The Health Cost of Internal Migration: Measuring the Effect of Visits on Malaria Incidence

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Abstract

Internal migration can critically impact the spread of infectious disease, specifically through the channel of short term visits taken by migrants to their place of origin. This important externality has been understudied due to a dearth in data on internal movement. Using mobile phone records, this paper is in a unique position to study these visits because it is able to capture day to day movements for all of Senegal. Internal migration is linked to visits back to the place of origin, with each internal migrant correlated with 1.8 visits per week, and with the correlation highest around important holidays. To study the negative impact of internal migration on health, it combines the data on visits with high frequency data on malaria in order to quantify the number of new cases attributed to these visits. Two channels through which visits can spread infectious disease are studied: visitors bringing the disease when they travel and residents becoming infected during a visit and bringing the disease home. The study finds one new case of malaria for every 100 visitors and four additional cases for every 100 residents returning after a visit. In some parts of the country, these represent almost all the cases of malaria. This study has implications for policymakers, who can use data generated by cell phone providers to track visits and employ more efficient and cost effective programs to fight infectious diseases. In cases where cell phone data is unavailable, the link demonstrated here between internal migration and visits can be used to predict the timing and number of visit.
1 Introduction

As internal migration and urbanization in many developing countries continues to grow (Nations [2013]), a number of negative externalities can arise in the form of underdeveloped institutions, increased unemployment, high traffic, and pollution. One understudied externality is the negative impact on health due to the spread of infectious disease. Not only can migration lead to the spread of disease as an individual migrates from one location to another, but it can also lead to the continual transfer and propagation of disease as the migrant visits their place of origin throughout the year to see friends and family left behind. Understanding this link between disease, short term visits and internal migration is critical to decrease the disease burden and costs arising from increased cases and ineffective policies. Yet inadequate data on internal migration and especially inability to measure short term visits within a country have made it difficult to study the effect on disease and quantify its impact. This is the first study to use countrywide high frequency data on both movement and disease to study the link between internal migration, short term visits and disease. It also helps to inform policy by providing a clear understanding of the timing and location at highest risk for disease due to migration and visits.

While internal movement can impact all infectious diseases, the paper focuses on malaria. Malaria infected almost 200 million people in 2013 and has negative economic consequences for the households affected as well as for the governments trying to fight the disease [World Malaria Report 2014, Shepard et al. 1991, Chuma, Thiede, and Molyneux 2006]. In addition, many studies have found movement of infected individuals to be a key factor for the resurgence or outbreak of malaria (Cohen et al. 2012, Lu et al. 2014).

Malaria and migration are studied in the context of Senegal. This is an apt case study because the country has seen a steady rise in internal migration (Nations 2013) and it has the necessary conditions for malaria to spread through movement: geographic heterogeneity of malaria prevalence and the existence of environmental factors that support malaria throughout the country. From a policy perspective, this is also a critical case because Senegal wants to reach the threshold for pre-elimination of malaria (less than 1 case per 1000 people) by the end of 2015, yet it had 345,889 cases and 815 reported deaths due to malaria in 2013 (World Malaria Report 2014). Modelling movement within the country and linking it to malaria cases would allow policy makers to better target interventions to the locations and during the times of year that are at highest risk, in this way more effectively reducing transmission and
reaching the threshold for pre-elimination.

This study is in a unique position to answer the question of what is the effect of short term visits on malaria prevalence in Senegal due to new data that provides high frequency information on movement and malaria. The data on movement is derived from cell phone records, which allow the movement of cell phone users to be tracked throughout Senegal. This data is ideal for measuring visits on a national scale, which cannot be tracked with most large data sources like the census. While previous studies have used cell phone data to determine areas that are sources of malaria and areas with higher risk due to movement (Tatem, Qiu, et al. 2009; Wesolowski et al. 2012; Enns and Amuasi 2013), this study goes a step further to quantify the effect of visits and determine the timing of transmission by combining the cell phone data with high frequency data on number of malaria cases. This makes it possible to measure the number of cases attributed to visits, the week in which the most cases arise after there has been a high number of visits, and the locations most at risk for increased cases due to visits. This type of analysis has not been done on a national scale before, but is necessary for the effective and efficient distribution of resources by the government.

The paper first establishes a link between short term visits and increased cases of infectious disease. There are two channels through which visits could impact disease. First, if visitors infected with a disease go to a different district, they could spread the disease to those living there. Second, if an individual visits a location where there is a high prevalence of a disease, then they could become infected and return home as a new case of the disease. In turn, they could also infect other people in their home location if they are not treated immediately, leading to additional cases. For both of these channels, it is necessary to have heterogeneity in prevalence. Visits lead to new cases of a disease because they either help to bring the disease from a place of high prevalence to a place of low prevalence, or else someone that would not be infected in their home area is put at risk of infection when they travel to a place of high prevalence. In a country where the disease prevalence is homogeneous, there should not be an effect of movement since travelling does not change a person’s probability of becoming infected. The analysis is conducted using an econometric model that measures the effect of movement on number of malaria cases controlling for time and district fixed effects as well as climatic factors.

Once the effect of visits on malaria is measured, the paper looks at the link between these visits and internal migration. While short term visits can occur for
various reasons, by narrowing down one reason for these visits, it is possible to come up with better policies to target the spread of disease through this channel. It clarifies the annual patterns of visits, since visits stemming from internal migrants are predictable. It also makes the results more generalizable to settings where cell phone data is not available to provide information on short term visits. In those cases, if there is census or household level data on internal migration, it would be possible for policymakers to use the longer term migration patterns to predict short term visits and thus apply similar policies of targeting locations at times that they are at highest risk. While there is qualitative evidence of short term visits occurring by internal migrants to maintain links at home (White and Lindstrom, 2005), as well as some quantitative evidence from small-scale surveys (Simkins and Wernstedt, 1971), the cell phone data makes it possible to establish this correlation at a country-wide level.

There are two patterns that might be expected between visits and internal migration. For those that have migrated close by, there could be a regular pattern of movement every weekend. This might especially be the case for temporary workers that only go to an area for work during the week and then come home on weekends. While this pattern could have some impact on the spread of disease, frequent movement implies closer proximity, which means the difference in malaria prevalence is lower. Less variation in malaria would mean that these types of visits should not influence the number of malaria cases.

The second pattern of visits would involve longer visits to places that are further away. In order for individuals to be able to take time off for longer visits, it makes sense that the majority of these visits would occur around public holidays when workplaces are closed and people have time off. In addition, some of the public holidays are religious holidays when there is an emphasis placed on spending them with extended family that often lives in the place of origin. With 92 percent of the Senegalese population practicing Islam, the biggest Muslim holidays would be the times where the most long term visits would be expected. These are the visits of most interest because when people travel further, they are more likely to visit a place with a different level of malaria from their home location. These are also the times during the year when there are the most visits. From a policy perspective, understanding the pattern of visitation makes it possible to target those holidays with policies for preventative measures as well as extra resources after the holiday. In addition, again this allows the applicability of these findings to other locations where policy makers can use internal migration patterns and holiday schedules to determine the times of year and locations at highest risk.
The analysis looks at the effect of visits for different lengths of time on number of malaria cases. It finds no positive effect of visits for 1-2 days. Looking at visits of 3 to 21 days, it finds a positive effect on number of malaria cases from people returning after a visit 3, 5, 6, and 8 weeks after that visit. There is also a positive effect of visitors on number of malaria cases in the place visited 5-7 weeks after a visit. For every 100 visitors, there is one additional case of malaria and for every 100 residents returning from a visit there are around four additional cases of malaria. As expected, short term visits of 1-2 days exhibit a pattern linked to weekends, while longer term visits over 3 days are related to holidays, with the highest number of visits occurring during the two Eids. In addition, each internal migrant is associated with an average 1.84 visits per week. The paper then shows the districts that have the highest correlation between internal migration and short term visits, which would be the most important to target with prevention and treatment policies around the time of holidays.

The paper begins with some background on the link between migration and the spread of disease. Section 3 describes the data used in the paper while section 4 describes how visits are measured. That is followed by the empirical specification in section 5. The results are presented in Section 6, policy implications are discussed in section 7, and the paper concludes with section 8.

2 Background

Malaria Biology

To model the effect of movement on malaria, basic understanding of the disease and its timing is necessary. Malaria is caused by parasites that are carried by the female mosquitoes of the anopheles genus. Although there are several malaria parasites, this paper focuses on \textit{P. falciparum}, which accounts for almost all cases of malaria in Senegal. Figure 1 shows the malaria prevalence for all arrondissements of Senegal.

The malarial cycle for \textit{P. falciparum} takes several weeks for completion as it travels

\footnote{While the current overview touches only on a few aspects of the disease and does not go into the details of the biological cycles, additional information on malaria transmission and the biological cycle can be found in Doolan, Dobaño, and Baird 2009, D. L. Smith and McKenzie 2004, Killeen, Ross, and T. Smith 2006, Johnston, D. L. Smith, and Fidock 2013, Wiser 2010.}
through both the mosquito and human hosts. Once an infected mosquito bites a hu-
man, the parasite goes through a growing stage in the liver that can vary in length,
but lasts on average 6-9 days (Wiser 2010, Doolan, Dobaño, and Baird 2009). Sym-
ptoms of malaria, including high fever and chills usually appear between 7 and 15 days
after the mosquito bite (Doolan, Dobaño, and Baird 2009). During the incubation
period before symptoms appear, the individual is not infectious, but becomes infec-
tious around the time that symptoms appear. Symptoms of the disease in humans
last for 1-2 weeks if left untreated (Wiser 2010). Once the person is infectious, an
uninfected mosquito that bites the infected person will experience a temperature de-
pendent extrinsic incubation period lasting 9 to 14 days (Killeen, Ross, and T. Smith
2006). During this incubation period, they cannot infect other humans, but once the
incubation period has passed, if the mosquito has survived, they can infect humans
by biting them and starting the cycle again. A timeline of this cycle is shown in
Figure 2 using average numbers for the different estimates of timing.

Movement and Malaria

The link between movement and the spread of communicable diseases is not a
and D. L. Smith 2010). Oster 2012 analyzes how higher exports, which increase the
movement of people through trucking, lead to more new HIV infections. Similar re-
search is undertaken by Jerome Adda who is studying the spread of viral diseases and
the health costs of various policies that impact movement of individuals (Adda 2014).

While the link between malaria and movement has not specifically been studied
in the economics literature, a number of case-control studies have been done looking
at the link between malaria and travel in a specific location. Researchers select a
group of people that is diagnosed with malaria and a comparable group that is not
and then conduct a survey that asks about travel history, along with other demo-
graphic characteristics that could contribute to malaria contraction (Siri et al. 2010,
Osorio, Todd, and Bradley 2004, Yukich et al. 2013). They find that recent travel,
from 8-14 days up to 30 days prior, is one of the main risk factors for contracting
malaria. These types of case-control studies have only been done on single locations
due to the cost and time necessary to collect travel history data. Some studies have
used census data or national surveys to measure migration in order to describe mi-
gration routes and how these relate to the presence of malaria in different parts of
a country (Lynch and Roper 2011, Stoddard et al. 2009). Yet the migration data
available, especially for internal migration, is often not sufficiently high resolution to
establish a link between internal movement and the spread of a disease. In addition, the movement captured by surveys and the census often times misses short term movements and cyclical migration (Deshingkar and Grimm 2004).

Data on movement in Senegal is only available nationally through the Senegalese Survey of Households (ESAM) and the Census, both of which only have data on migration and no measure of short term visits. Therefore, the only empirical study of movement and malaria is a project done in Richard Toll, one of the districts in Senegal that is covered in the data used for this paper. It tracked malaria cases over 12 weeks and used a questionnaire to learn more about how malaria was spreading (Littrell et al. 2013). The study found that one of the main risk factors for contracting malaria was travel that entailed an overnight stay. A country-wide study of malaria that includes regions with different levels of prevalence has not been done due to the prohibitive cost of tracing and interviewing all malaria cases.

Le Menach et al. 2011 is the closest paper to this research. Combining cell phone data for Zanzibar as well as a dynamic mathematical model of importation and transmission rates, they study the transmission from residents traveling to malaria endemic regions as well as visitors and immigrants coming from endemic regions. They find that residents traveling to malaria endemic regions contribute 15 times more imported cases than infected visitors. They also estimate the malaria importation rate to be 1.6 incoming infections per 1000 inhabitants per year. This study is limited in that it is focused on an island that has an extremely low rate of malaria, which makes generalizability to areas that might have higher rates of malaria difficult. In addition, it contains no measure of number of malaria cases and is only based on theoretical predictions of the prevalence and reproductive rates, which make a number of assumptions that could affect the estimates. Finally, the paper is attempting to estimate the total number of malaria cases generated over the span of the disease, which is estimated to last for 200 days within a person. In contrast, the goal of this paper is to estimate the number of weekly cases generated by a visit and the timing of those cases because that is most relevant for policy makers interested in targeting a specific time period when the largest impact is expected.
3 Data

Cell Phone Records

The data used to measure short term visits come from phone records made available by the mobile service provider Orange Telecom in the context of a call for projects with the objective to explore the potential of mobile call data to facilitate socio-economic development. The data consist of calling data for Senegal at arrondissement level for 146,352 individuals between January 1, 2013 and December 31, 2013 (Montjoye et al. 2014). The current study only focuses on phone calls made between 7pm and 7am in order to determine the locations where individuals reside rather than capturing work locations. In 2013, Orange had 9 million unique phone numbers on its network. The users in the random sample provided had to satisfy two specifications. First, they needed to have had at least one interaction on a minimum of 75% of the days of the year (273 days).\textsuperscript{2} Second, any phone that had more than 1000 interactions per week was excluded from being eligible for the sample because it was assumed to be a machine or a business rather than an individual.

Figure 3 demonstrates the total number of calls made each day between 7pm and 7am by the individuals in the dataset. At certain times during the year there are spikes in the number of phone calls. Vertical lines in the graph mark major holidays, which often correspond to the spikes in phone calls. Korité and Tabaski are the two biggest Muslim holidays, known also as Eid al-Fitr and Eid al-Adha respectively.

Several concerns can arise with the use of cell phone data. First, depending on the percent of the population with access to a cell phone, the data might be capturing movement of only a certain portion of the population, such as those that are high income. In 2013 there were 92.93 mobile phone subscriptions per 100 inhabitants in Senegal, implying that a majority of the population was using cell phones, which would mitigate bias arising from heterogeneous phone ownership (Union 2013). A second concern is that using data from only one mobile provider could lead to a bias if the carrier type is associated with certain characteristics of the user. Out of the three telecom providers in Senegal, Orange Telecom had between 56 and 62 percent of the cell phone market in 2013 (Régulation des Télécommunications et des Postes 2013). From anecdotal evidence, many individuals have phone cards from more than one provider in order to maximize the promotions of different providers. This explains why in 2013 there were 9 million unique users, which is a larger percentage of the population.

\textsuperscript{2}An interaction is defined as making or receiving either a call or a text message.
population than its market share. While these limitations are important to consider, in a context with limited data on internal movement, cell phone data provides an opportunity to study short term effects of movement within a country that would not otherwise be possible.

Census Data

Census data is used to measure internal migration. The census was conducted in 2013, and a 10 percent sample is used, consisting of 1,245,551 individual observations. The current home location is provided for each individual at the commune level, and there is a question that asks the home location of the individual one year ago, also at the commune level. This was aggregated up to the arrondissement level. For 14 percent of the individuals, the location in the previous year was not at a detailed enough level to assign an arrondissement, so those observations were removed. A matrix is then created of migration from each arrondissement to each other arrondissement based on where people were located in 2012 and in 2013.

Malaria Data

The data used to measure malaria prevalence comes from the Programme National de Lutte Contre le Paludisme (PNLP) (Bulletin de Surveillance Sentinelle du Paludisme No 1-46, 2013). This national program, which has the goal of controlling malaria in Senegal, has been collecting weekly data on number of malaria cases at twenty health posts around the country. This data has been collected starting in 2008 for some of the locations, but there is consistent data available online only starting in the middle of February 2013. Figure 4 shows the location of the 20 sites where data has been collected. The malaria cases included are ones that have been tested and were confirmed positive. During the period of data collection almost 100% of individuals coming to a health post and exhibiting symptoms were tested. The cases reported are new cases each week.

Scaling of the Data

Since weekly malaria data is available for only some health posts while the movement data is at the arrondissement level, it is necessary to adjust the data. There is data available on number of health posts in each health district in 2011 (Sanitaire 2011). This provides the ability to scale the malaria data up to the health district
level for the health districts in which the 20 health posts are located. Since the twenty health posts are distributed so that there are two per health district, the weekly malaria numbers for each pair of health posts is averaged and then scaled by the number of health posts in the district. This provides an estimate for the average number of weekly malaria cases in the health district for the ten health districts that are the focus of this study.

In order for the movement data to match the malaria data, the arrondissements are aggregated to the health district level. There are 123 arrondissements that were regrouped into 74 health districts. The movement numbers are then calculated at the health district level rather than the arrondissement level in order to make the spatial units of the movement data and malaria data the same.

Climate Data

There is a large literature that looks at the effect of climate on malaria. Therefore, rainfall, temperature and humidity are included in the model. Data on these three measures of climate come from Intellectual Ventures. The data was collected daily from twelve weather stations around Senegal in 2013. A map of the weather station locations is shown in Figure 5, along with data on percent of days that data was available at each station. Intellectual Ventures converted the data to high-resolution, 1 km by 1 km, gridded time series data based on methods described in Chabot-Couture, Nigmatulina, and Eckhoff 2014. For the analysis, the data points within each health district were averaged on a daily basis to create a daily rainfall, humidity, and average temperature measure for the district. A weekly measure for rainfall was created by summing the rainfall for each week. This is due to the fact that previous literature has shown the importance of cumulative rainfall (Silal 2012, Hoshen and Morse 2004). For humidity and average temperature, the daily values were averaged to get a weekly mean value for each health district.

4 Measuring Short Term Visits

In considering the effect of visits on disease, it is important to differentiate between two possible channels since the direction of the movement could affect the
spread of the disease, as demonstrated by Le Menach et al. [2011]. In considering the number of malaria cases due to movement in index district j, there are two channels through which the disease can spread. Residents of j visiting a high malaria place can become infected while they travel and upon returning to their home district j show up as a malaria case there. They could then spread the disease to others in the community if they are bit by mosquitoes who infect additional people. The second channel is infected visitors from other districts coming to j can spread the disease to local vectors and infect residents of j. To empirically test these two channels, both a “home” health district and a short term visit need to be defined.

A “home” district is assigned to each person based on where they have spent the most number of days out of the number of days in which they made phone calls in 2013. A location was assigned to each day based on the health district in which the person made the most number of phone calls between 7pm and 7am. For over 90 percent of individuals, they spent more than half of their days in the district labeled as “home”. Robustness checks were conducted where the analysis was done excluding those people who spent less than half of their days in the data in a single district. There was no significant difference between the results obtained with or without these individuals.

In terms of timing, there could be differences between the effect of visits of different lengths of time. As discussed, visits of 1-2 days might represent weekend visits home to places close by or workers that spend the weekdays at their place of work and live close enough that they can go home during the weekend. Not much of an effect is expected from these since the difference in malaria prevalence would not be as high. For visits longer than 3 days, it is possible that there might be some differences based on length, but in general, they probably represent similar visits that are over longer distances and occur during holidays. For this reason, separate analyses are run for visits of 1-2 days and visits of 3-7, 8-14, and 3-21 days. The bulk of visits are for 1-5 days, and much fewer visits for longer than 14 days, so to include visits of more than 14 days, it is necessary to combine all the visits together or there are not enough to run the analysis properly.

Figure 6 shows these expected differences between different lengths of visits. The top panel shows the number of visits each day of 2013 that lasted 1-2 days, while the bottom two panels show the patterns for visits of 3-7 and 8-21 days. In addition, the major public holidays are marked with dashed lines in order to see how the visits relate to the holidays.
As predicted, the visits of 1-2 days capture a pattern that remains relatively constant throughout the year. They are not particularly associated with holidays, except for a big drop in visits in July, which corresponds to Ramadan, the time of fasting. During this time people usually travel less since fasting all day as well as the practice of attending several prayers throughout the day makes travel harder. Instead of holidays, the spikes in travel throughout the year correspond to weekends, with people travelling on Friday and Saturday to one location and back on Sunday to where they came from. Although these moves might represent internal migrants going home every weekend, as discussed earlier, individuals are travelling to closer locations. It is more likely that the level of malaria is similar between these geographically proximate places and therefore there should not be an effect of these visits on malaria prevalence. The amount of movement for 1-2 days is also generally lower during the second half of the year, which could correspond both to increased difficulty in travel due to the rainy season, or to decreases in short term movement due to the high prevalence of malaria in certain regions. This potential change in behavior as a consequence of the disease is studied in a different paper.

The figures showing visits of 3-7 and 8-14 days are very similar and demonstrate that while there are these types of visits throughout the year, there are particular times during the year when there are big jumps in these visits. Unlike the visits of 1 to 2 days, these jumps correspond to important religious holidays, especially the two Eids, which are the biggest Muslim holidays (lines G and I in the graphs). Therefore, these visits of 3-21 days capture the notion of internal migrants going back to their home locations at the time of major holidays. It is important to note that the jumps in movement do not correspond strictly to number of phone calls seen in Figure 3, since Independence day is not a day when there were many calls, but there is a large jump in movement (line B). Therefore, the analysis is not being driven by number of phone calls.

5 Empirical Specification

To define the empirical specification, it is important to think about how the climate and visitation variables enter into the equation. Due to the complicated nature of the disease life cycle both within humans and mosquitoes and the various factors that affect this cycle at different times, timing is important to consider.

The importance of climatic factors for malaria is at different stages of the mosquito.
life cycle (Hoshen and Morse 2004). Rainfall is necessary to provide standing bodies of water for the mosquito to lay her eggs; the initial stages of the mosquito (egg, larvae and pupae) are dependent on temperature and humidity for the survival of the mosquito; and in the mature stage, when mosquitoes can infect people with malaria, the incubation period of the parasite within the mosquito is dependent on temperature. In the literature, on average 2 to 3 months is the most common lag for rainfall that is significantly correlated with malaria prevalence (Zhao et al. 2014, Silal 2012, Hoshen and Morse 2004, Briët et al. 2008, Luo et al. 2012). For temperature and humidity, the lag is closer to one month. While much of the literature looking at climatic factors has used monthly data, Zhao et al. 2014 use weekly malaria and climate values to analyze the most appropriate lags as well as to model the nonlinear effects of climate. To find the appropriate lags and polynomial structure with which rainfall, humidity and temperature should enter the model, a lasso approach is used including all lags from 1 to 12, as well as quadratic and third order polynomials of these lags. Based on the lasso method, the climatic factors that best predict malaria cases are the rainfall with lags 10, 11, and 12, temperature with lags 1 and 8, and humidity with lags 1 and 9.

As discussed, both visitors and residents returning after a visit could impact the number of malaria cases, therefore both variables are included. The variables consist of the aggregate number of visitors coming and residents returning from all other districts $i$ to district $j$ in a certain week $t$. In addition, the timing of when cases might show up from both channels is not straightforward due to the incubation periods, as well as the time before an infected person decides to visit a health post. Since the majority of the literature is focused on the number of cases arising from one case of malaria over the full span of the disease, which is 200 days, rather than the specific weeks when new cases are expected, there is no previous work on which to go by in deciding the lags that are most important. Therefore, all lags from 0 to 8 are included for both visitors and residents returning, which allows the data to show what are the most important lags.

Malaria in Senegal is seasonal, with almost all cases falling between July and December. This is largely driven by the rainy season which occurs during June to December, though has slight variations in timing depending on the region. Therefore, the analyses in this paper focus only on the weeks from July to December. Figure 7 shows for each of the ten health care districts with malaria data between July and December, malaria graphed on the left hand y-axis and number of people returning to the district after a visit on the right hand y-axis. Summary statistics by
district are also shown in Table 1 on average weekly malaria cases, number of health posts, the number of people in the cell phone data who’s “home” is assigned to that district and an estimate of the percent urban in the district.

In order to estimate the relationship between movement and malaria, the equation that follows is used:

\[
M_{jt} = \alpha_0 + \beta \sum_{w=0}^{8} R_{jt-w} + \delta \sum_{v=0}^{8} V_{jt-v} + \rho \left( \sum_{z=10}^{12} Rain_{jt-z} + \sum_{u=1,8} Temp_{jt-u} + \right.
\]
\[
\left. \sum_{x=1,9} Humid_{jt-x} \right) + \gamma_j + \lambda_t + \epsilon_{jt}
\]

\[
R_{jt} = \sum_{i=1}^{73} (R_{jit})
\]

\[
V_{jt} = \sum_{i=1}^{73} (V_{jit})
\]

where \(M_{jt}\) is the total number of malaria cases in location \(j\) in week \(t\), \(R_{jt-w}\) is a measure of the number of people from district \(j\) who visited a high malaria district and returned in week \(t - w\) to their home, \(V_{jt-v}\) is the number of people visiting district \(j\) from high malaria districts that begin a visit to \(j\) in week \(t - v\), \(Rain_{jt-z}\) is total weekly rainfall in week \(t - z\) in district \(j\), \(Humid_{jt-x}\) is average weekly humidity in week \(t - x\) in district \(j\), \(Temp_{jt-u}\) is average weekly temperature in week \(t - u\) in district \(j\), \(\gamma_j\) captures district fixed effects, \(\lambda_t\) captures week fixed effects, \(\epsilon_{jt}\) is the error term, \(R_{jit}\) and \(V_{jit}\) are the number of returnees and visitors from district \(i\) to district \(j\) during week \(t\).

All models included corrected standard errors for the panel structure of the data, where panels are defined as the health districts as well as correction for autocorrelation in the error term.\(^4\)

To study the link between visits and internal migration, the short term visits based on the cell phone data are regressed on the long term internal migration data from

\(^4\)This was done using the xtpcse command in Stata rather than using clustered standard errors due to the nature of the panel dataset which has a small number of panels, only 10, and a long set of time periods, 27. Panel corrected standard errors were chosen over feasible GLS because as shown in Beck and Katz 1995, the latter tend to be anticonservative when used with data having this type of panel structure.
the census. To first look at the link between visits and internal migration, all day to day movement within Senegal is studied. Each individual in the cell phone data is assigned an arrondissement location for each day based on the most number of phone calls made that day from one arrondissement. A movement measure is then created if an individual changes arrondissement from one day to the next. All of the movements between arrondissement pairs for the previous seven days are summed up for each day of 2013 starting with day seven, and this is regressed on the matrix of internal migration based on the census data. This is done controlling for arrondissement fixed effects.

Afterwards, the correlation specifically between visits of 3-21 days and internal migration is looked at, since that is most relevant for the current study. To look at this, the number of visitors to location \( j \) from location \( i \) is regressed on the number of internal migrants that left location \( j \) to move to location \( i \). We would expect to see a positive correlation since the more internal migrants that left \( j \) to go to \( i \), the more people will return to visit their place of origin \( j \). This is especially expected during major holidays when people have time off to visit and want to spend that time with their extended families. This is done at the health district level, to make it comparable to the analysis looking at the effect of visitors on malaria. This time health district fixed effects are used.

The following equation is estimated to study the link between internal migration and visits:

\[
V_{ji} = \beta_0 + \beta_1 (Mig)_{ij} + \gamma_i + \lambda_j + \epsilon_{ji}
\]

\( V_{ji} \) is the number of visitors from location \( i \) to location \( j \), where visitor is either measured as movement from \( i \) to \( j \) based on the daily location of individuals or as visits of 3 to 21 days. \((Mig)_{ij}\) is the number of internal migrants that migrate from \( j \) to \( i \), \( \gamma_i \) and \( \lambda_j \) are location fixed effects and \( \epsilon_{ji} \) is the error term.

\(^5\)The two arrondissements that contain locations considered holy and where big pilgrimages take place every year are removed from the data in order to focus on movement of internal migrants to their place of origin.
6 Results

Effect of Visits on Malaria

The main results are presented in Table 2. The four columns show the results if visits are defined as 1-2, 3-7, 8-14, or 3-21 days. The coefficients for all the lags of visitors and residents returning are shown. The climate variables and time and location fixed effects were included, but results are not presented in the table. As expected, there seems to be very little indication of a positive effect on malaria from visits of 1-2 days. For residents returning two weeks earlier and six weeks earlier, the coefficient is actually significantly negative. One possibility for why this is occurring is that individuals actually change their visitation behavior based on malaria prevalence and stop travelling during the weeks when there is higher malaria and resume travel once malaria cases have decreased. This change in behavior based on malaria prevalence will be examined in a different paper.

The effect of visitors and residents returning after a visit longer than two days is relatively consistent whether the timing is shorter (3-7 days) or longer (3-21 days). There is a very strong positive effect five, six and eight weeks after residents return. There is also an effect of visitors five and six weeks after the visit, though not as significant or large. When including all of the visits from 3 to 21 days, some other lags show up as significant as well, including three weeks after a resident returns and seven weeks after a visitor. This could be arising from the fact that there are more observations when all visits from 3 to 21 days are included, versus much fewer when looking only at 8-14 days. These results are also consistent with the idea that there should not be an effect from visits right away due to the incubation periods necessary for the disease and the amount of time it takes for symptoms to show up. It would be possible for some cases to show up earlier if it is a resident that was infected and came back. This is especially the case for those that were on longer visits and might have been infected early on in the visit, so that symptoms could appear soon after they return home. This would explain the significance after three weeks of residents returning when including visits from 3 to 21 days. Since our cell phone sample is around a one percent sample of the population, it implies that for every 100 visitors of 3-21 days there is one new case of malaria and for every 100 residents returning after a visit of 3-21 days to another health district there are 4 new cases of malaria. This is a much higher rate than was found by Le Menach et al. [2011] but it is also in a context where mosquito vectors and climatic conditions exist that allow the spread of the disease, which was not the case in Zanzibar. The findings are similar in that
the effect from visitors is much smaller than the effect from residents returning.

Since a large number of the visits of 3-21 days occur around the two Eids, and specifically during Tabaski, most of the identification is driven by the weeks around that holiday. This means that it could be something about the holiday that is causing the increase in malaria, rather than the movement. The way this is tested is by comparing a dummy for just the week when the holiday occurs (week 42 in 2013) to the two weeks when there is the biggest impact on movement around the holiday (weeks 42 and 43). In the upper panel, when including just the dummy for the week of Tabaski and comparing that to all other weeks, there is no effect when using no lags up to 5 lags. In the bottom panel, when using the dummy that measures the effect of Tabaski on movement (comparing the two weeks when there is the most movement from the holiday to all other weeks), there is a large and significant effect when using three and four lags. This suggests that this is not just a story about Tabaski affecting malaria, but movement associated with Tabaski.

**Link between Visits and Internal Migration**

First looking at the link between internal migration and all movement in the cell phone data, Figure 8 shows the results of the regressions that were done for each day based on the movement in the previous seven days. The graph also marks all of the major public holidays in Senegal in 2013. It shows that the movement occurring seven days prior to a holiday is negatively correlated with the internal migration matrix, implying that individuals are moving in the opposite direction from the internal migration pattern. Then, in the seven days after the holiday, movement is positively correlated with internal migration, which means that individuals are going in the same direction as internal migration patterns. Therefore, around holidays, when people have time off and also want to spend important religious holidays with family members, internal migrants return to their place of origin and then go back to their new home location after the holiday. If internal migration were to increase, it would imply an increase in these types of visits home. The correlations are strongest for the two Eids, the biggest Muslim holidays marked as G and I in the figure, which is in line with what was predicted.

Turning specifically to visits of 3 to 21 days, Figure 9 shows the correlation between visits and internal migration. The numbers were adjusted to reflect the fact that the cell phone data is a one percent sample of the population, while the census data is a ten percent sample. Therefore, we see that each internal migrant is correlated with
between 1.2 and 2 visits per week. The correlation is also affected by holidays, with a decrease during Ramadan, when there is less travel in general, and a big increase during Eid al-Adha, which is the most important Muslim holiday in Senegal. On average annually, each internal migrant is correlated with 1.84 visits per week. The $R^2$ is around .3 on average, implying that internal migration can explain about 30 percent of short term visits. Therefore, targeting these short term visits associated with internal migrants could lead to a substantial decrease in malaria cases.

### 7 Policy Implications

So far, the paper has shown a link between internal migration and short term visits and a link between visits and malaria prevalence. While stopping all internal migration or preventing individuals from returning to their place of origin during holidays might be effective policies in reducing disease, they are not practical. There are policies that can be implemented using this data though that would be more effective and efficient, saving the government money and reducing the disease burden.

The government of Senegal is already targeting resources to specific places that receive a lot of visitors, such as sending more rapid diagnostic tests. They specifically target the two locations where big pilgrimages take place bringing hundreds of thousands of people from around the country, which could lead to the spread of infectious disease. The current work makes it possible to conduct more specific targeting based on travel patterns throughout the year and how they link to internal migration patterns.

Based on the results in the previous section, for every 100 people that visit a health district from another health district, there is one new case of malaria per week, and for every 100 people that return after visiting another district, there are around four new cases of malaria per week. If the government wants to reach its goal of reducing malaria down to 1 case per 1000 individuals, it will be necessary to target these cases that arise from the short term visits done by individuals throughout the year. In order to effectively do this, both the timing and location of visits are important. In addition, if internal migration continues to rise, it is important to determine which areas of the country will be most affected and might see increased cases of malaria.

Running the same regression as is done for Figure 9, but separately for each health district, it is possible to see for which health districts internal migration has the highest correlation with short term visits. This was done using the weekly data and
clustering at the health district level. The districts that have a significant correlation are shown on the maps in Figure 10 in green. Some districts have a high correlation with visitors coming in, while other districts have a high correlation with residents returning after a visit. Using this information, policymakers can target these specific districts during the weeks in the year most likely to see rises in malaria due to visits. This can include targeted information campaigns that alert both those travelling and those in proximity to travellers about the increased risk of contracting malaria and encourage them to be tested as soon as possible. They can also calculate the number of extra cases that can be expected based on the number of visitors or residents returning and send the extra resources such as diagnostic tests and medication to detect and treat the cases right away and therefore prevent further spread of the disease.

In terms of timing, the analysis showed that the effect is coming from longer visits that correspond to important public holidays, and especially the two Eids. The regressions also showed the effects were lagged several weeks. Therefore, policies can be targeted 5, 6 and 8 weeks after major holidays in places where many residents return after visits, and 5 to 7 weeks in places that receive many visitors. These types of targeted policies are more cost effective because they allow the government to only spend resources on the areas that are most affected, and they also will lead to a higher reduction in the disease burden because cases can be detected earlier, preventing additional infection of mosquitoes and then people.

8 Conclusion

This paper takes a question that has been modeled and studied in epidemiology and applies innovative data in order to be able to quantify the number of cases of malaria that can be attributed to visits and how visits relate to internal migration. Previous literature has fallen into two categories of either only being able to look at a specific village or city in order to map out cases of malaria to episodes of movement, or looking at a country-wide scale but being unable to tie movement to specific cases of malaria and instead making predictions about where it should be expected that movement will contribute most to the spread of malaria. Yet, for effective policies to fight malaria, the combination of these two literatures is necessary. It is important to have information at a country-wide level since the effect of movement on malaria in one village might be different from another village with other characteristics, but at the same time, knowing the number of cases that can be expected from movement and the timing of when these cases are most likely is critical for targeted and cost-effective policies.
In effect, the research presented combines these two strands of literature by using big data to analyze outcomes for the whole country, but links it to micro data on malaria prevalence at a high frequency level. This analysis provides a measure of how many cases of malaria can be attributed to different types of short term visit, finding an effect of 4 new cases of malaria from residents travelling and getting sick and 1 new case of malaria from visitors. In future research, data on number of malaria cases in every district will be used to study heterogeneity in this effect based on various district characteristics.

The research also provides evidence for the importance of specific periods of time, such as the two biggest Muslim holidays, when the movement impact is the most important. This could directly influence policies to target resources during those specific weeks by providing bednets for travelers that might not have access during visits, training local health care workers to spot new cases of malaria early by taking stock of movements in and out of the village, and using information campaigns to inform travelers about the increased risk to them and their household members and providing tips for precautions that can decrease the risk. In future work, the cost effectiveness of different measures targeted both spatially and in time can be calculated.

From a theoretical point of view, this is the first paper to empirically test the model of short term movement and its effect on malaria incidence. It quantifies the number of new cases of malaria due to visits and links these visits to internal migration patterns. The paper can be used as a framework for policymakers to implement more effective programs and for researchers to further model how social, environmental, and economic factors that cause movement patterns to change will affect malaria prevalence.

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Yukich, Joshua O et al. (2013). “Travel history and malaria infection risk in a low-transmission setting in Ethiopia: a case control study”. In: Malar J 12, p. 33.

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Figure 1: Map of Malaria Prevalence in Senegal in 2013
Figure 2: Timeline of *P. falciparum* Malaria Transmission Cycle
Figure 3: Total Calls Per Day
Figure 4: Map of Health Posts with Weekly Malaria Data Collection
Figure 5: Location of Weather Stations Used for Climate Variables
(a) Visit of 1-2 Days

(b) Visit of 3-7 days

(c) Visit of 8-21 days

Figure 6: Total Number of People Starting a Visit
Figure 7: Weekly Cases of Malaria and People Returning Home During the Malaria Season after a visit of 3-21 days
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Table 1: Summary Statistics
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Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Table 2: Effect of Population Movement for 3-14 days on Malaria Cases
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Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 3: Comparing Importance of Tabaski on Malaria versus the Tabaski Movement Effect
Figure 8: Coefficients from Regressions for Each Day in 2013 of Net Movement Between Arrondissements in Previous 7 days on Long Term Net Migration.

Figure 9: Weekly Correlation between Internal Migrants and Visitors for 3-21 days
(a) Districts with Significant Correlation Coefficients Between Out-Migrants and Visitors of 3-21 Days

(b) Districts with Significant Correlation Coefficients Between In-Migrants and Residents Returning after a visit of 3-21 Days

Figure 10: District Correlation Coefficients Between Migrants and Visits