Potential versus revealed access to care during a dengue fever outbreak

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Working paper. Manuscript accepted in July 2016 for Transport and Health

Abstract
Dengue fever is a vector-borne disease which spreads quickly under suitable conditions and puts certain segments of the population at higher risk, especially in developing countries. Prompt diagnosis of the disease is critical to (1) substantially reduce risks of morbidity and mortality and (2) prevent further expansion of an existing outbreak. Suitable geographic access to medical care and effective prevention campaigns can help achieve these two objectives. This paper examines patterns of health care use based on travel time during an outbreak of dengue fever in the city of Cali, Colombia. We map patterns of diagnosis by facility and identify associated travel disparities. Results indicate that travel times exhibited significant spatial autocorrelation, showing that patients living in the periphery of the city experienced substantially greater travel times compared with patients residing in the north-south corridor of the city, owing to the proximity of health care centers. Revealed travel times were nearly six times longer than estimated travel to the closest hospital, suggesting that the healthcare center where care was received rarely coincided with the closest option (only in 8% of cases). A multilevel model, accounting for both individual and neighborhood characteristics, was developed to explain variation in travel estimates. Results revealed that males and patients from affluent neighborhoods were more likely to travel longer and beyond their closest facility to receive care. These findings are important for policy related decisions such as (1) timely allocation and training of health personnel and (2) organizing informative campaigns aiming at increasing the awareness about the disease, especially for the population that is at high risk and/or most vulnerable.

Keywords: dengue fever, revealed and potential accessibility, travel times, multilevel modeling.

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1 Introduction

Dengue fever is an arboviral disease with a presence in more than one hundred tropical and subtropical countries (Kittayapong et al. 2008). The disease has gradually re-emerged across the global South, particularly affecting urban areas of the tropics and sub-tropics. In 2015, 2.35 million cases were reported in the Americas alone where severe cases resulted in 1181 deaths. In Colombia, the fatality rate for the year 2010 was 2.28% which was above the 2% threshold imposed for the virus (Rojas 2011). In that year, there were 146,354 dengue cases, of which 5420 were categorized as severe, resulting in a total of 174 deaths (Salud 2016).

The dengue virus (DEN) comprises of four serotypes (DENV-1, DENV-2, DENV-3 and DENV-4) and is transmitted by the Aedes Aegypti mosquito. The virus passes from one individual to another through the bites of the female Aedes mosquito and is acquired by the mosquito while feeding on an infected person (WHO 2016). After approximately 10 days, the virus spreads to the salivary glands of the mosquito and the virus can be transmitted to other humans. Once a human is infected, and after an incubation period of 4 to 10 days, symptoms - which include fever, joint and back pain, severe headache, and nausea - will last for 2 to 7 days. Once infected, humans become the main carriers and multipliers of the virus, serving as a source for uninfected mosquitoes.

The female Aedes Aegypti typically spend their lifetime in or around the houses where they emerge as adults. The transmission of the virus is thus focal (Kuno 1995, Morrison et al. 1998, Getis et al. 2003). Female Aedes Aegypti usually fly no more than 400 meters. This means that people, rather than mosquitoes, rapidly move the virus within and between communities and places. The virus has the potential to develop into a life-threatening version identified as severe dengue fever. There is no vaccine for dengue, but early detection and proper access to health care lowers fatality rates below 1% (WHO 2016). Treatment includes rehydration and may require blood transfusions for severe cases (Kolivras 2006). Timely diagnosis prevents existing outbreaks from expanding.

Several studies have used Geographic Information Systems (GIS) to document the temporal and spatial variation of the Aedes mosquito (Morrison et al. 2004, Koenraadt et al. 2008) and to identify clusters of dengue fever outbreaks (Mammen et al. 2008, Siqueira-Junior et al. 2008, Vazquez-Prokopec et al. 2010, Aldstadt et al. 2012, Hsueh et al. 2012, Delmelle et al. 2013a). However, no study has examined how individuals access health services during such outbreaks. Travel impedance may impact the timely receipt of health services, which is particularly critical since delays in diagnosis are likely to impact the outcome of the disease (Noor et al. 2003).

In this paper, we examine revealed travel patterns of individuals diagnosed with dengue fever during the 2010 outbreak in Cali, a rapidly expanding urban environment of Colombia, Latin America. For each diagnosis, we estimate travel time from the geocoded residential address of each patient to the healthcare facility where care was received. We compare actual travel time to the time necessary to reach the closest healthcare facility where care could have been received, or potential accessibility. Second, we develop a multilevel model, accounting for both individual and neighborhood characteristics to explain variation in travel estimates. The study therefore
identifies potential disparities in access to healthcare, but also highlights the increased choice of facilities available to those with greater resources to travel.

Our approach is descriptive and helps to (1) determine the adequacy and equity of health services, (2) identify areas characterized by an imbalance between revealed and potential accessibility and (3) determine whether patients who died from complications were at a disadvantage in accessing a health facility. Answers to these issues will inform health authorities on strategies to better plan preventive and control actions against dengue fever.

2 Background

Access is a fundamental measure of health care quality. This notion has been categorized into five different dimensions including: availability, affordability, acceptability, appropriateness, and accessibility (Penchansky and Thomas 1981). The focus of this study is on spatial accessibility, or the ability to reach a particular service from a given location (Luo and Whippo 2012, Levesque et al. 2013). Factors that may impact spatial accessibility include the supply of health care and the distribution of patients, as well as geographic impedance which is linked to the transport system (Delamater et al. 2012).

Various metrics have been developed to measure spatial accessibility ranging from the simpler distance or travel time to the nearest service (Rosero-Bixby 2004, Haynes et al. 2006, Tanser et al. 2006, Delamater et al. 2012, McGrail 2012, Leese et al. 2013), to metrics based on the notion of gravity, or the idea that larger and closer facilities are more attractive (Delmelle and Casas 2012, McGrail 2012, Hu et al. 2013, Wang and Tang 2013), and population-to-provider ratios (Schonfeld et al. 1972, Connor et al. 1995, Phillips and Lindbloom 2000). Improvements to these methods have also been proposed including inclusion of distance-decay functions and the use of variable catchment sizes (McGrail and Humphreys 2009, Dony et al. 2015). As expected, a large number of studies in access to health have been conducted in the developed world (Arcury et al. 2005, Langford and Higgs 2006, Delamater et al. 2012, Wong et al. 2012). However, recently there have been more conducted in the developing world (Rosero-Bixby 2004, Tanser et al. 2006, Friedman et al. 2013, Hu et al. 2013).

Spatial accessibility can be distinguished between potential and revealed accessibility; the former is based on the possibility for health care use given the services offered, while the latter is based on the actual utilization of the services and the act of receiving health care (Guagliardo 2004). The presence of geographical barriers affects access to service and may further result in unbalanced—or inaccessible—supply (Joseph and Phillip 1984, Haynes 1986, Jones and Bentham 1997, Perry and Gesler 2000). The overwhelming majority of studies in the literature examine potential accessibility (Luo and Whippo 2012, McGrail 2012, Hu et al. 2013, Kaljee et al. 2013, Wang and Tang 2013); while those on revealed accessibility less common given that they require revealed preference or utilization data sets which are expensive and time consuming to acquire (Parker and Campbell 1998, Perry and Gesler 2000, Brabyn and Skelly 2002, Buor 2003, Haynes et al. 2003, Rosero-Bixby 2004, Haynes et al. 2006, Tanser et al. 2006, Delamater et al. 2012).

This literature has generally recognized that the use of health services varies according to the
patient’s age, gender and income as well as with the separating distance between the patient and
the place where care is received. An individual may elect to travel further than the closest facility
when specific medical procedures are required (Buchmueller et al. 2006).

In developing countries, access to health care is uneven (Fosu 1989, Delmelle and Casas
2012) as the planning of the distribution of health services often does not consider socio-medical
priorities or how services are used (Fosu 1989). This makes measuring access to health care in
the developing world difficult (Bahr and Wehrhahn 1993), not only due to the populations’
characteristics (remoteness and lack of infrastructure to reach rural communities), but also the
costs involved in the process. However, countries in Latin America, for example, have made
substantial and consistent investments in research for health (Council on Health Research for
Development 2006).

In building upon work previously conducted by Casas et al. (2010), which illustrated how a
particular hospital in the city of Cali served a population well beyond its intended service area,
this paper presents results of an empirical study on access to health care by patients diagnosed
with dengue fever. The focus is on both potential and revealed access to healthcare facilities.
Factors influencing the choice of healthcare facility are examined at the individual and
neighborhood level using multilevel analysis. This paper contributes to the literature by
examining a disease of an endemic nature that constitutes a health threat in most of the countries
where it is present. It also contributes by presenting a revealed accessibility travel scenario that
helps in understanding individual choice and identifying estimation differences in travel times
when compared with potential destinations.

3 Data and Study Area

3.1 Study Area

Cali is the third largest city in Colombia with approximately 2.3 million people according to
the 2013 population census (Cali 2014). The city is characterized by a tropical climate with two
rainy seasons, its yearly precipitation totals 100mm while an average temperature of 26°C
provides a thriving environment for the reproduction of the Aedes Aegypti mosquito. The city of
Cali is administratively divided into twenty-two Communes (see Figure 1a), representing
groupings of neighborhoods exhibiting homogenous demographic and socioeconomic
characteristics. Neighborhoods are classified into six classes based on socioeconomic strata, six
being the highest and one the lowest (see Figure 1b). The stratification process is based on two
aspects: (1) the external physical characteristics of the housing stock and (2) its immediate
surroundings and urban context. Variables are observed under each aspect including, but not
limited to things such as: front yard, garage, door material, façade material, access road,
sidewalks, poverty, urban deterioration, and industry (DANE 2016). The stratification reflects
the urbanization process of the city from the old colonial core centered in communes three and
nine, suggesting an expansion pattern along the spinal corridor to the north and south and
subsequently on a radial pattern towards the periphery. Peripheral areas are characterized by
unplanned urbanization (Restrepo 2006), resulting in various squatter settlements with poor infrastructure.

Figure 1: (a) Administrative units in the city of Cali and (b) socio-economic strata at the neighborhood level.

### 3.2 Dengue Fever Data

The city of Cali has been an endemic region for dengue fever since the reemergence of the virus in the 1970s. Outbreaks were reported in 1995, 2002, 2005, 2010 (Cali 2010b) and more recently in 2013, with 2010 being the second worst in the last 25 years. Positively diagnosed cases of dengue fever are reported to the health municipality and recorded in the “Sistema de Vigilancia en Salud Pública” (SIVIGILA, English: Public health surveillance system). Individual information includes: patient’s data (sex, age, race and patient’s occupation), date of diagnosis, epidemiological week, day symptoms started, whether the patient was hospitalized, their final condition (dead or alive), and apparent symptoms. The database also includes the reporting institution (i.e., the health facility where the patient was diagnosed). Data used here corresponds to the 2010 outbreak and from SIVIGILA patient data (sex and age) and the reporting institution are included in the models. After standardizing the data to a format that would allow address
matching, residential addresses of patients were geocoded at the street intersection level. This is done to mask the data and maintain the privacy of the patients (Kwan et al. 2004). A total of 8,668 cases are included in the data set (see Figure 2a) for 2010 with clusters of patients in various neighborhoods throughout the city (see Figure 2b).

Figure 2: (a) Spatial distribution of dengue fever patients reported in 2010, (b) kernel density estimation, and (c) locations of hospitals utilized at least once by patients.

### 3.3 Healthcare Centers

In the city of Cali, medical services are provided by private and public (state owned) facilities (Cali 2010a). Healthcare facilities are further categorized based on their level of service (I: basic services with no beds, II: specialized services with no beds, level III: teaching university hospital with beds; level IV has recently been added to this list to refer to a particular private health facility with state of the art technology and infrastructure, the Fundación Clínica Valle del Lili in Figure 2c). Health posts are the simplest of all the healthcare facilities, followed by healthcare centers, hospital centers, and hospitals (or clinics) and other private and cooperative institutions providing more complex services. Cooperatives are a special kind of facility where a group of people come together to provide themselves associatively with services, therefore individuals are owners and members of the facility (Table 1).
<table>
<thead>
<tr>
<th>Institution</th>
<th>Number of Units</th>
<th>Institution</th>
<th>Number of Units</th>
</tr>
</thead>
<tbody>
<tr>
<td>Health Posts</td>
<td>66</td>
<td>Comfandi (cooperative)</td>
<td>13</td>
</tr>
<tr>
<td>Healthcare Centers</td>
<td>34</td>
<td>Comfenalco (cooperative)</td>
<td>5</td>
</tr>
<tr>
<td>Hospital Centers</td>
<td>5</td>
<td>Police Clinics</td>
<td>1</td>
</tr>
<tr>
<td>Hospitals – Level II</td>
<td>5</td>
<td>Private Clinics</td>
<td>22</td>
</tr>
<tr>
<td>Hospitals- Level III</td>
<td>2</td>
<td>Private Health Promoters</td>
<td>82</td>
</tr>
</tbody>
</table>

Table 1: Types of healthcare facilities in the city of Cali, 2010

In 2010, the patients who were diagnosed with dengue fever visited 167 different healthcare facilities (Figure 2c). However, due to incomplete data filed at the municipality, healthcare facilities reported by some patients could not be linked to the health facility database resulting in the removal of those cases (938 cases removed from 9606).

4 Methods

Potential and revealed accessibility are calculated for each geocoded patient. Potential accessibility is estimated based on the one-way travel time by private car from each patient’s residential address to their closest health facility, while revealed accessibility is estimated using the travel time to the health facility where the patient was diagnosed with dengue virus. Private car ownership for the year 2010 was reported based on the number of cars per 100000 people as 15418.9 cars (2244536 individuals/ 346082.76 cars). Motorcycle ownership was 4410 motorcycles per 100000 people (total of 98984 motorcycles for the city). The number of trips by public transport was not reported for 2010 because there was a complete change in the public transit system with a move to a BRT system. However, in 2008 the number of trips per 100000 people by public transport was 1862.4. Travel time is used as a proxy for travel cost (Martin et al. 2002, Apparicio et al. 2008, Shahid et al. 2009). Similar to Delmelle et al. (2013b), travel time is estimated in a commercial GIS environment, using the Dijkstra shortest-path algorithm. A road network to estimate travel impedance for the city of Cali is used, assuming a 40km/h travel speed. Excess travel is estimated as the difference in travel time between the closest hospital (potential) and the hospital where diagnosis was confirmed (revealed). Higher values of excess travel are indicative of patients incurring longer travel than if they had received care at the closest facility.

To explain variations in travel time among patients and to determine what factors might influence travel time, a multi-level modeling framework is utilized. This approach considers the nested structure of the data: patients are clustered within urban neighborhoods. Such clustering would violate the assumption of data independence in an ordinary least squares regression model. In this mixed model, two levels of independent variables are selected: individual and neighborhood. Unfortunately, patient data limitations restrict the availability of many individual level factors, however, age and gender of the patient is accounted for. Given the potential non-linear relationship between age and travel time (i.e., both older and younger adults potentially
have different travel behaviors than middle-aged patients), age is categorized into the following
groups: (1) Less than 10 years old, (2) 10-20 years old, (3) 20-50 years old, and (4) greater than
50. At the neighborhood level, the socioeconomic strata of the neighborhood is included as well
as the average travel time from a neighborhood’s centroid to all city hospitals. This latter
variable serves as a proxy for urban centrality while the former serves as a proxy for income.
For instance, for individuals residing in neighborhoods along the periphery who choose not to
visit their closest hospital, the next closest will be much further away than for those located
toward the urban core that have a greater number of hospitals to choose from within a closer
proximity.

5 Results and Discussion

The sample is composed of 8,668 patients, with a similar number of males and females,
however nearly 50% of the patients are younger than 20 years old. Studies have previously
shown that children are at a higher risk of contracting dengue fever than other age cohorts (WHO
2009, Martín et al. 2010). From the sample, 8,049 had the classic manifestation of dengue fever,
while 609 exhibited severe symptoms. A total of ten patients died as a result of contracting the
virus.

5.1 Demand Side

The demand side analysis presents accessibility results from the patient’s perspective, using
travel times from the patient’s home to the healthcare facility where they were diagnosed. On
average, the revealed travel time is nearly 6 minutes longer than the time needed to reach the
closest health facility suggesting that individuals traveled beyond their closest option (see Table
2). The average potential travel time to healthcare facilities for patients with dengue fever is
estimated to be approximately 1 minute (median: 54 seconds; range: 0 – 6.79 minutes). Nearly
60% of patients had to travel 1 minute or less to their closest health facility, but in reality the
revealed pattern departed significantly from the potential, pointing to an important
underestimation in travel time (6.82 minutes, median: 6.15 minutes; range: 0 – 24.94 minutes).

Separating data by age groups results in similar patterns. The difference is largest in children
younger than 10 years old. When analyzing excess travel grouped by age groups (less than 10,
10-20, 20-50, and greater than 50), a slightly greater mean in travel time difference is identified
for the youngest and oldest patients as compared with the two middle groups. The distribution
according to revealed travel time alone is identical.

Stratifying patients by type of dengue virus suggests significant differences in revealed travel
times (see Table 3). Individuals diagnosed with classic dengue fever travel on average 6.6
minutes to a health facility, while individuals diagnosed with the severe type travel almost 9
minutes. Travel times increase even more to 10.3 minutes when the person died as a result of the
virus. Some of this variation can be explained by the protocol used to treat dengue fever. If an
individual suspects he/she presents symptoms aligned with the severe dengue type or they have
been diagnosed at a healthcare facility and symptoms suggest a severe type, the patient needs to
be hospitalized. Not all healthcare facilities are equipped to care for this type of complication, therefore an individual may have to travel a longer distance to receive appropriate services which may require a referral (this is also the case for patients who died of complications). There is a significant difference in revealed travel times for dengue and severe dengue ($t= 10.68, p=0.0001$).

<table>
<thead>
<tr>
<th></th>
<th>Mean (min)</th>
<th>Median (min)</th>
<th>St. Deviation (min)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Travel Time – Revealed</td>
<td>6.82</td>
<td>6.15</td>
<td>4.53</td>
</tr>
<tr>
<td>Travel Time – Potential</td>
<td>1.03</td>
<td>0.89</td>
<td>0.68</td>
</tr>
<tr>
<td>Excess Travel Time</td>
<td>5.78</td>
<td>5.09</td>
<td>4.46</td>
</tr>
<tr>
<td>Total Patients</td>
<td>8668</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 2: One-way travel time for patients with dengue fever.

<table>
<thead>
<tr>
<th></th>
<th>Dengue</th>
<th>Severe Dengue</th>
<th>Deaths</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean (min)</td>
<td>St. Deviation</td>
<td>Mean (min)</td>
<td>St. Deviation</td>
</tr>
<tr>
<td>Travel Time – Revealed</td>
<td>6.67</td>
<td>4.49</td>
<td>8.69</td>
</tr>
<tr>
<td>Travel Time – Potential</td>
<td>1.03</td>
<td>0.68</td>
<td>1</td>
</tr>
<tr>
<td>Excess Travel Time</td>
<td>5.64</td>
<td>4.38</td>
<td>7.6</td>
</tr>
<tr>
<td>Total</td>
<td>8049</td>
<td>609</td>
<td>10</td>
</tr>
</tbody>
</table>

Table 3: One-way travel time, aggregated by type of dengue virus.

A significant difference in revealed travel times is observed among private and public healthcare facilities ($t= 16.29, p<0.01$). Table 4 shows that almost twice as many individuals were diagnosed at a private health facility and that those individuals were willing to travel longer. Private healthcare facilities tend to have more resources. Therefore, people demonstrate a preference for these facilities under the assumption that they will receive better care (e.g., more doctors, shorter wait time, and better quality of service).
### Table 4: One-way travel time, aggregated by type of health facility.

<table>
<thead>
<tr>
<th>Type of Hospital</th>
<th>Cooperative</th>
<th>Private</th>
<th>Public</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Mean (min)</td>
<td>St. Deviation</td>
<td>Mean (min)</td>
</tr>
<tr>
<td>Travel Time – Revealed</td>
<td>7.67</td>
<td>3.672</td>
<td>7.34</td>
</tr>
<tr>
<td>Travel Time – Potential</td>
<td>1.00</td>
<td>0.68</td>
<td>1.02</td>
</tr>
<tr>
<td>Total Patients</td>
<td>613</td>
<td>5314</td>
<td>2741</td>
</tr>
</tbody>
</table>

The analysis of travel time from the perspective of patients seeking a diagnosis suggests that in spite of distance being a barrier, individuals find a way to overcome it to obtain better care. As the disease becomes more life threatening (i.e., severe dengue) the desire or need to do so becomes even greater. That is also the case when children and the elderly are affected. It is important to note that dengue fever is similar to other endemic hemorrhagic fevers (e.g., malaria and leptospirosis) and misdiagnosis could occur, leading patients to search for more qualified doctors. It is clear that patients have a preference for privately owned healthcare facilities and are willing to travel further to reach those. The results further suggest that it is important to consider individual’s preferences in regards to health care when an endemic disease is the subject of study. Personal knowledge of the disease and how it affects them might influence their willingness to overcome distance barriers to obtain proper treatment.

### 5.2 Supply Side

The supply side analysis presents accessibility results from the healthcare facility perspective where the patient was diagnosed with dengue fever virus. Average one-way travel time for each health facility is estimated by aggregating all the travel times of that facility. The pattern in Figure 3a clearly indicates that longer travel times are incurred at those facilities located in the center of town and along the north-south spinal corridor. Assignment of patients to the facility that minimizes travel time (‘closest assignment’) is often a desirable outcome of public facility location decisions. Intuitively, hospitals with the longest travel time are also the ones with the least number of closest assignments (correlation = -0.68, *p* < .01, Figure 3b). Comparing Figures 3a and 3b, it is clear that if patients were to use their closest health facility, there would be a more even distribution of services within the city. However, this would be ideal if all facilities provided hospitalization comparable services, had similar carrying capacities, and were equally equipped, which is not the case (Table 1).

Facilities which are more evenly distributed throughout the city, health posts and healthcare centers, are located and designed to serve neighborhoods. They correspond to level I service which results in a general doctor’s visit. At this level, dengue fever can be diagnosed but no treatment can be provided if the patient is diagnosed with the severe type. In 2004, the *Isaías Duarte Cancino Hospital* (HIDC) was built in the eastern side of the city to help serve the demand for health services (Casas et al. 2010, see Figure 2c). However, the results show that individuals have a preference for hospitals that are further away.
Figure 3: (a) Average one-way travel time, aggregated at the facility level, (b) percentage of closest assignments: A larger dot denotes a healthcare center that receives patients for whom that center is their closest choice.

5.3 Neighborhood Level

Travel times are aggregated at the neighborhood level (Figure 4), as this scale of aggregation allows us to account for socio-economic information when modeling travel time. In the three figures, a darker blue color indicates regions where a health facility could not be accessed within a 15 minute driving budget. Lighter blue colors are reflective of a shorter travel time, pointing to a higher level of geographic accessibility. Significant geographic differences in potential travel time are observed across different neighborhoods of the city. Patients residing along the north-south corridor experience better geographic access to healthcare facilities than patients living in the periphery, owing to the geographical proximity of healthcare centers. This is the result of the city’s urbanization process, where many services concentrated in the core and along the spine. Following a health reform in the early 1990s (Echeverri 1996), existing newer and smaller healthcare facilities were transformed to comply with the new directives. The new directives proposed a health system model based on free regulated competition with demand subsidies to
protect the poor population. This also resulted in the construction of new facilities and the
delineation of service areas.

Excess travel results are shown in Figure 4c. Small values are indicative of patients treated at
their closest healthcare centers, while larger values (dark blue) indicate longer diagnostic travel
times. The differences are smaller in the center of the city along the North-South corridor and
greater along the Eastern edge of the city. An outlier to the southwest of the city corresponds to
the Fundación Valle del Lili, the only level IV facility containing state-of-the art technology and
facilities; it is the only one of its kind in the city.

Figure 4: (a) and (b) Potential and revealed one-way travel time aggregated at the neighborhood level, respectively,
(c) excess travel time (revealed minus potential) by car for patients. Neighborhoods forming a significant local
cluster of higher (lower) travel time are outlined in white (orange) (LISA statistic).

The local Moran’s I statistic (Anselin 1995) is used to test whether neighborhoods in close
spatial proximity to one another have similar travel impedance values. A cluster of high excess
travel is found in the neighborhoods in the Eastern edge of the city, while another cluster of low
excess values is found in the old center of Cali. The former suggests that people do not utilize the
newly created public hospital in the area. This might be for lack of knowledge of what kind of
services are available, for safety reasons (the hospital is in an area characterized by the presence
of gangs), or the belief that private institutions provide a better service. Collectively, the results
in Figure 4 demonstrate that while the potential access to a healthcare facility appears quite even
throughout the city, the revealed access paints a very different picture.
5.4 Multi-Level Model Results

Results of the regression analysis are displayed in Tables 4 and 5. Three models are run in sequential order: a null model with no explanatory variables, a second, model which incorporates individual-level independent variables, and a third model which adds neighborhood-level explanatory factors.

For the first dependent variable, travel time to the visited hospital for each patient, the null model indicates that the variance component associated with the random intercept is 5.95. Given the variance component of the residual, the intraclass correlation coefficient is computed revealing that 28 percent of the variation in travel time is attributed to neighborhood-level factors. The intercept of the fixed effect indicates the average travel time for all individuals to their chosen hospital across neighborhoods is 6.86 minutes. In the second model, individual-level variables are incorporated to explain variations in travel time. These include three age categories and gender. The age category of 20-50 is used as the reference category. Results suggest that compared with this latter group, those aged 11-20 have significantly lower travel times, while those in the oldest age group have significantly higher travel times to reach care. Compared with females, travel times for males are statistically significantly higher.

Finally, in the third model, two neighborhood-level variables are incorporated to help account for some of the neighborhood variation: the neighborhood’s socioeconomic strata and the average travel time from a neighborhood’s centroid to all city healthcare facilities, which serves as a measure of urban centrality. Both variables are statistically significant at $p < 0.05$. Those living in neighborhoods of a higher socioeconomic strata have longer travel times to reach care while those with longer average travel time to all healthcare facilities (less centrally located) similarly experience longer travel. The coefficient and significance of socioeconomic strata indicates that it is the more important factor in explaining longer travel times. The results support those found by others which suggest that access to healthcare facilities varies by age, sex, and income (Ensor and San 1996, Parker and Campbell 1998, Arcury et al. 2005). In terms of model fit, the AIC and BIC is lowest in the third model indicating the best fit for the data.

In the second set of models, excess travel is used as the dependent variable. The null model produces nearly identical results to the prior set of models with an interclass coefficient of 26 percent. The second model with individual-level factors suggests that compared with patients in the middle age category (ages 20-50), younger patients (ages 11-20) have significantly less excess travel to health care and older patients (aged 50 and above) have significantly longer excess travel times. Consistent with the previous set of models, males have significantly more excess travel as compared with females. Finally, in the third model, when neighborhood factors are accounted for, the socio-economic strata of a neighborhood is positively associated with excess travel, but the variable representing the average travel time to all healthcare facilities is not significant. This latter result stands in contrast to the previous models explaining travel time alone where this variable was positive and significant. In both sets of models, neighborhood socioeconomic strata serves as a proxy for the socioeconomic status of individuals, assuming that residents sort themselves in neighborhoods according to education, income leading to relatively
homogeneous groupings of individuals in each neighborhood. This variable is significant and positive in both models suggesting that residents of a higher socioeconomic status travel farther and are more likely to travel to a hospital farther from their closest facility. This is plausibly the result of an increased choice set amongst the more well-off. Given that traveling further distances incurs as a greater cost (both monetarily as well as in respect to travel time), the decision to travel a farther distance to utilize a particular hospital. Lower-income residents may also be restricted by transportation options such as the availability of private vehicles to get to particular destinations.

<table>
<thead>
<tr>
<th>Fixed Effects</th>
<th>Model 1</th>
<th>Model 2: Individual level variables</th>
<th>Model 3: Individual and Neighborhood</th>
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</thead>
<tbody>
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<td>6.75* (0.17)</td>
<td>1.49* (0.31)</td>
</tr>
<tr>
<td>Aged 10 and Younger</td>
<td>0.12 (0.10)</td>
<td>0.19 (0.10)</td>
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</tr>
<tr>
<td>Aged 11-20</td>
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<td>-0.29* (0.11)</td>
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<tr>
<td>Aged 20-50 (Ref.)</td>
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<td>-0.09 (0.11)</td>
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</tr>
<tr>
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<td>0.21* (0.08)</td>
<td>1.17* (0.04)</td>
</tr>
<tr>
<td>SES Strata</td>
<td>1.17* (0.04)</td>
<td>1.17* (0.04)</td>
<td>1.17* (0.04)</td>
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<tr>
<td>Average distance</td>
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<td>0.002* (0.0004)</td>
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<tr>
<th>Random Effects</th>
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<tbody>
<tr>
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<td>5.99 (2.44)</td>
<td>6.13 (2.47)</td>
</tr>
<tr>
<td>Residual</td>
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<td>15.05 (3.88)</td>
<td>13.49 (3.67)</td>
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</table>

<table>
<thead>
<tr>
<th>Model Fit Statistics</th>
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<tr>
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<td>47899.10</td>
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<tr>
<td>BIC</td>
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<td>48863.96</td>
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<td>-23940.55</td>
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<td>47881.10</td>
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<td>8668</td>
<td>8668</td>
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<td>Number of Groups</td>
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<td>327</td>
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*Significant at p<0.05; Standard errors shown in parentheses

Table 5: Multi-level model results: dependent variable travel time to health facility by car.
Dependent Variable = Excess Travel

<table>
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<tr>
<th>Fixed Effects</th>
<th>Model 1 (Null)</th>
<th>Model 2: Individual level variables</th>
<th>Model 3: Individual and Neighborhood</th>
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<tr>
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<td>1.28* (0.30)</td>
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<tr>
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<td>0.12 (0.11)</td>
<td>0.20* (0.10)</td>
</tr>
<tr>
<td>Aged 11-20</td>
<td></td>
<td>-0.29* (0.11)</td>
<td>-0.28* (0.11)</td>
</tr>
<tr>
<td>Aged 20-50 (Ref.)</td>
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<td></td>
<td></td>
</tr>
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<td>Aged &gt;50</td>
<td></td>
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<td>0.20 (0.13)</td>
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<tr>
<td>Male</td>
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<td>0.21* (0.08)</td>
<td>0.22* (0.08)</td>
</tr>
<tr>
<td>SES Strata</td>
<td></td>
<td></td>
<td>1.17* (0.04)</td>
</tr>
<tr>
<td>Average distance</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Random Effects</td>
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<td>5.41 (2.44)</td>
<td>5.44 (2.33)</td>
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<tr>
<td>(Neighborhood)</td>
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<td>5.88 (2.43)</td>
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</tr>
<tr>
<td>Residual</td>
<td>15.15 (3.89)</td>
<td>15.09 (3.88)</td>
<td>13.52 (3.68)</td>
</tr>
<tr>
<td>Model Fit Statistics</td>
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<td></td>
<td></td>
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<td>Deviance</td>
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<tr>
<td>Number of Observations</td>
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<td>8668</td>
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<td>Number of Groups</td>
<td>327</td>
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<td>327</td>
</tr>
</tbody>
</table>

*Significant at p<0.05; Standard errors shown in parentheses

Table 6: Multi-level model results: dependent variable excess travel time to health facility.

Taken together, these results suggest that those located on the outer periphery of the city travel longer, in general, to reach health care, but their spatial location does not dictate whether or not they are willing to travel beyond their closest hospital to reach care. This choice is a factor of the socio-economic conditions of that individual’s neighborhood and of other individual characteristics. Regardless of their proximity to the overall offering of urban healthcare facilities, those with greater resources seem to be willing to overcome spatial barriers to access better care. In this final model, the variable representing the youngest patients is positive and statistically significant. Given the vulnerability of these patients, it makes sense that they would be taken for care at a health facility with more critical care resources that may not be their closest facility. Model fit criteria point to the third model as the best fit with the data.

6 Conclusions

Improving access to primary health care can have a direct impact in improving health outcomes (Perry and Gesler 2000). Although travel time for patients diagnosed with dengue fever in the city of Cali may appear relatively small (average = 6 minutes), the departure from the potential travel time to the closest facility is significant, revealing an underestimation of potential travel time. The map illustrating the distribution of potential access to the closest healthcare facility indicates an equitable distribution of potential travel times, however, the
revealed travel times pointed to significant clusters of longer travel times throughout the urban area. Given that the overwhelming majority of accessibility studies are potential in nature – often used for evaluating the equity of the distribution of facilities or a transportation network – this study emphasizes that actual travel times may depart from these estimations and highlight inequalities that are not apparent in potential access scenarios.

In this study, we found that both individual and neighborhood characteristics helped explain travel times and excess travel times, or the difference between the travel time to the closest facility and the chosen facility. Individuals in neighborhoods of a higher socioeconomic status chose to travel to facilities located further away than their closest facility. Travel times also increase for patients diagnosed with severe dengue fever and those whose diagnosis resulted in death. There are other endemic hemorrhagic fevers (e.g., malaria and leptospirosis) similar to dengue fever, that can lead patients to search for more qualified doctors to obtain an accurate diagnosis. In the year 2010, there were 608 cases of malaria (Municipal 2012) and 344 of leptospirosis (Pública 2011). Even though these numbers are not comparable to those of dengue for the year 2010, there is potential for misdiagnosing diseases.

It is important to note that besides comparisons in travel times, the results suggest that patients favor healthcare facilities located in the city’s central core. This area has a concentration of services with facilities that (1) are better equipped to treat the virus if necessary, (2) are mostly privately owned and (3) have been in operation for at least 30 years or more. In the rest of the city, a more uniform distribution of public healthcare facilities can be observed. A personal choice to receive private or public health care may thus motivate individuals to travel further. The multi-level models show that travel time is influenced mainly by income and distance to the facilities. This corroborates findings by Ensor and San (1996), Parker and Campbell (1998), and Arcury et al. (2005) and again may point to a wider choice set of hospitals for wealthier residents. Those living in neighborhoods of a higher socioeconomic status were more likely to travel farther and go beyond their closest facility to receive care, while residents in lower income neighborhoods were more likely to use the closest facility.

### 6.1 Assumptions and Limitations

This study relied on several assumptions which may affect the validity of our results. First, we estimated travel impedance as the distance between the patient’s residential address to the hospital where the diagnosis was conducted. The residential address may not have been the place where the patient was infected. Second, travel was assumed to be done by private automobile and not by public transportation. Third, our measure of travel impedance does not account for road construction/congestion and as such our distances are likely to be underestimates of the true travel. Fourth, geocoding was conducted at the nearest intersection from the place of residence; this choice is motivated by a lack of accurate address ranges and an effort to preserve patient’s privacy. Fifth, we did not incorporate information related to the capacity of each healthcare center (such as the number of doctors and nurses). This may influence the decision to seek health care service elsewhere.
6.2 Strengths

Despite these limitations, our paper demonstrated several strengths. To the authors’ knowledge, this is the first attempt to estimate spatial accessibility to health care center during a dengue fever epidemic. Second, the paper estimates accessibility using healthcare center discharge information. The quasi majority of studies modeling spatial accessibility have used potential accessibility metrics, which are based on the estimated travel impedance to the closest healthcare center. As demonstrated in this paper, the closest healthcare center is rarely the patient’s choice. Third, our accessibility is estimated at the individual level unlike most studies which use aggregated information.

6.3 Implications

Results from this work are very valuable to health officials to design and plan protocols for prevention and control of the dengue virus. For example, campaigns geared towards children showing where they can be most efficiently treated can be designed as to capitalize on the facilities which can provide this particular service (i.e., children’s hospital). Second, awareness can be raised as to the effects of the virus on this vulnerable group. Knowing which facilities are preferred by patients for treatment will help focus resources at these locations to educate people on how to prevent such disease. This is all the more important given that facilities offer different services and it is important not to waste resources if they are not needed. Not all public facilities can be equipped the same way, which is why the different levels exist. Being aware of patients’ preferences regarding their choice of facilities can help officials in resource allocation. It is also possible to identify focal points of the virus by identifying locations that are overwhelmed with dengue patients. Knowledge on the distribution of the *Aedes Aegypti* inside the household and the existence of the larvae and pupae can further aid in this process (Getis et al. 2003).

6.4 Future Research

Although data availability has constrained the ability to identify other potential variables that could influence patients’ choice for a healthcare facility, personal interviews geared towards the decision making process will help in the collection of such data. For instance, if symptoms were discovered shortly after the incubation period, an individual may have more time to choose among different health care facilities. Alternatively, a late discovery may require a more urgent diagnosis and an individual may decide to visit the closest facility. Second, future research will investigate how public transit affects travel estimates and its impact on the patient’s choice of healthcare facility. Third, we will compare our travel estimates to the ones from online providers, such as Google Maps (see for instance Delmelle et al. 2013a). Finally, it would be valuable to contrast the results of this study for individuals who are diagnosed with severe hemorrhagic dengue fever symptoms.
7 Acknowledgments

The authors would like to thank MetroCali for providing the city’s street network and the Public Health Secretariat of the city of Cali for the dengue fever surveillance data.
8 References


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---. 2016. Dengue and dengue haemorrhagic fever - Fact sheet no. 117. WHO.