikely to have strategically placed its radio mast in order to capture a specific location that is near the border of a coverage streak. Therefore the locations near the borders of these streaks received coverage in an as-if random fashion. Using these streaks of spill-through coverage, I use a geographic regression discontinuity design to estimate the effects of coverage on different

outcomes.

One outcome variable I use is malaria incidence among children, as measured by the Malaria Atlas Project (Bhatt et al., 2015). Malaria is prevalent throughout all regions in Ghana and is the largest cause of mortality in the country. Radio has the potential to warn listeners of the risks of malaria and give information on how to prevent it. One way in which radio informs about malaria and other health-related issues is through "edutainment" programs. These are entertaining shows such as soap operas that also include informative messages such as how to prevent contracting diseases. I find that individuals in areas that receive coverage experience an additional 1% drop in malaria incidence within a five-year period over a baseline drop of 7%. To explore the mechanism behind this result, I merge the radio coverage data with Demographic Health Survey data. I find that areas with radio coverage are 17% more likely to have their children sleep under mosquito bed nets. Another outcome variable I use is nighttime luminosity as seen from space, which has been used in the literature as a proxy for local GDP. Nighttime luminosity increases an additional 15% over the baseline after a 5-year period.

Since radio makes use of a limited frequency spectrum, radio stations are subject to significant policy oversight. Stations typically compete in oligopoly markets, involving many dynamic and strategic interactions. In order to study the effects of regulation on radio station entry, it is necessary to estimate a dynamic structural model in order to capture these strategic interactions. Furthermore, a structural model is necessary to evaluate counterfactual regulation schemes.

In the model, potential entrants choose whether or not to obtain broadcasting licenses based on their expectations of the number of future competitors and the number of potential listeners. The technology of radio broadcasting allows for a natural measure of competition and market size for each station, rather than using administrative areas to partition the country into separate markets. Radio stations compete if their coverage areas overlap and the potential listenership of a station is the population living within the station's coverage area. The overlapping coverage areas form a network of competing stations across the country. The model can incorporate spillovers throughout the network, where stations that indirectly compete can react to deviations in firms' strategies.

I evaluate counterfactual regulation schemes using the estimated structural model together with estimates of the positive effects of radio coverage. One regulation imposed on commercial radio stations is a maximum broadcasting radius. I consider a counterfactual where stations are allowed to have transmitters that are twice as strong. The effect of such a policy change on entry is not obvious ex ante. On the one hand, radio stations could have

a larger base of listeners which would make entry more attractive. On the other hand, however, they may experience more competition, which would make entry less attractive. I find that allowing stronger transmitters modestly increases the overall number of radio stations but expands coverage to locations that did not receive coverage before. In another counterfactual, I find that reducing entry costs increases overall entry substantially, but does not increase the number of extra individuals covered as much as the previous counterfactual of allowing stronger transmitter strengths. Given that I find that the positive external benefits of radio coverage are mostly on the extensive margin, a policy allowing stronger transmitter strengths would be more effective in delivering the benefits of radio to communities.

The main contributions of this paper are as follows. Radio coverage maps and irregular terrain have previously been used to estimate the effects of radio and television coverage. However, my identification strategy differs from previous work in that I use coverage streaks in a geographic regression discontinuity design. This paper adds to the literature exploring the effects of mass media, focusing on the effects of radio on malaria incidence and growth. I also contribute to the estimation of dynamic entry models literature by incorporating a number of unique features to the model. In structural entry models, it is common to partition the country into independent markets. Since radio stations compete if they overlap in radio coverage, I let the coverage areas of the stations determine which stations compete with one another. This implicitly forms a network among the radio stations and incorporates the possibility of spillovers from a station's actions throughout the network. Using the coverage maps in the model also allows for the estimation of unique counterfactual experiments, such as the effects of doubling transmitter strengths on stations' entry decisions.

Related Literature

There is a wide literature studying the effects of mass media on an array of outcomes. Gentzkow (2006), Oberholzer-Gee and Waldfogel (2009), Gentzkow et al. (2011) and Cagé (2017) study the effect of media on voter turnout while Gerber et al. (2009), Enikolopov et al. (2011), Larreguy et al. (2014), Garcia-Arenas (2016) and Durante et al. (2017) its effect on political leaning. Strömberg (2004), Besley et al. (2002) and Snyder and Strömberg (2010) find that government responsiveness and political accountability are greater in areas with better media coverage. Farré and Fasani (2013) find media lowers migration and Keefer and Khemani (2014) find positive effects on parental investment in children's education. Jensen and Oster (2009) find an increase in women's status in the household and lower domestic violence. La Ferrara et al. (2012) find that soap operas lower fertility and Kearney and Levine (2015) find that reality TV

leads to fewer teenage pregnancies.

Not all of the effects of mass media are positive, however. Olken (2009) finds that radio and television lower social capital and trust. DellaVigna et al. (2014) find increased nationalism and ethnically offensive graffiti from cross-border coverage and Yanagizawa-Drott (2014) finds increased violence in Rwanda from propaganda on the radio. Paluck (2009) and Paluck and Green (2009), however, find that educational radio soap operas reduced violence in Rwanda. Notwithstanding, the majority of the effects of mass media are positive, particularly for radio. This motivates studying how regulation and competition affect the entry decisions of radio stations, as they can deliver important benefits.

This paper also adds to the literature on the estimation of dynamic games of imperfect competition. Bajari et al. (2007), Aguirregabiria and Mira (2002, 2007), Pakes et al. (2007) and Pesendorfer and Schmidt-Dengler (2008) each provide two-step methods to estimate these models based on Ericson and Pakes (1995). Applications of these methods include Ryan (2012), Collard-Wexler (2013), Dunne et al. (2013), Lin (2015) and Ahokpossi and Walsh (2017). A notable difference in this paper, however, is that I do not partition the country into a set of independent markets ex ante. Rather, I allow the network of overlapping coverage areas from each radio station decide which stations compete with one another.

There has also been previous work on the radio broadcasting industry. Berry and Waldfogel (1999) and Berry et al. (2016) find that there is more entry than is socially optimal in US radio markets. In this paper, I find that radio is underprovided in a number of communities. Sweeting (2009, 2010, 2013) studies advertising times, mergers and musical performance rights and Jeziorski (2013, 2014a,b) studies ownership caps and mergers in the US radio industry. However, due to data limitations, exploring these issues in this setting would be beyond the scope of this paper.

2 Background: FM Broadcasting in Ghana

Ghana has a population of approximately 27 million and has a land mass similar to the state of Oregon or the United Kingdom. It is located on the coast of West Africa, bordering Côte d'Ivoire, Togo and Burkina Faso. Ghana achieved independence from the United Kingdom in 1957. Since then, the country went through various military governments where the media was under state control and used as a means of propaganda. This ended in 1992 when a new constitution allowed the entry of private media in Ghana. However, the government at the time delayed the provision and allocation of broadcasting licenses to private owners. In 1994, a pirate radio station, Radio EYE, was set up in the nation's capital Accra as a form of protest

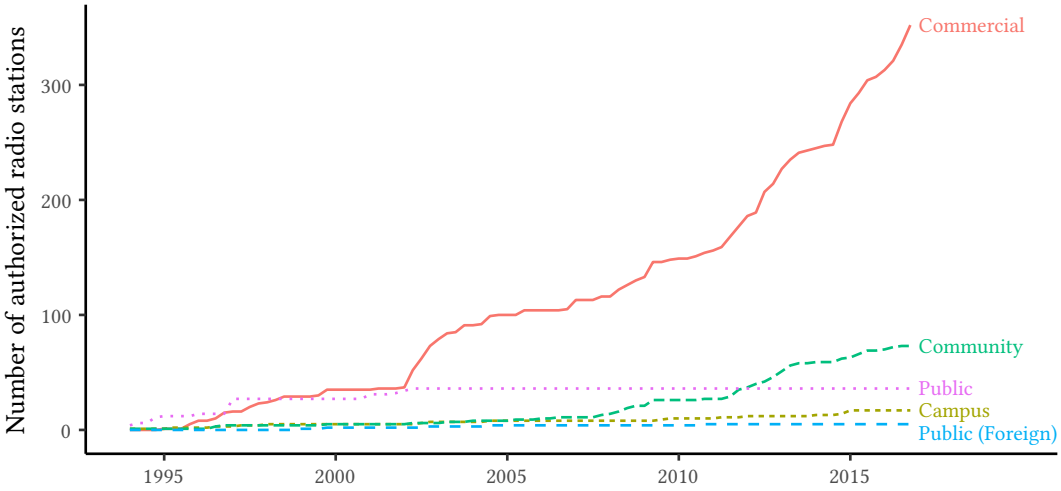


Figure 1: Number of authorized radio stations by license type since liberalization.

which pressured the government to begin issuing licenses. The National Communications Authority (NCA) was then established as the regulator overseeing the issuing broadcasting licenses.

Radio is arguably the most important form of mass media in Ghana, as well as in other developing countries. For many individuals, radio may be the only form of mass media available to them. According to the 2010 Housing and Population Census, adult literacy was 74.1% which rules out newspapers for a quarter of the population. Only 64.2% of households reported using electricity. Even those with electricity, power outages (known locally as *Dumsor*) are very frequent. This rules out televisions for a large portion of the population. Furthermore, only 7.9% of households owned a desktop or laptop computer and only 7.8% of the population 12 years and older had access to the internet. In rural areas, literacy, electricity and internet penetration are even lower. Radios are inexpensive and do not always require electricity to operate. They can be run on batteries and hand crank radios are also available. Radio stations can operate at a very local level due to the lower cost of creating content compared to television, allowing them to broadcast in the local language of the community. The country has a population of 27 million, yet there are over 50 actively spoken languages.

For licensing purposes, radio stations in Ghana are classified as one of five types: Public, Public Foreign, Commercial, Community and Campus. The National Communications Authority describes each of these types as follows. *Commercial* stations are those that are privately owned, controlled and operated for profit by independent commercial groups or individuals. *Public* stations are stations that are owned and operated by the Ghana Broadcasting

Corporation (GBC) or any other stations established by the Government of Ghana while *Public Foreign* stations are stations established by foreign governments, such as the BBC. *Community* stations are non-profit and provide service for a specific marginalized community. Ownership and management of community stations are representative of the community. Finally, *Campus* stations are stations operating within the ambit of educational institutions. The license type is important because it determines how stations can generate revenue, the permissible size of its coverage radius and the application fees, initial fees and annual fees the stations must pay. In the entry model of this paper, I will focus mostly on commercial radio stations since an overwhelming majority of the entry the took place is from commercial stations. Figure 1 shows the cumulative entry of commercial radio stations compared to other types. In 2016, there were over 350 authorized commercial stations with 480 authorized stations overall. In per capita terms, the country now has approximately one third of the number of radio stations in the US.

For the most part, commercial radio stations are independently owned. Outside of the public stations run by the Ghana Broadcasting Corporation, 19 companies held two broadcasting licenses and 6 companies held three broadcasting licenses. That leaves 296 independently-owned commercial stations. Since the opening of multiple stations happens rarely in the data I abstract away from network expansion in the structural model, as that would increase the computational burden significantly. There are a number of reasons why multiple ownership is rare in the data. As a relatively young market, most stations have not yet grown enough to expand into multiple markets. This can also be exacerbated by poor credit markets as opening multiple stations would require large startup funds. Another reason is that Ghana's markets are heterogenous with many different languages and ethnic groups.

Commercial stations are required to pay initial authorization fees and annual spectrum fees. Commercial stations and Public Foreign stations are restricted to have a 45km coverage radius while Community and Campus stations are restricted to (approximately) a 5km radius. Public stations, on the other hand, do not have any coverage limitations. The coverage limitations on commercial stations may affect their entry decisions, which will be explored in this paper.

3 Data

3.1 Radio Station Data

Data on the entry and exit of radio stations come from Ghana's National Communications Authority (NCA). A convenient aspect of the radio broadcasting industry is that the licensed radio stations need to be well documented so that stations with similar frequencies in nearby areas do not overlap in their coverage areas. The NCA lists of all the license holders which show all the authorization dates of license holders since the first authorizations in 1995. The NCA also have reports which document whether the stations are currently "On Air" or "Off Air" which are available from 2009Q3-2016Q3[1]. This enables me to observe entry and exit in the data at a quarterly frequency during this period. There is very little exit in the data, so in the model I focus solely on the entry decisions of radio stations. I supplement this data with data from FMLIST, a worldwide radio station database. These data contain various other information about the transmitters, such as their height above ground, wattage and GPS coordinates. Missing information for stations on antenna height and transmitter power were imputed. Due to regulations on stations' broadcasting radii, these were mostly homogeneous. Some of the quarterly reports from the National Communications Authority were also missing. However, for almost all radio stations, the station was active before and after the missing period or inactive before and after.

I use the Longley and Rice (1968) Irregular Terrain Model to compute the field strength of each radio station's coverage. I use the command-line tool *SPLAT!*[2] (a radio frequency Signal Propagation, Loss, And Terrain analysis tool) to perform these calculations. This model was initially used by the Federal Communications Commission to predict the extent of stations' coverage areas to ensure that the coverage from stations with the same frequency in different locations did not overlap. The model computes how the field strength of radio transmission degrades as the signal reaches obstructions such as hills and mountains. For these obstructions, I use data from the Shuttle Radar Topography Mission (Farr et al., 2007), which is a worldwide digital elevation model at 3 arc seconds (roughly $90m^2$).

Figure 2 shows an example of this calculation for one radio station. The left panel in Figure 2 shows the elevation near the city of Kumasi in Ghana. Brighter areas represent areas with higher elevation. The red point represents the location of one radio station's mast. The right panel in Figure 2 shows the signal strength of that radio station's coverage in the same area. The signal strength is measured in decibel-microvolts per meter (dBμV/m). Bright

[1]Newer data have since become available and merging them is currently work in progress.
[2]More information is available here: `https://github.com/jmcmellen/splat`

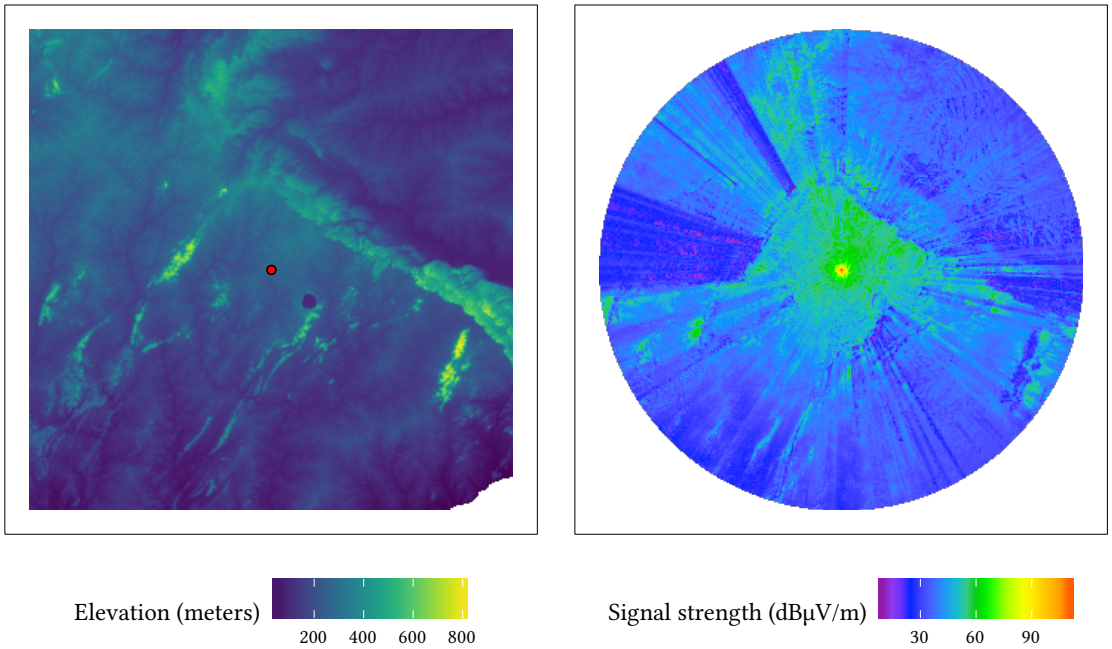


Figure 2: Example radio station coverage output. The left figure show the elevation in a particular area where the red point indicates the location of a radio station's mast. The right figure shows computed signal strength of that radio station in the same area, measured in decibel-microvolts per meter.

green areas represent where the signal quality is high and blue areas represent where the signal quality is very poor. As the signal reaches mountainous obstructions, the color darkens rapidly, indicating a sharp drop in signal quality. The Federal Communications Commission, as well as other regulating bodies around the world, consider 60 dBμV/m to be the threshold of signal strength for FM radio broadcasting. In this paper, I will also use the 60 dBμV/m cutoff.

The resulting coverage data is at a $90m^2$ resolution which results in several million data points for each station. In order to merge this data with other data sources, I aggregate to 30 arc seconds (as opposed to 3 arc seconds) which makes the resolution approximately $900m^2$.

It should be noted that these coverage predictions are computed from a model and as a result are not perfect. The elevation data does not take into account other obstructions, such as forests and large buildings. Kasampalis et al. (2013) perform a validation exercise comparing predictions of the model to actual field readings of field strength. They find that *SPLAT!* has an average error of -0.5 dBμV/m and a standard deviation of 5.5 dBμV/m. Since 60 dBμV/m is considered the minimum field strength required for a station to be picked up, the average error is very small. I also aggregate the data from 3 arc seconds to 30 arc seconds

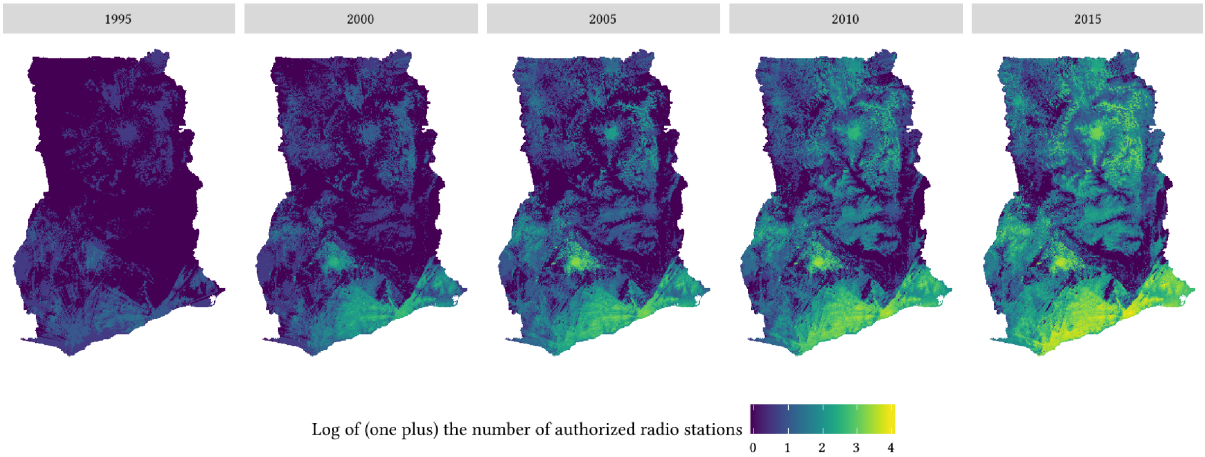


Figure 3: The log of the number of authorized stations available at each point in Ghana at approximately 900m^2 resolution, 1995-2015.

which would reduce this error. I have also tested the *SPLAT!* software by computing the coverage areas of different radio stations in the Greater Boston Area, using data from the Federal Communications Commission. Using a simple portable FM radio, I found consistent coverage predictions from the model.

Figure 3 shows the output from generating the coverage maps for every radio station. The figure shows the log total number of authorized stations available at each point at five-year intervals at approximately 900m^2 resolution using the 60 dBμV/m coverage threshold. This does not distinguish whether the station is commercial, public, community or campus. There is a large variation in the number of stations across the country, as well as large variation over time. The country's capital Accra, the coastal city in the southeast, has the most stations. The northern regions have very few stations, with many areas not having any coverage even by the end of the data.

3.2 Other Data Sources

For the reduced-form section of the paper exploring the outcomes of radio coverage and for the structural model of radio station competition, I use the following data sources for either outcomes of radio coverage or control variables.

Malaria Incidence

One outcome of radio coverage I will examine is malaria incidence among children. Malaria accounts for 33.4% of all deaths in children under five years of age and 36% of health cen-

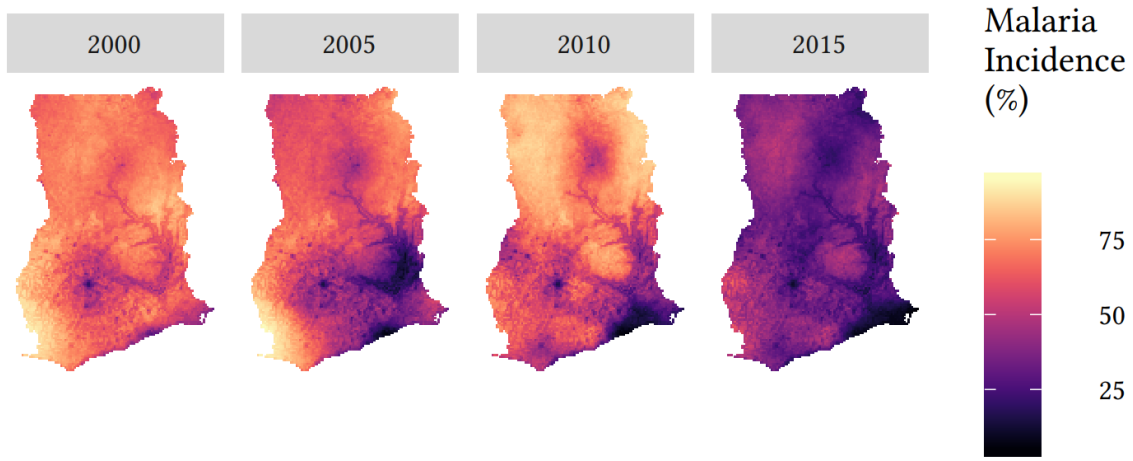


Figure 4: Malaria incidence rate in 2-10 year olds over time. Data source: Malaria Atlas Project.

ter admissions[3]. The Malaria Atlas Project (Bhatt et al., 2015) constructed detailed maps of malaria incidence in Sub-Saharan Africa for the years 2000-2015 at a 15-arc second resolution. The maps are estimated using a geostatistical model which uses different survey datasets and climate data. Figure 4 shows the malaria incidence rate in 2-10-year-olds from 2000-2015. The incidence rate is high throughout most of the country, in particular in earlier periods in the sample. Larger cities have a lower incidence rate and the incidence rate is falling over time.

Nighttime Luminosity Data

Another outcome of radio coverage I will examine is nighttime luminosity as seen from space. Night lights data have been used as proxies for local GDP in an ever-increasing number of applications, for example, Henderson et al. (2011, 2012), Bleakley and Lin (2012), Gennaioli et al. (2013), Michalopoulos and Papaioannou (2013). These data come from the National Oceanic and Atmospheric Administration. These are satellite images captured by the US Air Force at night between 8:30 PM and 10:00 PM local time around the world. These images are then processed and cleaned to represent the average amount of light emanating from a geographic location during a year. Observations obstructed by clouds are excluded, as well as observations with light coming from forest fires, gas flares, sunlight (from the summer months) and moonlight. Night lights data are available from 1992-2013 at a 30-arc second resolution around the world (approximately 900m^2 in Ghana). Values in the data are represented on a scale that ranges from 0 to 63 which measures the amount of light captured by the camera's sensor. This scale is top-coded at 63, although top-coding is rare in Ghana. Only 0.04% and

[3]Source: http://defeatmalaria.org/ghana

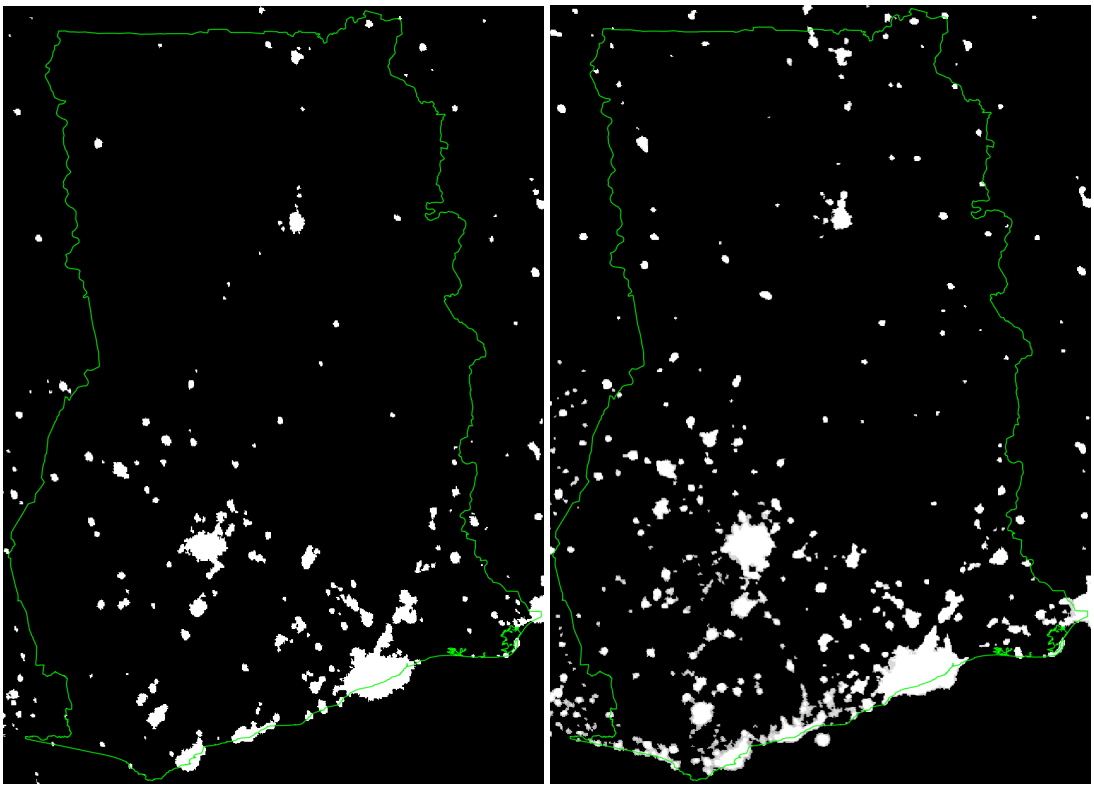


Figure 5: Nighttime luminosity as seen from space in Ghana in 1993 (left) and 2013 (right). The green outline represents Ghana's national border. Data source: National Oceanic and Atmospheric Administration.

0.14% of observations are top-coded in 1992 and 2013 respectively. For a portion of the years available, data from two different satellites are available. In these cases, I take averages across satellites. Figure 5 shows night lights in Ghana for 1993 and 2013.

Road Network Data

Distance to the nearest road will be a control variable in the reduced-form regressions. Road network data is from OpenStreetMap which is more detailed than other readily-available administrative data as it contains smaller roads. However, these data are not time-varying and only contain the present road network. The road network for the country is shown in Figure A.1 and distance to the nearest road is shown in Figure A.2.

Demographic Health Survey Data

To further explore the effect of radio coverage on malaria incidence I examine mosquito bed net usage in the Demographic Health Survey (DHS) data. The DHS program has conducted

more than 300 surveys of population, health and nutrition in over 90 countries. In Ghana, they have conducted six repeated cross sections from 1993 to 2016. However, the questions vary year-by-year and information on mosquito bed net usage are only contained in the surveys since 2003. The DHS provide approximate coordinates of each survey cluster which allows matching with the coverage data. The survey cluster locations for each year are shown in Figure A.3. The surveys span most of the country but some of the underpopulated areas are omitted. To preserve the anonymity of the survey respondents, the DHS purposefully add error of up to 2km for urban areas and 5km for rural areas. Thus matching the coverage data with the DHS data on the coordinates that they provide will introduce measurement error. To reduce this measurement error I take the average amount of coverage available within a radius around the cluster locations, rather than taking the number of available radio stations at the latitude-longitude pair given in the data. The radius I use for each survey cluster corresponds to the maximum possible error introduced by the DHS (2km for urban clusters and 5km for rural clusters).

Population Data

For the structural model, an important variable is the potential listenership of a radio station. Population data at administrative areas finer than the district level are not readily available for Ghana. However, NASA's Socioeconomic Data and Applications Center (SEDAC) provide rasterized population estimates at a 30 arc second resolution (approximately 900m^2) (Balk et al., 2006). These maps were constructed using administrative data at the district and town level and satellite and road data were used to estimate the urban extent of the cities. Unfortunately, these population rasters are only available for 1990, 1995 and 2000. I create a population raster for 2010 using a similar methodology to that used by NASA SEDAC. I first obtain district-level population counts from the 2000 and 2010 census from the Ghana Statistical Service. A number of districts in Ghana split or merged between 2000 and 2010 so in these cases I merge districts to remain consistent between years[4]. Then, using a shapefile of Ghana's districts[5], I rasterize the district populations in both years to be comparable to the population raster. I also use 2000 and 2010 night lights data. To smooth out measurement error in the night lights data I use the average of 1999-2001 and 2009-2011 as proxies for 2000 and 2010 respectively. I then fit a LASSO model predicting the values of each cell in the 2000 population raster using 2000 census data, 2000 night lights, the 1990 population raster and their interactions and higher-order terms. I then predict a 2010 population raster using the

[4]The history of Ghana's district splits and merges are available at http://www.statoids.com/ygh.html
[5]Available at http://gadm.org/

estimated model with the updated predictors. The resulting population raster produces aggregate counts and growth rates similar to the census figures at the district level. Maps of log population are shown in Figure A.4. To obtain values for population before and after 2010 I interpolate and extrapolate linearly using the 2000 and 2010 values.

4 Effects of Radio Coverage

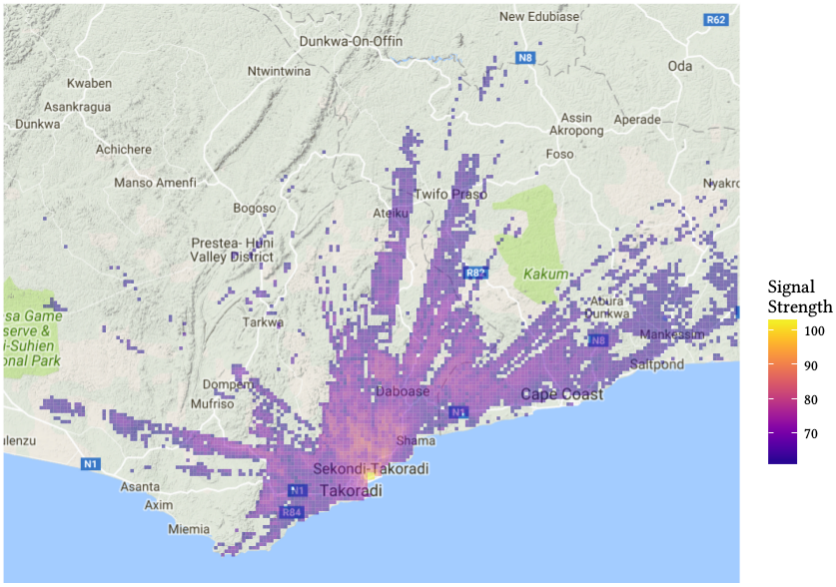
In the literature review, we learned that radio and other forms of mass media affect a host of different social outcomes. In this section, I show that these positive effects continue to hold in this context for outcome variables where we have data.

4.1 Identification Strategy

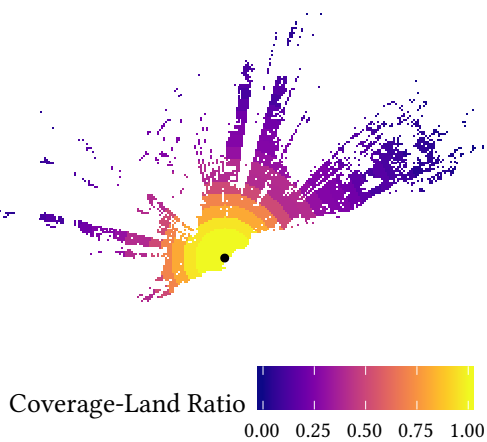
Radio coverage is not randomly assigned throughout the country, as stations prefer to locate in areas with higher population and less competition. However, irregular terrain creates some randomness in radio coverage which can be exploited. Consider Figure 6a which shows the coverage area for a radio station in a Sekondi-Takoradi. This city has a population of approximately half a million people and the coverage area of the station encompasses the city and some surrounding areas. As a result of hills away from the station, the coverage stops abruptly in certain areas. However, there are some gaps in the hills which allows some "streaks" of coverage to spill through into some rural areas. Given the population living in these streaks is a small fraction of the station's main coverage area in the city, I argue that the station is not positioning its radio mast strategically to include certain areas beyond the hills. If we believe that the locations of these streaks of coverage are random, then we can perform a geographic regression discontinuity comparing outcomes on either side of the borders of these streaks. These coverage streaks appear for many radio stations. With all radio stations together, there are many locations throughout the country that receive coverage in an as-if random fashion.

4.2 Implementation

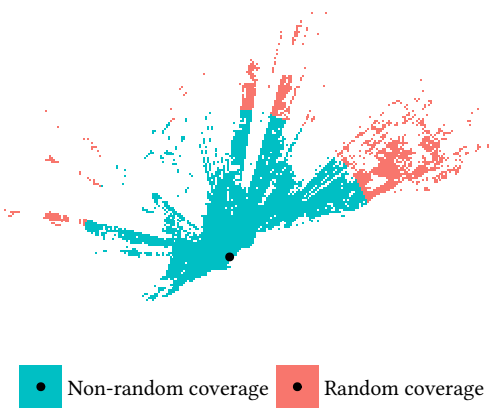
I discretize the country into a grid with a resolution of 30 arc seconds. Each tile in the grid has an area of approximately 900m^2. Each observation is then a *tile-year*. The task is to identify tiles which are near the border of a coverage streak in a particular year. I systematically identify coverage streaks as follows. First, for every station, I find the ratio of coverage to land at distance bins away from the transmitter. I call this the *coverage-land ratio*. This is shown in Figure 6b. Tiles very close to the station have a ratio of one because all tiles with



(A) Example radio station coverage map. The identification strategy compares outcomes in locations near the borders of "coverage streaks", which are caused by gaps in mountainous areas.



(B) Identifying coverage streaks. For each station, I compute the ratio of coverage to land at distance bins away from the station. Coverage streaks occur when the coverage-land ratio is sufficiently low.



(C) Areas included in the design are areas where (i) the coverage-land ratio is low, (ii) where the coverage is far away from the nearest transmitter and (ii) nearby elevation changes are small. Estimation compares outcomes on the border between the red areas and the white areas.

Figure 6: Identification Strategy for the Geographic Regression Discontinuity.

land at those distances have coverage. Further away, however, the ratio falls as some coverage gets blocked by hills. I identify streaks of coverage where the ratio of coverage to land is below some threshold.

It is also possible that the coverage-land ratio is small near the source. In these cases, the station may have intended for coverage to reach those locations. Therefore we only want to include tiles that are far away from the station. I include only areas that are in an upper quintile of distance away from the station. Figure 6c shows an example of the random part of a station's coverage area: tiles where the coverage-land ratio is less than 0.2 and the distance of coverage is in the outer quintile away from the transmitter. The tiles that will get included in the regression discontinuity are the tiles near the border of these outer coverage streaks.

The elevation change causing the coverage streak should also be far away from a location, as local elevation changes may affect outcomes directly. Therefore I exclude locations with elevation changes exceeding fifty meters in the nine surrounding tiles of the observation. Finally, it is possible a location is in near a coverage streak of one station but in the immediate (non-random) coverage area of a different station. Only locations near coverage streaks that are not in the immediate coverage of other stations are included.

The estimating equation is then:

$$y_{\ell,t+\tau} - y_{\ell t} = \beta \times coverage_{\ell t} + \boldsymbol{x}'_{\ell t}\boldsymbol{\gamma} + f\left(d_{\ell t}\right) + \varepsilon_{\ell t}$$

The dependent variable is the change an outcome of interest. $coverage_{\ell t}$ is an indicator for whether that tile had radio coverage and $\boldsymbol{x}_{\ell t}$ is a vector of control variables. $d_{\ell t}$ is the distance to the nearest coverage streak border and $f(\cdot)$ is a flexible polynomial of positive and negative negative values of $d_{\ell t}$.

One control variable is a measure of hilliness which is the maximum elevation change in a radius around the tile. Since coverage spills through gaps in hills, it is also possible that roads also follow the path through gaps in the hills. Therefore I also include two measures of road connectnedness as controls. One measure is the distance to the nearest road. However, a location at the intersection of two roads is more connected than a location next to one road. Therefore I also use a measure which I call road connectedness. It is the percentage of tiles with roads within a $N \times N$ matrix of tiles around the observation. An example of this calculation is shown in Figure A.5.

4.3 Outcome Variables

For this identification strategy it is necessary to have outcome data at a very fine geographic level, as only a small proportion of the country will be close to a coverage streak. One dataset at a fine geographic level is the malaria incidence rate among children aged 2-10 from the Malaria Atlas Project (Bhatt et al., 2015). News programs and "edutainment" programs on the radio can inform individuals about how to avoid contracting malaria. According to those surveyed in the Demographic Health Surveys in 2003, 2008 and 2014, 80% stated they heard messages about malaria on the radio. For television and newspapers, this number was 52% and 15% respectively.

Another outcome variable I can use is nighttime luminosity from space, which represents a catch-all for development in the area. Individuals may learn about improved farming practices or employment opportunities, which can increase growth in the area.

4.4 Results

Table 1 shows the results for the change in malaria incidence among children aged 2-10. The dependent variables are the changes in malaria incidence over a 5 and 10 year period. In the full sample, we see that areas receiving radio coverage experience a faster drop in malaria incidence. Columns (1) and (2) show that over a 5-10 year period, the malaria incidence rate falls on average by 2-3 percentage points. The geographic regression discontinuity results in columns (3) and (4) are somewhat smaller in magnitude to the full sample. One reason for the full sample having a larger coefficient is that stations prefer to locate in urban areas. In urban areas, individuals may learn how to avoid contracting malaria from other sources.

Table 2 presents the regression results using night lights data. Areas receiving radio coverage may learn about more productive practices, such as better farming methods, and therefore grow faster than areas not receiving coverage. The dependent variables are the changes in night lights over a 5 and 10 year period. Columns (1) and (2) show the results using the full sample while columns (3) and (4) show the geographic regression discontinuity results. In the full sample, coverage has a positive effect and the effect is increasing over time. In the regression discontinuity, the coefficients have the same sign as the full sample but the magnitudes are much smaller. This is because stations prefer to locate in areas that are expected to grow faster over time. Using Ghana's aggregate GDP values (in constant 2010 US dollars from the World Bank) together with the aggregate sum of nighttime luminosity values for the country, one unit of night lights in one 900m^2 cell represents local GDP of approximately \$145,000. Therefore cells receiving coverage in a coverage streak on average experience an increase of

	Full sample $m_{t+5} - m_t$ (1)	Full sample $m_{t+10} - m_t$ (2)	RD sample $m_{t+5} - m_t$ (3)	RD sample $m_{t+10} - m_t$ (4)
Coverage	$-0.021^{\star\star\star}$	$-0.037^{\star\star\star}$	$-0.010^{\star\star}$	$-0.014^{\star\star}$
	(0.005)	(0.010)	(0.005)	(0.006)
Road and elevation controls	Yes	Yes	Yes	Yes
Distance to cutoff polynomials	Yes	Yes	Yes	Yes
N	3083637	1681949	287682	164359
Mean dependant variable	-0.074	-0.123	-0.075	-0.101
R^2	0.007	0.025	0.002	0.017

$^{\star}p < 0.1$, $^{\star\star}p < 0.05$, $^{\star\star\star}p < 0.01$. Standard errors are clustered at the district level. Dependent variables are the change in malaria indicidence rate, m_t, per tile over 5 and 10 years. The independent variable, *Coverage*, is an indicator for whether or not the tile has coverage from any radio station. The RD sample includes tiles directly neighboring a discrete change in coverage in coverage streaks. Coverage streaks are defined as coverage with a coverage-to-land ratio of less than 0.2 and in the upper quintile of distance from the station.

Table 1: Geographic Regression Discontinuity Results for Changes in Malaria Presence

	Full sample $\ell_{t+5} - \ell_t$ (1)	Full sample $\ell_{t+10} - \ell_t$ (2)	RD sample $\ell_{t+5} - \ell_t$ (3)	RD sample $\ell_{t+10} - \ell_t$ (4)
Coverage	$0.14^{\star\star\star}$	$0.15^{\star\star\star}$	$0.02^{\star}$	$0.06^{\star\star\star}$
	(0.03)	(0.04)	(0.01)	(0.02)
Road and elevation controls	Yes	Yes	Yes	Yes
Distance to cutoff polynomials	Yes	Yes	Yes	Yes
N	4768075	3365769	332291	210320
Mean dependant variable	0.13	0.16	0.01	0.03
R^2	0.02	0.03	0.00	0.00

$^{\star}p < 0.1$, $^{\star\star}p < 0.05$, $^{\star\star\star}p < 0.01$. Standard errors are clustered at the district level. Dependent variables are the change in night lights, ℓ_t, per tile over 5 and 10 years. The independent variable, *Coverage*, is an indicator for whether or not the tile has coverage from any radio station. The RD sample includes tiles directly neighboring a discrete change in coverage in coverage streaks. Coverage streaks are defined as coverage with a coverage-to-land ratio of less than 0.2 and in the upper quintile of distance from the station.

Table 2: Geographic Regression Discontinuity Results for Changes in Night Lights

$2,900 over a five-year period. While this number seems low, GDP PPP per capita is currently $4,650 and the population density in coverage streaks tends to be lower than the rest of the country.

4.5 Demographic Health Survey Data

To explore the mechanism behind the effect of radio coverage on malaria incidence I use Demographic Health Survey (DHS) data. I cannot implement the geographic regression discontinuity identification strategy using these data for two reasons. The DHS purposefully introduce error in the geographic coordinates of the survey cluster locations in order to preserve the anonymity of respondents. In rural areas, this error can be as large as 5km. Furthermore, there are too few survey clusters that would be near coverage streaks. Therefore I must employ an alternative identification strategy. One possible strategy would be to use local elevation as an instrument for coverage as elevation is negatively correlated with radio coverage. However, using such an instrument would be problematic if elevation affects outcomes directly. For example, areas that are hilly are more disconnected from society and as result obtain less information from other villages. To side-step this problem I use distant hilliness as an instrument. The motivation is as follows. Local elevation affects the amount of radio coverage a village receives, but the elevation far away from the village also affects the amount of coverage. This is because it does not matter if the obstruction between the radio tower and the village is closer to the village or further away nearer to the radio tower. However, the distant elevation from the village is less likely to affect the village directly compared to local elevation. Therefore I use distant hilliness to instrument for coverage.

With this strategy, I construct the instrument as follows. I draw two circles around each cluster location in the DHS data with radii 10km and 15km respectively. These two circles form a ring. I then take the standard deviation of elevation values within the ring as a measure of distant hilliness. Figure 7 shows an example ring around a survey cluster on top of an elevation heatmap.

Table 3 shows the regression results. Since coverage only varies at the cluster-year level, I aggregate the data to that level and use robust standard errors. The first column shows the results from an ordinary least squares regression of percentage of households where children use a mosquito bed net on radio station coverage. I control for year fixed effects, region fixed effects and a host of demographic controls. I also control for local malaria presence using the average incidence within a 5km radius of the survey cluster. Coverage increases the probability of mosquito bed net usage on average by about 4.2%. The second column shows the

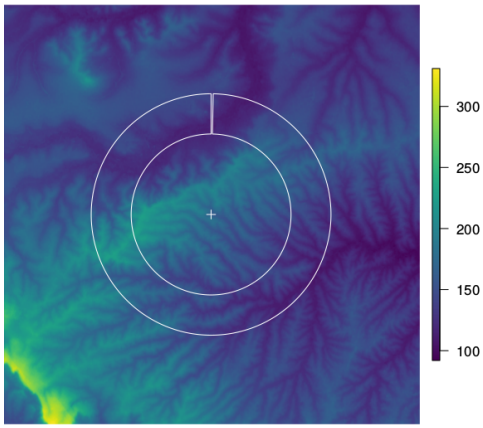


Figure 7: Example ring around a survey cluster overlaid on an elevation heatmap (measured in meters). The instrument for coverage is the standard deviation of elevation within the ring.

	Children sleep under bed net OLS (1)	Coverage from any commercial station OLS (2)	Children sleep under bed net IV (3)
Coverage from commercial station	0.042★★		0.169★★
	(0.020)		(0.072)
SD of elevation in ring around cluster		−0.003★★★	
		(0.000)	
Demographic controls	Yes	Yes	Yes
Region Fixed Effects	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes
N	1142	1142	1142
Adjusted R^2	0.389	0.504	
F-statistic	25.243	39.608	

★★★ $p < 0.01$, ★★ $p < 0.05$, ★ $p < 0.1$.

Robust standard errors in parentheses. Data is collapsed at the survey cluster-year level. Demographic controls include gender, age, education attainment, religion, ethnicity, literacy, newspaper readership, television viewership, urban/rural. Local malaria presence is also controlled for using Malaria Atlas Project data.

Table 3: Instrumental variable regressions using standard deviation of elevation within ring around survey cluster as an instrument for FM coverage.

results from the first stage of the instrumental variables regression. The standard deviation of elevation in the ring around the survey cluster has a strong negative effect on coverage. In the instrumental variables regression, coverage on average increases the probability of mosquito bed net usage by 16.9%. One possible explanation for the higher coefficient in the instrumental variable regression compared to ordinary least squares is measurement error in coverage, resulting from the built-in error in DHS survey cluster coordinates.

This result supports the geographic regression discontinuity results in Table 1 and provides a supporting mechanism. Areas receiving radio coverage are informed of ways to reduce to the risk of malaria, which is partly a result of increased bed net usage among children.

5 A Model of Radio Station Entry

With estimates of the positive effects of radio coverage on health and economic outcomes, we are now interested in how regulation and competition affects the entry decisions of commercial radio stations. I study this using a dynamic structural model of radio station entry. A

dynamic structural model is necessary because the entry decisions of stations are complex, involving many dynamic and strategic interactions. In particular, whether or not a radio station enters today may affect the entry decisions of its rivals in the future. A static model would not be able to capture the preemptive incentives of the radio stations. In this section, I present a model based on previous models in the estimation of dynamic games literature. I adapt the model to include features of this industry.

5.1 Model Setup

Each player $i \in \mathcal{N} = \{1, \ldots, N\}$ is a commercial radio station. Players are endowed with a fixed location denoted by coordinates (x, y) which are distributed across various points in the country. Endowing players with a location rather than allowing them to choose a location is made for computational reasons during estimation. The life cycle of a radio station is illustrated in Figure 8. Players begin as potential entrants with no broadcasting license. In each period t, a potential entrant can choose to obtain a broadcasting license or stay out of the market. Call the set of actions $a_{it} \in \mathcal{A} = \{0, 1\}$, where $a_{it} = 0$ denotes staying out of the market and $a_{it} = 1$ denotes obtaining a broadcasting license. If they choose to obtain a license, stations pay an entry cost and then must wait a setup time before they can begin broadcasting. There is some uncertainty as to how long the setup time is: each period after authorization, there is a probability λ that they are ready to begin broadcasting. This is motivated by the fact that stations do not immediately begin broadcasting in the data. Some stations begin broadcasting a few months after authorization, others can take two years to begin broadcasting. Only actively-broadcasting stations earn profits. Finally, once the radio station is actively broadcasting it may shut down and exit the market. Exit is not a choice for the station, but rather happens exogenously each period at an arrival rate κ. This choice is made because exit is very rare in the data. There are also $\mathcal{P}$ potential public radio stations which can enter at different points in the country in a similar manner.

Let $\boldsymbol{s}_t \in \mathcal{S} \subseteq \mathbb{R}^S$ denote the market state at time t, where S is the number of different state variables. The state variables include which potential entrants have licenses, their coverage maps, the population at each point in the country and the current year.

5.2 Payoffs

Each period, potential entrants receive action-specific private information shocks, ν_{it}^0 and ν_{it}^1, which are unobservable to rival stations, where $\boldsymbol{\nu}_{it} = \left(\nu_{it}^0, \nu_{it}^1\right) \in \mathcal{V} \subseteq \mathbb{R}^2$. For potential entrants choosing to stay out of the market, this can be interpreted as the entrant's outside

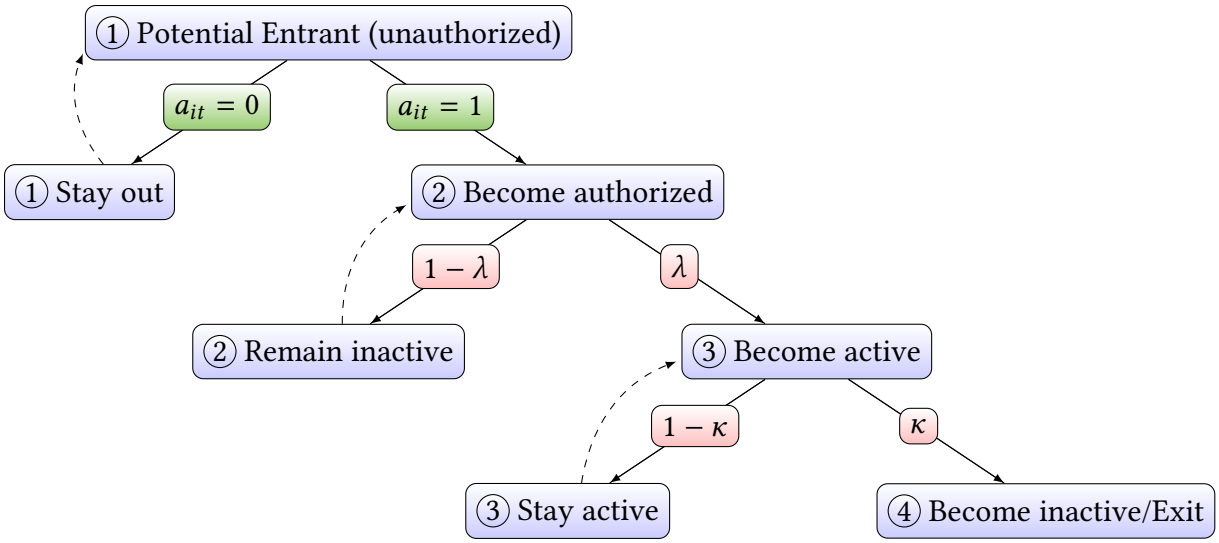


Figure 8: Life cycle of a radio station in the model. Potential entrants can choose to become authorized, $a_{it} = 1$, or stay out, $a_{it} = 0$. After authorization, stations pay an entry cost θ_{EC} and wait a setup time. The probability the station completes setup each period is λ. Actively-broadcasting stations earn profits $\pi_i(\boldsymbol{s}_t, \boldsymbol{\theta})$, which depend on the market state, $\boldsymbol{s}_t$, and the structural parameters, $\boldsymbol{\theta}$. When the station becomes active there is an exogenous probability κ each period that it becomes inactive. If the station exits it earns a payoff of zero and cannot reenter.

option. For potential entrants choosing to enter, this can be interpreted as a shock to entry costs. These private information shocks are assumed to follow a Type I extreme value distribution. Actively-broadcasting stations' profits will depend on the market state and a vector of structural parameters, $\pi_i(\boldsymbol{s}_t, \boldsymbol{\theta})$. The profit function is parameterized as:

$$\pi(\boldsymbol{s}_t, \boldsymbol{\theta}) = \theta_M M_{it} + \theta_C C_{it} + \theta_P P_{it} + \theta_T t$$

M_{it} is a measure of the population within the station's coverage area. C_{it} and P_{it} are measures of the competition facing the station from rival commercial stations and public stations respectively. Stations who exit earn a payoff of zero.

5.2.1 Coverage Areas

To measure the payoffs for each station, we need to define their coverage areas. Let $f_{it}^{dB\mu V/m}(x, y)$ be the field strength in decibel microvolts per meter of station i's coverage at coordinates (x, y). Higher values of $f_{it}^{dB\mu V/m}(x, y)$ indicate that that the listening quality of the station is higher at that point. $f_{it}^{dB\mu V/m}(x, y) = 0$ indicates either that station i is either off air at time t or that its signal does not reach that point. For simplicity, instead of using this continuous

measure of field strength, I use a cutoff field strength of 60 dBμ V/m where for all x, y such that $f_{it}^{dB\mu V/m}(x,y) \geq 60$ there is coverage from station i and no coverage otherwise. The FCC uses the 60 dBμV/m cutoff for frequency planning purposes, as well as other regulatory agencies. Therefore I define:

$$f_{it}(x,y) = \begin{cases} 1 & \text{if } f_{it}^{dB\mu/m}(x,y) \geq 60 \\ 0 & \text{otherwise} \end{cases}$$

Using a cutoff rather than a continuous measure is natural to some degree. People will only listen to a station if its quality is above some acceptable level that makes it understandable.

5.2.2 Market Size

Let $p_t(x,y)$ be the population density at (x,y) at time t. I measure market size for firm i at time t as:

$$M_{it} = \log\left(\int_{-180}^{+180}\int_{-90}^{+90} f_{it}(x,y)\, p_t(x,y)\, dydx\right)$$

This measure gives the log of total population within firm i's coverage area. This is the total potential listenership of the station. An example of this calculation is shown in Figure 9. The first panel shows a station's coverage area where each pixel equals 1 if there is coverage and 0 otherwise. The second panel shows the population density of each pixel in the same area. The third panel then multiplies the first two figures together. The market size variable is then found by taking the sum of all the pixel values in the third panel and taking the log.

5.2.3 Competition

Station i competes with other stations only if their coverage areas overlap. Two stations compete more intensely with one another the more their coverage areas overlap. To measure competition for a station, I sum the share of overlap with every other radio station. This is calculated according to:

$$C_{it} = \sum_{j \in \mathcal{N} \setminus \{i\}} \frac{\int_{-180}^{+180}\int_{-90}^{+90} f_{it}(x,y)\, f_{jt}(x,y)\, dydx}{\int_{-180}^{+180}\int_{-90}^{+90} f_{it}(x,y)\, dydx}$$

If there are only two stations and they overlap one-for-one, the competition measure is 1. If there are only two stations and each overlap by 50%, the competition measure is 0.5. If there are three stations and one station overlaps another one-for-one and another 50%, the

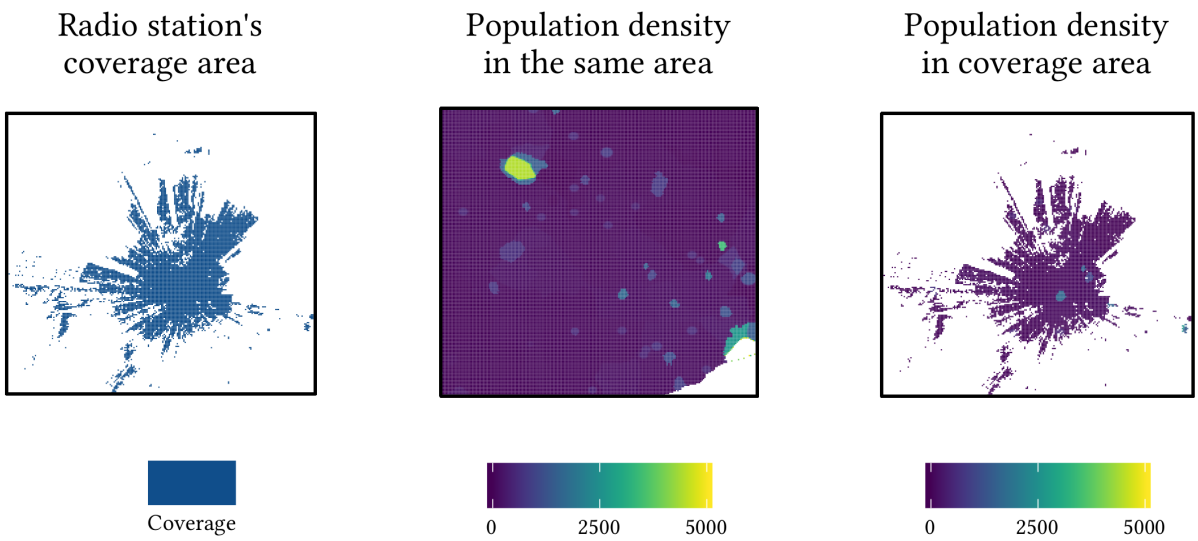


Figure 9: Example calculation of market size within a firm's coverage area. The first panel shows a radio station's coverage area. In the second panel, the population density of the same area is shown. The third panel multiplies the two figures together. The market size measure is then found by summing all the pixels in the third panel.

competition measure is 1.5[6]. An example of this calculation for the simple case of two firms is shown in Figure 10. The left figure shows two stations which are approximately 42km away from each other. The red area is where there is only coverage from station A and the blue area is where there is only coverage from station B. Due to a stretch of hills between the two stations, their coverage areas hardly overlap and their overlap shares are close to zero. In the right figure, the two stations are approximately 7km apart. As a result, their coverage areas partially overlap, indicated by the green area in the figure. While these examples only contain two stations, the competition measure sums the overlap shares with all other radio stations. Competition with public stations is defined in an analogous way. I ignore competition from campus and community stations because those stations have very small coverage areas due to their limitation on transmitter strength.

[6]In practice C_{it} is calculated as follows. Let $\boldsymbol{M}$ be the overlap matrix where $\boldsymbol{M}_{ij}$ is what proportion of i's coverage area is covered by j's coverage area. Let $\boldsymbol{a}$ be a vector which indicates which stations are actively broadcasting. Then the vector of competition measures for each firm is $\{C_{it}\}_{i \in N} = \boldsymbol{M}\boldsymbol{a} - \boldsymbol{a}$.

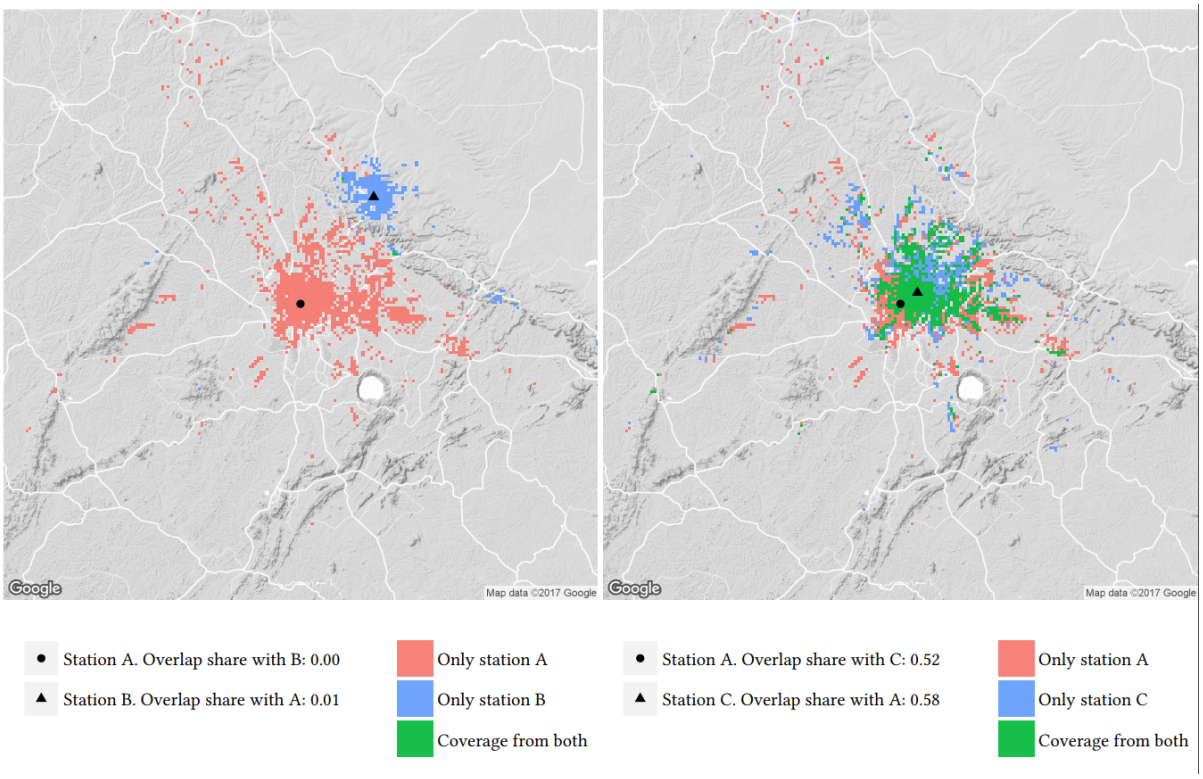


Figure 10: Examples of calculating the competition variable. In the left panel, the two stations have an overlap of close to zero. In right panel, the two stations' coverage areas partially overlap, resulting in overlap measures of 0.52 and 0.58. Competition is measured by the sum of the overlap shares with all other stations.

5.3 Value Function

Station i's ex-ante expected present discounted value from entering is:

$$V_i^1(\boldsymbol{s}_t, \boldsymbol{\theta}) = -\theta_{EC} + \sum_{\tau=1}^{\infty} (1-\lambda)^{\tau-1} \lambda \beta^{\tau} \sum_{s=0}^{\infty} \beta^s (1-\kappa)^s \, \mathbb{E}\left[\pi_i(\boldsymbol{s}_{t+\tau+s}, \boldsymbol{\theta}) \,|\, \boldsymbol{s}_t\right]$$

Entering requires paying the sunk cost of entry, θ_{EC}, plus receiving the expected discounted value of profits into the future. Recall λ is the probability the station finishes its setup time each period. The first sum over τ is the weighted sum over each period the station could begin earning profits the future, weighted by the probability that the station starts earning profits in that period. $\beta \in [0, 1)$ is the discount factor. When the station begins earning profits, the discount factor is scaled by the exogenous probability of exit, κ.

If the station does not enter, the station will have the choice to enter or not in the following period. Therefore the ex-ante value of not entering today is the expected value of the

maximum of the values of entering or not entering in the following period:

$$\begin{aligned} V_i^0(\boldsymbol{s}_t, \boldsymbol{\theta}) &= \beta \mathbb{E}\left[\max\left\{\mathbb{E}\left[V_i^0(s_{t+1}, \boldsymbol{\theta})\middle| \boldsymbol{s}_t\right], \mathbb{E}\left[V_i^1(s_{t+1}, \boldsymbol{\theta})\middle| \boldsymbol{s}_t\right]\right\}\middle| \boldsymbol{s}_t\right] \\ &= \beta \log\left(\exp\left(\mathbb{E}\left[V_i^0(s_{t+1}, \boldsymbol{\theta})\middle| \boldsymbol{s}_t\right]\right) + \exp\left(\mathbb{E}\left[V_i^1(s_{t+1}, \boldsymbol{\theta})\middle| \boldsymbol{s}_t\right]\right)\right) \end{aligned}$$

Here I use the assumption that the private information shocks are distributed with a Type I extreme value distribution. It is optimal for a station to enter today if

$$V_i^1(\boldsymbol{s}_t, \boldsymbol{\theta}) + v_{it}^1 \geq V_i^0(\boldsymbol{s}_t, \boldsymbol{\theta}) + v_{it}^0$$

The ex-ante probability of entry is:

$$\Pr(a_{it} = 1|\boldsymbol{s}_{it}) = \frac{\exp\left(V_i^1(\boldsymbol{s}_t, \boldsymbol{\theta})\right)}{\exp\left(V_i^0(\boldsymbol{s}_t, \boldsymbol{\theta})\right) + \exp\left(V_i^1(\boldsymbol{s}_t, \boldsymbol{\theta})\right)}$$

5.4 Strategies and Equilibrium

Following the literature on the estimation of dynamic games, the equilibrium notion used in this game is Markov Perfection. Call $\sigma_i : \mathcal{S} \times \mathcal{V} \to \mathcal{A}$ firm i's Markov strategy. This strategy is a function which maps the current market state and the firm's private information shocks into an action. Let $\boldsymbol{\sigma} = \{\sigma_i\}_{i \in \mathcal{N}}$ be a profile of Markov strategies. We say that the strategy profile $\boldsymbol{\sigma}$ is part of a Markov Perfect Equilibrium if for all players i such that $\sigma_i(\boldsymbol{s}_t, v_{it}) = 0$ we have that:

$$V_i^0(\boldsymbol{\sigma}, \boldsymbol{s}_t, \boldsymbol{\theta}) + v_{it}^0 \geq V_i^1(\boldsymbol{\sigma}_{-i}, \boldsymbol{s}_t, \boldsymbol{\theta}) + v_{it}^1$$

and for all players i such that $\sigma_i(\boldsymbol{s}_t, v_{it}) = 1$ we have that:

$$V_i^1(\boldsymbol{\sigma}, \boldsymbol{s}_t, \boldsymbol{\theta}) + v_{it}^1 \geq V_i^0(\boldsymbol{\sigma}_{-i}, \boldsymbol{s}_t, \boldsymbol{\theta}) + v_{it}^0$$

where $\boldsymbol{\sigma}_{-i}$ is the Markov strategy profile for all players other than i. That is, no firm has an incentive to unilaterally deviate from their current strategy given the other players play according to $\boldsymbol{\sigma}$.

6 Estimation

6.1 Potential Entrant Locations

The game is played by N players which consist of the stations observed in the data, as well as the hypothetical potential entrants who never chose enter. Ideally there would be a potential entrant at every location where a station could conceivably enter, such as every settled town in the country. I take the locations of every station observed in the data, as well as an extra potential entrant in every settlement in the country. To locate these settled areas, I first find clusters of night lights using the latest period of night lights data. There are 256 of these clusters. I add one potential entrant to the centroid of these clusters. These clusters and their centroids are shown in Figure A.6a. In Figure A.6b shows all the potential entrants in the model, which are the radio stations in the data and the centroids of the night lights clusters combined. Many of the new potential entrants are very close to existing radio stations. However, a number are quite distant to other radio stations. These are towns and villages that never received a radio station. In total there are 608 players throughout the country.

6.2 Two-Step Estimation

Estimation of the structural parameters relies on the assumption that players are behaving optimally on average. With this assumption, the Markov strategy profile $\boldsymbol{\sigma}$ is the profile of strategies that we observe in the data. Given structural parameters $\boldsymbol{\theta}$, for each observation we need to simulate the value function for the choice that the firm made in the data, $V_i^a(\boldsymbol{\sigma}, \boldsymbol{s}_t, \boldsymbol{\theta})$, and the value function for the choice they did not make, while all other firms play according to the strategy, $V_i^{1-a}(\boldsymbol{\sigma}_{-i}, \boldsymbol{s}_t, \boldsymbol{\theta})$.

Simulating the value function is computationally costly. Therefore I follow Bajari et al. (2007) and exploit that fact that using a payoff function that is linear in the structural parameters implies that the value function is linear in the parameters. To see this, first define ς_{it} to indicate which stage in the lifecycle the firm is in:

$$\varsigma_{it} = \begin{cases} 1 & \text{if station is unauthorized} \\ 2 & \text{if station is authorized but not yet active} \\ 3 & \text{if station is active} \\ 4 & \text{if station exited} \end{cases}$$

With this, we can write the payoff of a firm at any point in the lifecycle as a linear function

of the parameters:

$$\begin{aligned}\tilde{\pi}_i(\boldsymbol{s}_t, \boldsymbol{\nu}_{it}, \boldsymbol{\theta}) &= \nu_{it}^0 \mathbb{1}\{\varsigma_{it} = 1\} + \left[\nu_{it}^1 - \theta_{EC}\right] \mathbb{1}\{\varsigma_{it} = 2, \varsigma_{it-1} = 1\} + [\theta_M M_{it} + \theta_C C_{it} + \theta_P P_{it} + \theta_T t] \mathbb{1}\{\varsigma_{it} = 3\} \\ &= \boldsymbol{\Psi}_i(\boldsymbol{s}_t, \boldsymbol{\nu}_{it}) \boldsymbol{\theta}\end{aligned}$$

where $\boldsymbol{\theta} = (\theta_{EC}, \theta_M, \theta_C, \theta_P, \theta_T, 1)$ and

$$\begin{aligned}\boldsymbol{\Psi}_i(\boldsymbol{s}_t, \boldsymbol{\nu}_{it}) = (&-\mathbb{1}\{\varsigma_{it} = 2, \varsigma_{it-1} = 1\}, \mathbb{1}\{\varsigma_{it-1} = 3\} M_{it}, \mathbb{1}\{\varsigma_{it-1} = 3\} C_{it}, \mathbb{1}\{\varsigma_{it-1} = 3\} P_{it}, \\ &\mathbb{1}\{\varsigma_{it-1} = 3\} t, \nu_{it}^0 \mathbb{1}\{\varsigma_{it} = 1\} + \nu_{it}^1 \mathbb{1}\{\varsigma_{it} = 2, \varsigma_{it-1} = 1\})\end{aligned}$$

$\boldsymbol{\Psi}_i(\boldsymbol{s}_t, \boldsymbol{\nu}_{it})$ does not depend on the structural parameters $\boldsymbol{\theta}$. Therefore the value function from pursuing the action chosen in the data becomes:

$$\begin{aligned}V_i^a(\boldsymbol{\sigma}, \boldsymbol{s}_t, \boldsymbol{\theta}) &= \mathbb{E}\left[\sum_{\tau=t}^{\infty} \beta^{\tau-t} \tilde{\pi}_i(\boldsymbol{s}_\tau, \boldsymbol{\nu}_{i\tau}, \boldsymbol{\theta}) \middle| \boldsymbol{\sigma}, \boldsymbol{s}_t\right] \\ &= \mathbb{E}\left[\sum_{\tau=t}^{\infty} \beta^{\tau-t} \boldsymbol{\Psi}_i(\boldsymbol{s}_\tau, \boldsymbol{\nu}_{i\tau}) \boldsymbol{\theta} \middle| \boldsymbol{\sigma}, \boldsymbol{s}_t\right] \\ &= \underbrace{\mathbb{E}\left[\sum_{\tau=t}^{\infty} \beta^{\tau-t} \boldsymbol{\Psi}_i(\boldsymbol{s}_\tau, \boldsymbol{\nu}_{i\tau}) \middle| \boldsymbol{\sigma}, \boldsymbol{s}_t\right]}_{\equiv \boldsymbol{W}_i^a(\boldsymbol{\sigma}, \boldsymbol{s}_t)} \boldsymbol{\theta}\end{aligned}$$

Similarly, the value function for the firm when it deviates while all other firms continue according to $\boldsymbol{\sigma}$ is

$$V_{it}^{1-a}(\boldsymbol{\sigma}_{-i}, \boldsymbol{s}_t, \boldsymbol{\theta}) = \boldsymbol{W}_i^{1-a}(\boldsymbol{\sigma}_{-i}, \boldsymbol{s}_t) \boldsymbol{\theta}$$

The equilibrium definition can then be rewritten as:

$$\left[\boldsymbol{W}_i^a(\boldsymbol{\sigma}, \boldsymbol{s}_t) - \boldsymbol{W}_i^{1-a}(\boldsymbol{\sigma}_{-i}, \boldsymbol{s}_t)\right] \boldsymbol{\theta} \geq 0 \qquad \forall i, \forall t$$

By linearizing the value function this way we now only need to estimate $\boldsymbol{W}_{it}^a(\boldsymbol{\sigma}, \boldsymbol{s}_t)$ and $\boldsymbol{W}_{it}^{1-a}(\boldsymbol{\sigma}_{-i}, \boldsymbol{s}_t)$ once, rather than for each trial value of the structural parameters $\boldsymbol{\theta}$.

6.3 Simulating $\boldsymbol{W}_i^a(\boldsymbol{\sigma}, \boldsymbol{s}_t)$ and $\boldsymbol{W}_i^{1-a}(\boldsymbol{\sigma}_{-i}, \boldsymbol{s}_t)$

To estimate $\boldsymbol{W}_i(\boldsymbol{\sigma}, \boldsymbol{s}_t)$, we first need to choose a number of periods to simulate forward, $\mathcal{T}$, high enough such that it approximates infinity well, given the chosen discount rate. I use $\beta = 0.9$ and $\mathcal{T} = 50$. With $\beta = 0.9$, the first 50 periods makes up 99.54% of the present value

of an infinite stream of constant values. In order to form the expectation in the value function, I simulate forward many times with many different random draws and take the average. With P simulations, the estimator of $\boldsymbol{W}_{it}^{a}(\boldsymbol{\sigma}, \boldsymbol{s}_t)$ is then:

$$\widehat{\boldsymbol{W}}_{it}^{a}(\boldsymbol{\sigma}, \boldsymbol{s}_t) = \frac{1}{P}\sum_{p=1}^{P}\sum_{\tau=t}^{t+\mathcal{T}} \beta^{\tau-t}\boldsymbol{\Psi}_i^a\left(\boldsymbol{s}_{\tau p}, \boldsymbol{\nu}_{i\tau p}\right)$$

I use $P = 200$ as forward simulation is computationally intensive and also since estimation needs to be run multiple times to obtain standard errors. At $\tau = 0$, the components of $\boldsymbol{\Psi}_i^a\left(\boldsymbol{s}_{\tau p}, \boldsymbol{\nu}_{i\tau p}\right)$ are computed directly from the data. Future values of $\boldsymbol{\Psi}_i^a\left(\boldsymbol{s}_{\tau p}, \boldsymbol{\nu}_{i\tau p}\right)$ come from simulation. The estimator of $\boldsymbol{W}_i^{1-a}(\boldsymbol{\sigma}_{-i}, \boldsymbol{s}_t)$ is analogously defined as:

$$\widehat{\boldsymbol{W}}_{i}^{1-a}(\boldsymbol{\sigma}_{-i}, \boldsymbol{s}_t) = \frac{1}{P}\sum_{p=1}^{P}\sum_{\tau=t}^{t+\mathcal{T}} \beta^{\tau-t}\boldsymbol{\Psi}_i^{1-a}\left(\boldsymbol{s}_{\tau p}, \boldsymbol{\nu}_{i\tau p}\right)$$

At $\tau = 0$, $\boldsymbol{\Psi}_i^{1-a}\left(\boldsymbol{s}_{\tau p}, \boldsymbol{\nu}_{i\tau p}\right)$ differs from $\boldsymbol{\Psi}_i^{a}\left(\boldsymbol{s}_{\tau p}, \boldsymbol{\nu}_{i\tau p}\right)$ in that we deviate firm i's action at time t. Future values of $\boldsymbol{\Psi}_i^{1-a}\left(\boldsymbol{s}_{\tau p}, \boldsymbol{\nu}_{i\tau p}\right)$ will depend on firm i's deviation and on other firms' reactions to this deviation.

To simulate the components of $\boldsymbol{\Psi}_i^{a}\left(\boldsymbol{s}_{\tau p}, \boldsymbol{\nu}_{i\tau p}\right)$ and $\boldsymbol{\Psi}_i^{1-a}\left(\boldsymbol{s}_{\tau p}, \boldsymbol{\nu}_{i\tau p}\right)$ forward I use number of first-stage reduced-form estimates. Population at each 30-arc second grid is assumed to continue to grow exogenously at the rate observed in the data, with normally distributed shocks. To obtain the probability of a station entering given the current market state, I use a logit model from the observed entry decisions. To estimate the exogenous probability of becoming active each period after becoming authorized, I fit the observed transitions to a Poisson distribution. To estimate the exogenous probability of exit, I take the average exit rate observed in the data. Finally, the entry decisions of public radio stations are assumed to be known in advance. This final assumption is made because plans for the entry of regional public stations are made public in advance (Heath, 2001). Furthermore, there is very little entry of public stations during this time period.

For one simulated path, p, a sequence $\left\{\boldsymbol{\Psi}_i^{a}\left(\boldsymbol{s}_{\tau p}, \boldsymbol{\nu}_{i\tau p}\right)\right\}_{\tau=t}^{t+\mathcal{T}}$ for each observation starting from time period t in the data can be obtained as follows:

Step 1: Calculate the probability of each station moving forward in their life cycle and take random draws using those probabilities.

Step 2: Simulate population and public station entry forward.

Step 3: Recalculate the market size and competition variables for each station.

Step 4: Compute the elements of $\Psi_i^a\left(s_{\tau p}, \nu_{i\tau p}\right)$ for each player $i \in \mathcal{N}$.

Step 5: Repeat steps 1-4 for $\mathcal{T}$ periods incrementing τ.

The steps for each sequence of $\left\{\Psi_i^{1-a}\left(s_{\tau p}, \nu_{i\tau p}\right)\right\}_{\tau=t}^{t+\mathcal{T}}$ are similar except at period t we deviate firm i's action from what we observe in the data. Therefore calculating $\widehat{W}_i^{1-a}\left(\sigma_{-i}, s_t\right)$ is more computationally intensive as this needs to be done separately for every observation.

If station A only overlaps with station B, but station B overlaps with both station A and C, then station A indirectly competes with station C. In the model, many of the radio stations indirectly compete with one another. Figure A.7 shows networks of the radio stations for various cutoffs of overlaps. If I define a connection as having at least 10% or 25% overlap, the majority of stations are indirectly connected with each other. To ease computation when calculating $\widehat{W}_i^{1-a}\left(\sigma_{-i}, s_t\right)$, I only track reactions of stations near the deviating firm. Specifically, I track the reactions up to and including two nodes away from the station. I do this because it is unlikely a deviation is unlikely to spill all the way through the network. I have also estimated the model cutting off at different numbers of nodes and the parameter estimates do not change substantially when using a higher number of nodes.

6.4 Second Stage

Once we have obtained the estimates $\widehat{W}_i^a\left(\sigma, s_t\right)$ and $\widehat{W}_i^{1-a}\left(\sigma_{-i}, s_t\right)$ from the first stage for every observation, we know the value functions for any trial parameter vector θ. Since the private information shocks follow a Type I extreme value distribution, the probability that observation (i, t) chooses the action observed in the data given the parameter vector θ is:

$$\Pr\left(a_{it} \mid \theta\right) = \frac{\exp\left(\widehat{W}_i^a\left(\sigma, s_t\right)\theta\right)}{\exp\left(\widehat{W}_i^a\left(\sigma, s_t\right)\theta\right) + \exp\left(\widehat{W}_i^{1-a}\left(\sigma_{-i}, s_t\right)\theta\right)}$$

I use maximize likelihood to estimate θ:

$$\widehat{\theta} = \arg\max_{\theta} \frac{1}{NT} \sum_{i=1}^{N} \sum_{t=1}^{T} \log\left(\Pr\left(a_{it} \mid \theta\right)\right)$$

Standard errors using the Hessian of the likelihood do not take into account simulation error in $\widehat{W}_i^a\left(\sigma, s_t\right)$ and $\widehat{W}_i^{1-a}\left(\sigma_{-i}, s_t\right)$. Therefore I obtain confidence intervals by drawing subsamples of complete histories of clusters of nearby stations and reestimating the model. I partition the network of radio stations using the community walktrap algorithm developed by Pons and

Latapy (2005). This algorithm finds clusters of stations by simulating many random walks between stations in the network, using the share of overlap between stations to calculate the probabilities. This algorithm results in 25 separate clusters shown in Figure A.8. I take many draws of 12 of these 25 clusters, weighted by the number of observations in each cluster, and reestimate the model to obtain standard errors.

6.5 Identification

There are five parameters to be identified: the entry cost parameter, and the effects of market size, competition (commercial and public) and the time trend. I cannot identify a fixed cost parameter as there is very little exit in the data. Without exit, the entry cost and the fixed cost are not separately identified as the entry cost without exit can be interpreted as an annuity of the fixed cost. Since population facing one station in a location does not vary substantially over time, the population parameter is identified through cross-sectional variation in population. The competition parameters are identified through the timing of stations' entry decisions. Two nearby stations at a particular location have similar expectations about the evolution of the state variables. If one station enters in one period, and they other chooses not to enter in the following years, this captures the deterrent effects of competition. The time trend parameter is identified through greater overall entry in later time periods in the data.

7 Structural Model Results

7.1 First Stage Results

Table 4 shows the results from a reduced-form logit regression of the entry decision on lagged values of the state variables. I show multiple specifications with and without region fixed effects, year fixed effects and a time trend. The coefficient estimates correspond with prior expectations and are mostly robust across specifications. Stations are more likely to enter in more populated locations and less likely to enter in locations with more competition from rival commercial stations. The time trend is positive, corresponding to larger amounts of entry in the later years of the sample. This regression is used in the forward simulation algorithm to calculate firms' reactions to the actions of their rivals. In the forward simulation, I use specification (2) which includes region fixed effects but uses the time trend instead of the year fixed effects. This is because using year fixed effects would involve simulating the year

Dependent variable: Entered this period	(1)	(2)	(3)	(4)
Log Population	0.162**	0.140*	0.164**	0.131
	(0.080)	(0.083)	(0.082)	(0.086)
Commercial Competition	−0.025	−0.056***	−0.033*	−0.064***
	(0.017)	(0.020)	(0.018)	(0.021)
Public Competition	0.126*	0.213**	0.174**	0.276**
	(0.074)	(0.097)	(0.082)	(0.107)
Time Trend	0.194***	0.212***		
	(0.014)	(0.016)		
Region Fixed Effects	No	Yes	No	Yes
Year Fixed Effects	No	No	Yes	Yes
N	5928	5928	5928	5928

Table 4: Reduced-form estimates of radio stations' entry decisions. Robust standard errors in parentheses, clustered at the district level (137 clusters). Specification (2) is used to predict radio stations' reactions in the forward simulation.

coefficients forward. Since I only use 21 years of data, such a function would be estimated imprecisely.

After a station becomes authorized, it must wait some time before it can begin actively broadcasting. The amount of time this takes for each firm is not correlated with observable variables so I assume it to be random. Therefore I model the transition from being authorized to actively broadcasting as a Poisson process with arrival rate λ. To estimate λ, I find the number of quarters between the date the station first became authorized and when it started actively broadcasting and fit a Poisson distribution to it. The resulting estimate is 5.16 quarters which results in a probability of 0.194 of becoming active each quarter after authorization. This corresponds to an annualized rate of 0.578. The fit is illustrated in Figure A.9 which captures the transitions well.

Once a station is actively broadcasting, there is an exogenous probability that it exits. I take the average exit rate in the data which is 0.0055 per year. There are too few exits to obtain a precise function predicting exit.

7.2 Structural Parameters

Table 5 shows the profit function parameter estimates. The entry cost is positive and is a large multiple of variable profits for all stations (between 7 and 14 times annual profits). More populated areas have higher profits and higher competition erodes profits. The positive time trend indicates that profits are increasing over time, explaining the larger observed entry in the

	Estimate	Standard Error
Entry Cost	83.919	(5.083)
Log population	0.742	(0.051)
Commercial Competition	−0.057	(0.006)
Public Competition	−0.079	(0.025)
Time Trend	0.030	(0.003)

Standard errors were obtained by drawing 200 subsamples of clusters of station locations and reestimating the model.

Table 5: Entry cost and profit function parameter estimates.

later time periods. The subsampled standard errors are slightly larger than what would have been obtained using the Hessian of the likelihood, although each parameter is statistically different from zero in either case.

Without detailed data on profits or costs on the stations, interpreting these coefficients in dollar terms is difficult, as they are scaled relative to the variance of the error terms. However, Yordy (2008) collected data on the startup costs and annual costs of many radio stations in Africa, including a commercial station in Ghana. Classic FM in Techiman which entered in 1999 had a startup cost of 52,041.60 USD and has annual costs of 122,235.36 USD. If we take Classic FM to be representative, then one unit in the estimates can be interpreted as 2,240.79 USD. The model then implies that the profit per person in Classic FM's coverage area is about 19 cents. While this number may seem small, Pandora earns only $12.44 in advertising revenue annually per active monthly user. Given the 13-fold difference in per capita GDP PPP between Ghana and USA, and that not everyone in Classic FM's coverage area will actively listen to the station, these numbers are comparable.

8 Counterfactual Simulations

There is a large literature documenting various effects of radio and other media through the information transmission channel, as discussed in the literature review. For the most part, these effects for radio are positive. These positive effects continue in the current setting, as radio coverage is found to decrease malaria incidence among children and increase night lights growth. However, regulations facing the radio stations may lead radio coverage to be underprovided in certain less-profitable, rural areas. Alternative regulation schemes could expand coverage to rural areas, allowing more communities to experience the benefits of radio. In this section I simulate the effects of counterfactual regulation schemes that aim to

increase radio coverage.

For the purpose of the counterfactual simulations, it is necessary to discretize the state space. I divide each of the continuous state variables (population, commercial station competition and public station competition) into five bins and leave time as a discrete variable. I use the Pakes and McGuire (1994) algorithm to solve for the new equilibrium value functions and strategies.

8.1 Larger Broadcasting Radius

Commercial radio stations in Ghana are restricted to a 45km broadcasting radius. In rural areas, a small broadcasting radius may not make it worthwhile to enter. The coverage from stations operating in larger towns will also not spill further into rural areas. An alternative policy would have been to allow stations to have a larger broadcasting radius. The outcome of such a policy is not obvious ex ante. On one hand, a larger radius increases the potential listenership of a station which increases profits. However, this could also increase the amount of competition a station faces, which would decrease profits. Figure 11 shows an example of a station's coverage area if the transmitter power doubled. Doubling the transmitter power does not double the broadcasting radius, but rather depends on the surrounding terrain. There is some concern that allowing stronger transmitters will cause interference among stations' frequencies. However, the radio market in Ghana is young and, outside of the capital city, the frequency spectrum is not constrained.

For each location in the model for commercial stations, I recalculate what the coverage would have been if stations were allowed to double their signal strength. This results in a new overlap matrix of how much the coverage from each location in the model overlaps with every other location. I use this new overlap matrix to solve for the new equilibrium strategies for the firms.

The results from this counterfactual are shown in Figure 12. For each of the statistics shown, I draw actions for each player from the new policy functions and take the average of many draws. In the first figure we see that relative to the baseline, more stations enter under this policy overall. However, when analyzing the effects of radio coverage, it is the extensive margin which matters for the positive outcomes of radio coverage. In the second figure, I calculate the proportion of the country which has access to radio coverage. Over time, coverage is spreading throughout the country. With stronger transmitter strengths, between 8.6% and 13.9% more of the country has radio coverage. While a lot more of the country is receiving coverage, it may be in areas with very low population. In the third figure I use the

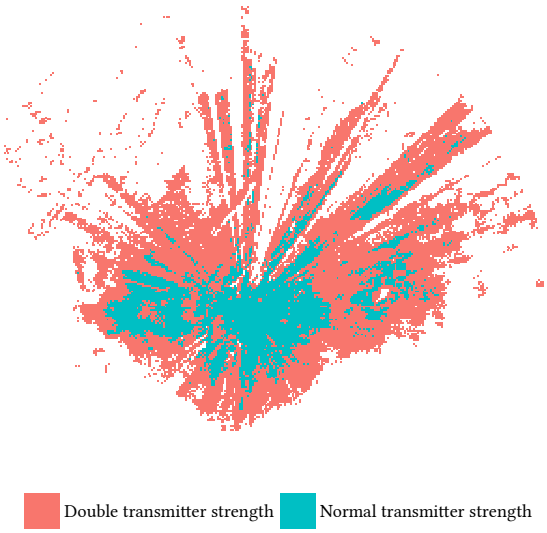


Figure 11: Example change in coverage area by doubling transmitter strength.

population maps shown in Figure A.4 to calculate the population receiving coverage. Using this, between 1.2 and 1.8 million additional individuals are covered over time.

According to the 2010 census in Ghana (Ghana Statistical Service, 2012), approximately 20% of the population are in the 2-10 age range. This is the age range at which the malaria incidence estimates are based on. Using the estimated 1% reduction in malaria incidence rate from coverage, there are a predicted 2,400-3,600 fewer incidences for children aged 2-10 under this policy. While this number is small for a country with over 5 million children, this policy does not involve the policymaker using funds to subsidize the stations. Rather the stations provide the additional coverage voluntarily. Furthermore, radio coverage will bring other benefits to these communities.

8.2 Entry Subsidy

An alternative way to increase entry in rural areas would be to provide a subsidy to the stations. In this counterfactual I alter the entry cost parameter faced by the stations. Recall that since there is very little exit in the data, the entry cost and fixed cost are not separately identified and as such the entry cost can be interpreted as the entry cost plus an annuity of the fixed costs. Therefore a small change in this parameter results in a large change in sum of discounted profits for the stations. I present the change in entry patterns for a 5% and a 10% reduction in the entry cost. Figure 13 presents the results. A change in the entry cost

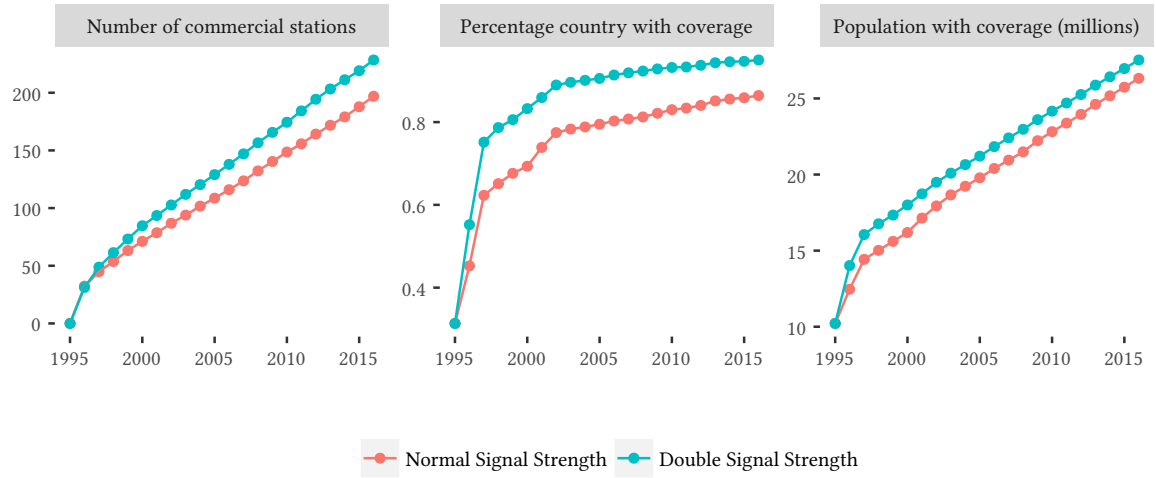


Figure 12: Results from counterfactual simulations where stations in the model have stronger transmitter strengths.

results in a large increase in the overall number of station. However, while the change in the total number of stations is much larger than under the policy with stronger transmitter strengths, it does not have as profound an impact on the percentage of the country receiving coverage or the population receiving coverage. Even with the 10% reduction in the entry cost parameter, the counterfactual with stronger transmitter strengths reaches more people on average. Therefore the preferred policy would be to allow stronger transmitter strength, as this does not result in lost revenue to the regulator.

9 Conclusion

Radio has been found to have effects in many facets of life, including political participation, education and health. This is especially important in developing economies where radio is more common than other forms of mass media. Complementing the previous research of the effects of media, I find that radio coverage reduces malaria incidence and increases night lights growth using a novel identification strategy. This identification strategy exploits using streaks of coverage spilling through gaps in mountainous areas. The result concerning malaria incidence is also supported using Demographic Health Survey data, where individuals with coverage are found to be more likely to have their children use mosquito bed nets. These positive effects of radio make it important for broadcasting regulators to understand commercial radio stations' entry and exit motives. Regulations on transmitter strengths and entry costs could deter entry in rural areas, resulting in less information provision. A struc-

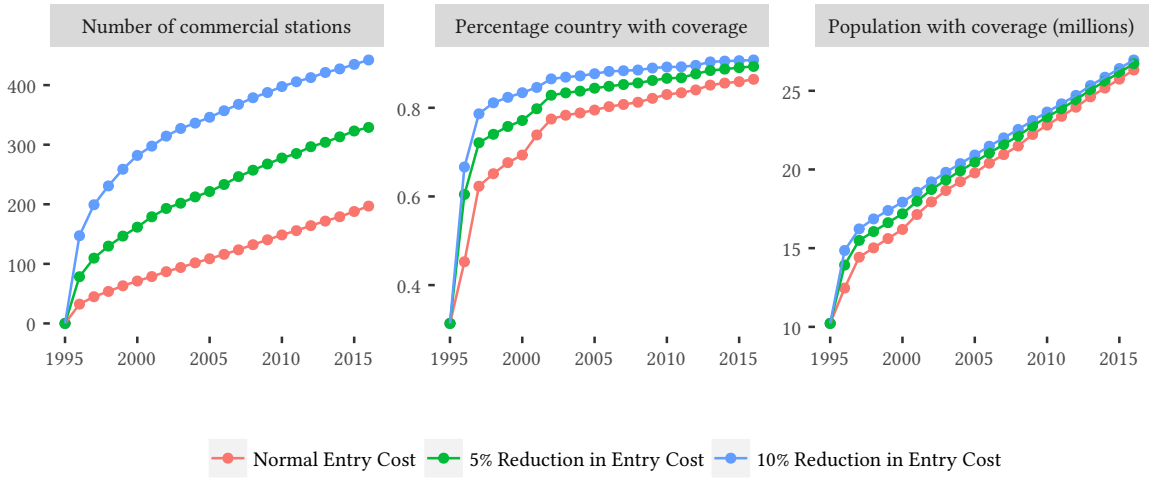


Figure 13: Results from counterfactual simulations where all stations in the model are subsidized.

tural model is necessary to find such effects as the decision to enter is inherently dynamic by nature and the reactions of rival stations need to be considered. I develop a dynamic structural model of entry which takes into account the overlap of stations' coverage areas and uses those to measure market size and competition. The model allows stations to react to other stations' actions through the network of overlapping coverage areas. Using this model, I simulate counterfactual policies with different regulation schemes. In one such policy, the stations are allowed to have stronger transmitter strengths which would expand each station's coverage area. More stations enter under this policy, and their radio coverage expands to more rural areas. More individuals receive radio coverage and receive the benefits that come with radio coverage, such as lower malaria incidence and increased growth. In an alternative counterfactual, I simulate entry where stations receive an entry subsidy. This policy increases the overall number of stations, but mostly in urban areas which already have radio coverage. A more effective policy to expand coverage to rural areas is therefore to allow stronger transmitter strengths.

A Appendix

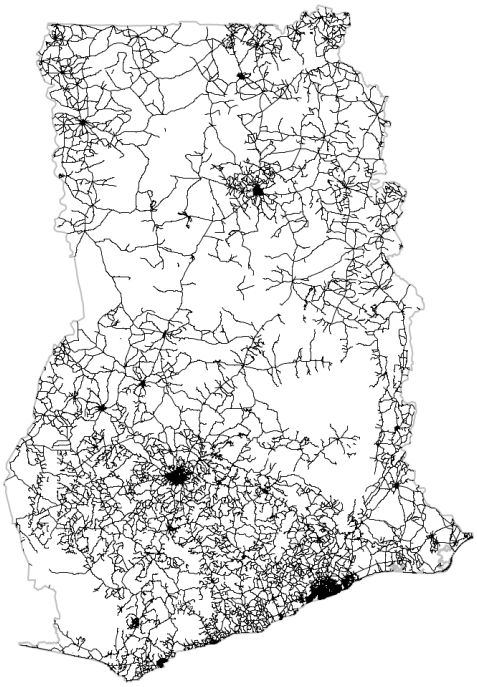


Figure A.1: Road Network in Ghana (Data Source: OpenStreetMap)

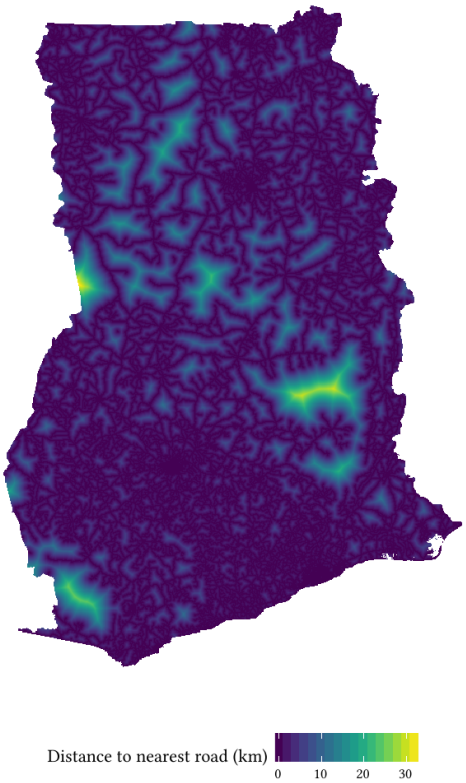


Figure A.2: Distance to nearest road (in kilometers)

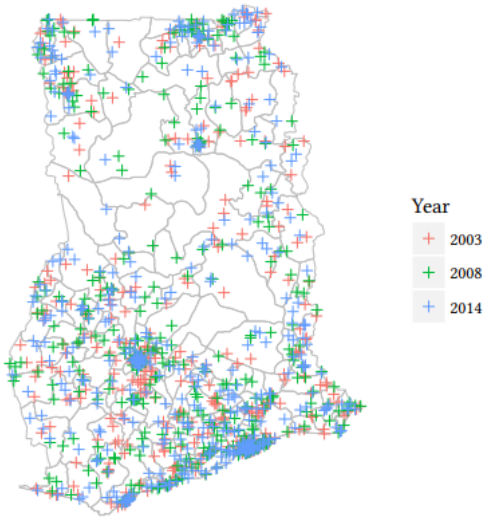


Figure A.3: Demographic Health Survey cluster locations by year.

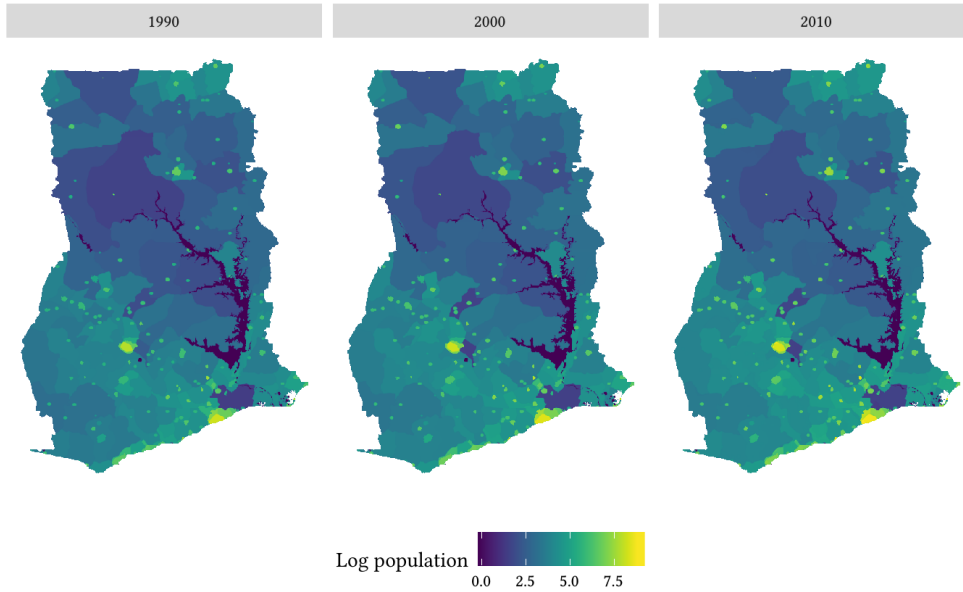


Figure A.4: Maps of log population in 1990, 2000, 2010. Years 1990 and 2000 come directly from NASA SEDAC. 2010 was generated using census and night lights data.

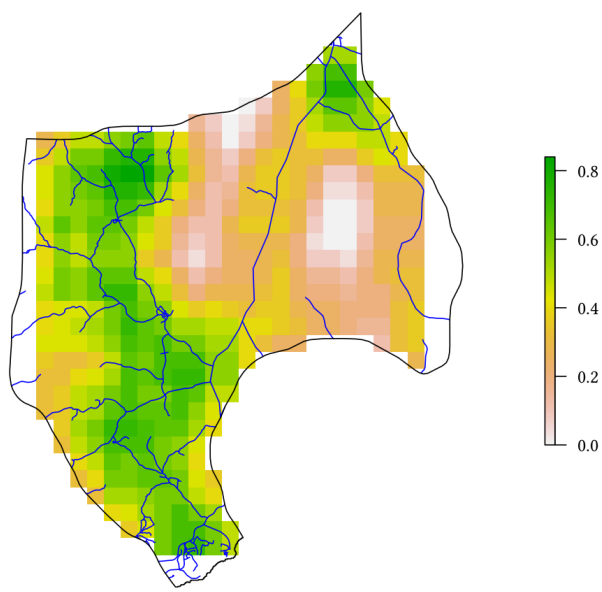
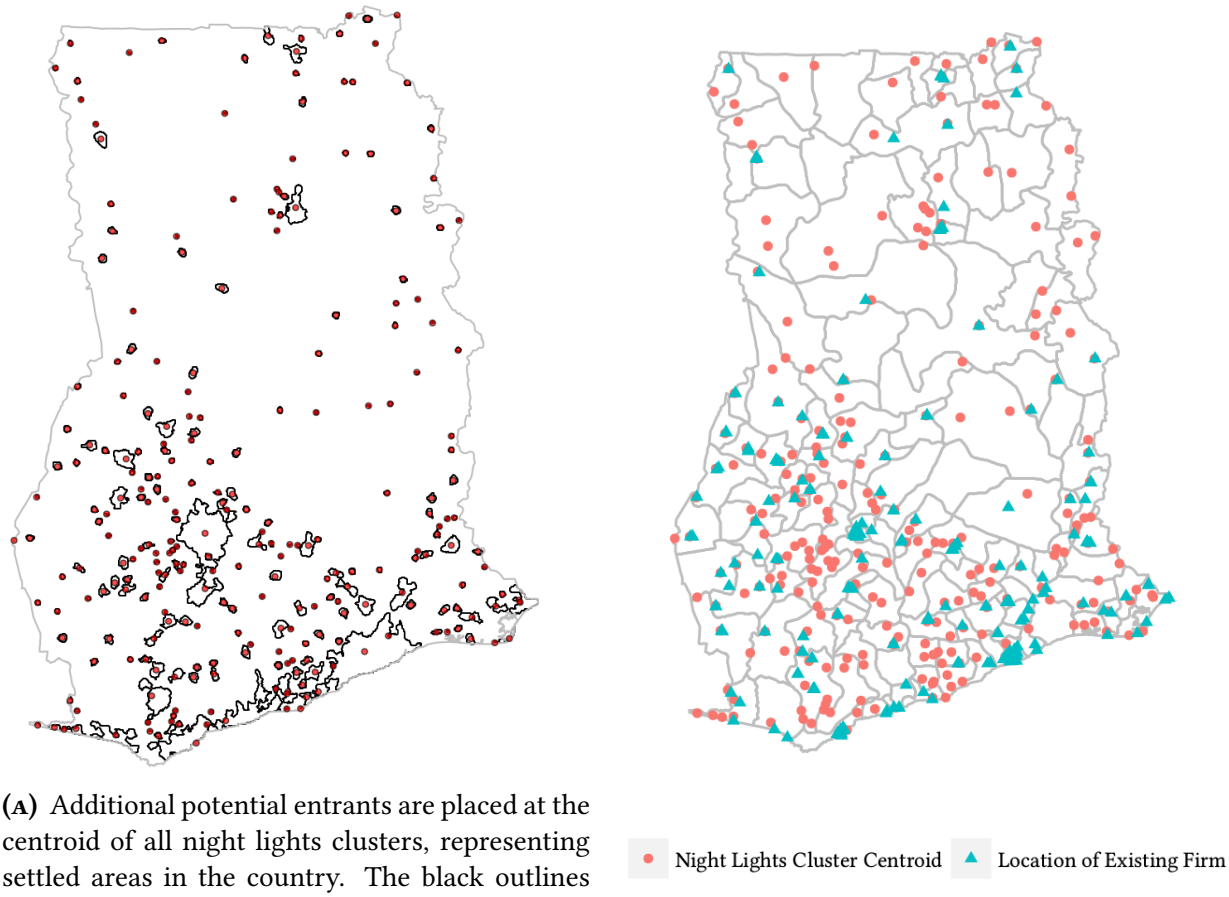


Figure A.5: Road connectedness example using only one district for the purpose of illustration. Road connectedness measures the percentage of tiles with an $N \times N$ grid around a tile with a road. The above is shown for $N = 5$ where the blue lines represent the roads and the heatmap represents road connectedness.



(A) Additional potential entrants are placed at the centroid of all night lights clusters, representing settled areas in the country. The black outlines are the night lights clusters and the red points are their centroids.

(B) Locations of all potential entrants, both firms from data and centroids of night lights clusters.

Figure A.6: Potential entrant locations.

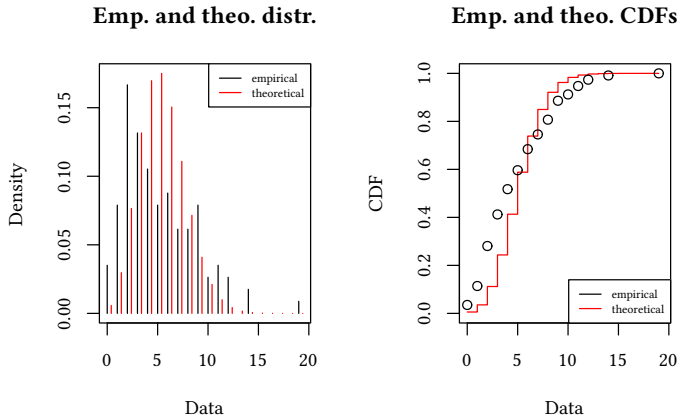
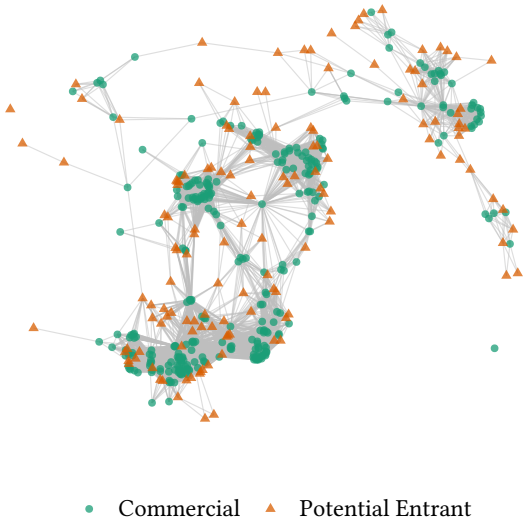
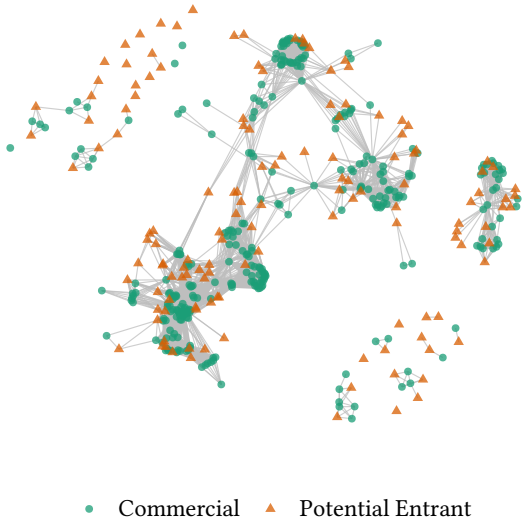


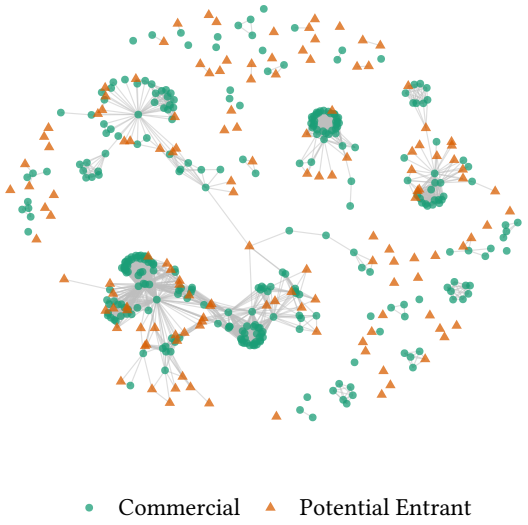
Figure A.9: Fit using a Poisson process to model the transition between becoming authorized and actively broadcasting. Time periods are in quarters.



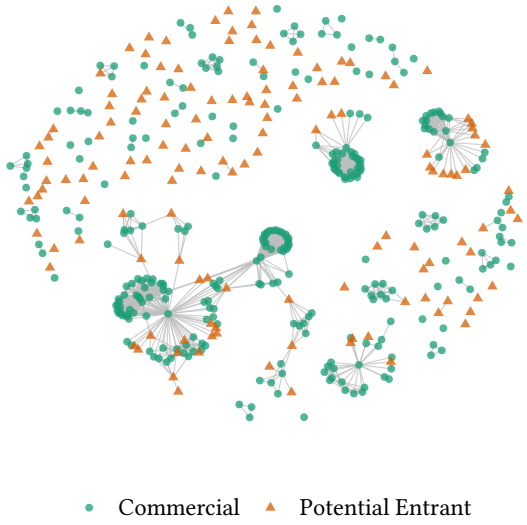
(A) Share at least 10% of coverage.



(B) Share at least 25% of coverage.



(C) Share at least 50% of coverage.



(D) Share at least 75% of coverage.

Figure A.7: Networks of radio stations where a connection between two stations is defined as the stations sharing at least a certain percentage of coverage.

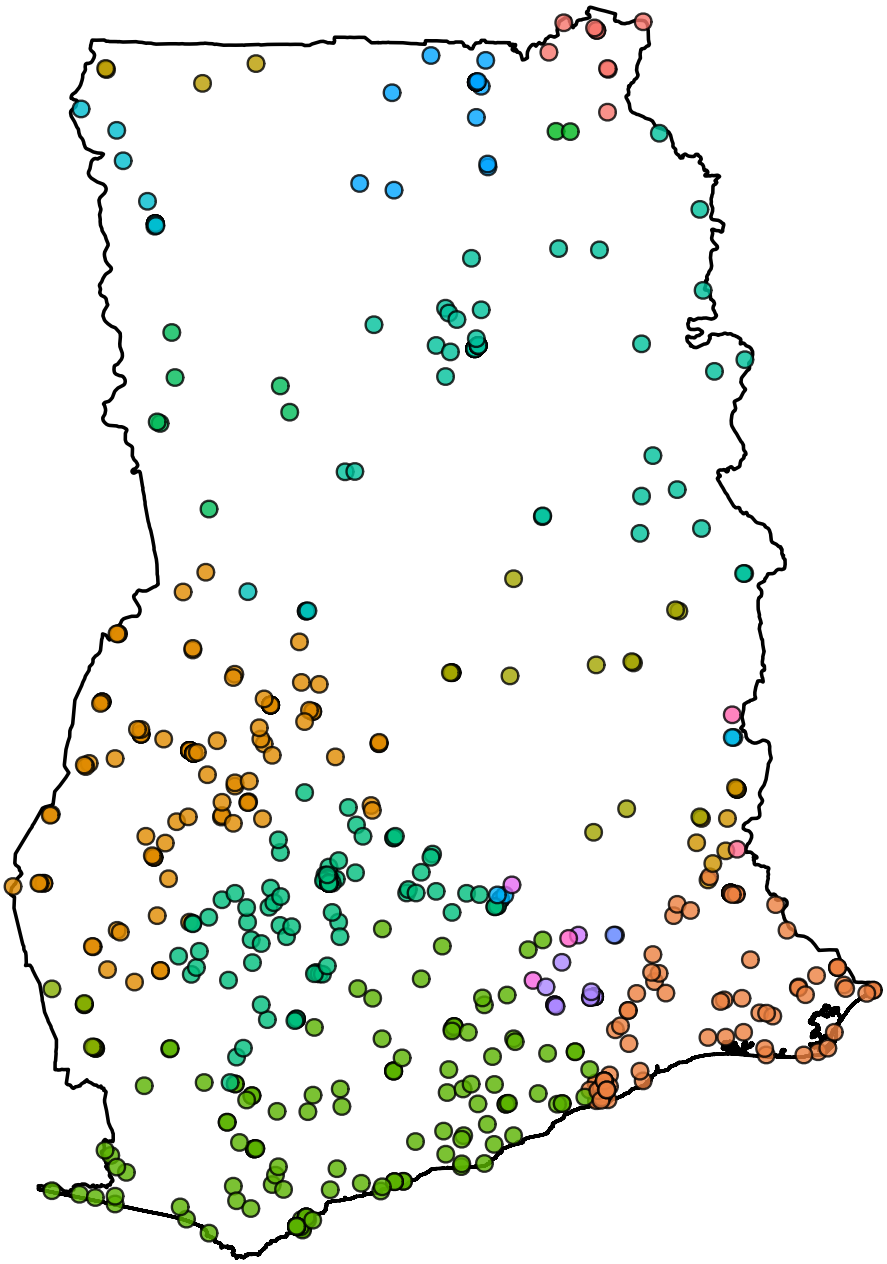


Figure A.8: Clusters of radio stations found by the community walktrap algorithm in Pons and Latapy (2005). Points with the same color are grouped in the same cluster.

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