Estimating the Impact of Improved Roads on Access to Health Care

Evidence from Mozambique

Atsushi Iimi
Abstract

The paper recasts light on the linkage between transport infrastructure and human capital development. Health care access is an important challenge in many developing countries. In particular in remote rural areas, it is not easy to access good quality health care services. Among others, transport connectivity is often an important constraint. The paper estimates the impact of transport connectivity on access to health care services in Mozambique, especially focused on people’s decision about whether they visit and ask for advice at a health facility if they have a fever. This is a critical question in Mozambique where malaria is still a life-threatening disease. About three-quarters of the total population does not have access to health facilities by walking. The paper shows that transport connectivity to health facilities is a significant determinant of people’s health care access. Owning transport means, such as a bike or a motorcycle, is also instrumental to promoting people’s access to health care. The rich are more likely to benefit from health care services, suggesting a need for other complementary policies, such as a health care subsidy and insurance, to improve health care accessibility.

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Estimating the Impact of Improved Roads on Access to Health Care: Evidence from Mozambique

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Key words: rural roads; health care access; transport connectivity; probability regression estimation.

JEL classification: C25, C26, I15, R42.

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I. Introduction

Health care access is still an important challenge in many developing countries. In particular in remote rural areas, it is not easy to access good quality health care services (e.g., Gamm et al. 2003; Institute of Medicine 2005; Bourke et al. 2012). Even in the United States, the rural elderly living in remote areas are 13 percent less likely to visit the emergency department than their urban counterparts (Lishner et al. 2000).

Transport connectivity is among the most important constraints in remote areas. Travel distance for rural people to visit a health facility is often much longer than that for urban dwellers (Gamm et al. 2003). This is particularly true in developing countries. In Zambia, for instance, about 75 percent of urban residents, but only 30 percent of rural residents, live within 2 kilometers of the nearest health facility (Zambia Central Statistical Office 2012). In Liberia, about 40 percent of rural residents must spend more than 2 hours to walk to the nearest health facility (Kruk et al. 2010). In Africa, about 70 percent of the total rural population do not have access to any all-weather road (Roberts et al., 2006). Transport services to visit health facilities are also not be available in rural areas even though the road network exists (e.g., Klemick et al. 2009).

Notably, however, the potential impact of better transport connectivity on people’s health care access is less obvious than we might think. There are a variety of effects on both the demand and supply sides, which make it difficult to measure the true impact of transport connectivity. For instance, rural residents may have less reliable transport connectivity to health facilities, but their household income is often lower than that in urban areas. Subscription to health insurance is also lower in rural areas (Jovanovic et al. 2003). Health insurance is an important policy measure to improve people’s health care access in developing countries (see, e.g., Spaan et al., 2012). Because of the lack of proper insurance, rural residents are less likely to use emergency medical services (Fan et al., 2011).
On the supply side, limited connectivity complicates other factors as well. For instance, doctors and nurses are generally less available in rural health facilities. In the United States, only 9 percent of physicians practice in rural areas where about 20 percent of the total population lives (Rosenblatt and Hart 2000). As a result, rural physicians often have to see more patients than urban doctors do, therefore, potentially compromising the level of services they provide. In rural areas, fewer medical ancillary services are provided (Bronstein et al., 1997). Medical supplies may also be insufficient in rural and remote areas because of unreliable transport accessibility (Iimi and Rajoela, 2018). These supply-side constraints further reduce the rural residents’ demand for health services.

The current paper attempts to estimate the net impact of transport connectivity on people’s health care service access, by taking advantage of spatially disaggregated rich micro data from Mozambique. It will be focused on the people’s decision-making process on whether or not they visit a health facility when they have a fever. This is a critical decision in particular in many African countries. To prevent illness and death, it is essential to have good access to primary care services (e.g., Starfield et al., 2005). According to Laditka et al. (2009), rural residents are more likely to be hospitalized for ambulatory care sensitive conditions. This could have been prevented if people had better access to primary care, but because they do not, their condition tends to deteriorate.

Despite recent marked progress, malaria remains an important risk in many developing countries, including Mozambique. Children aged under 5 years are the most vulnerable group affected by malaria. Globally, it is estimated that 228 million cases of malaria occurred worldwide in 2018 and 405,000 people died from malaria (WHO 2019). Africa accounts for about 94 percent of global malaria deaths. Nigeria accounts for 24 percent, followed by 11 percent in the Democratic Republic of Congo, 5 percent in Tanzania and 4 percent in Mozambique.

From the methodological point of view, the paper also contributes to exploring the way of combining rich micro data in the health sector with emerging spatial data, which can be used
for measuring transport connectivity in different ways, while avoiding potential endogeneity caused by infrastructure placement. The primary data come from the Demographic and Health Surveys (DHS) carried out in Mozambique at two different points of time: 2011 and 2018. During this period, the government invested heavily in the road network, presumably resulting in significant improvement in connectivity. The paper exploits such variations observed over time to examine how people changed their behavior when they have a fever. To mitigate the potential bias caused by unobservables, household-, facility- and location-specific characteristics are controlled.

The following sections are organized as follows: Section II describes some country background in the health and transport sector. Section III develops a methodology and summarizes our data. Section IV presents the main estimation results and discusses policy implications. Then, Section V concludes.

**II. Country context**

In Mozambique, various health indicators have been improved in recent years. Life expectancy increased by nearly 9 years since 2001, from 48.8 to 57.6. Infant mortality, expressed as the number deaths per thousand live births, fell from 99.1 in 2003 to 68.1 in 2011 (World Bank, 2020). The share of children under 5 years old who slept under an insecticide-treated net (ITN) increased from 35 percent in 2011 to 73 percent in 2018 (DHS 2019). The number of malaria deaths declined from over 3,000 in 2014 to about 1,000 in 2018 (Figure 1).

Still, malaria remains one of the most important challenges to the country. Mozambique has one of the highest malaria death rates in the world. Importantly, while the number of deaths significantly declined, the total number of malaria cases reported has not reduced. According to the WHO statistics, the number of confirmed cases increased from 3.4 million in 2010 to 5.5 million in 2015 and 9.3 million in 2018. While antimalarials only cost a few U.S. cents to a few dollars at most, malaria treatment costs can be considerable. Though no comparable
data are available in Mozambique, the average treatment cost for even uncomplicated malaria is estimated at US$31.5 per case in Nigeria (Ezenduka et al., 2017). If the same cost is applied, Mozambique is estimated to spend US$294 million for malaria treatment every year, which accounts for about 2 percent of the country’s GDP.

From a geospatial point of view, Mozambique has a well-established health network covering the entire nation. According to the regional data developed by WHO (Maina et al., 2019), there are 1,579 health facilities all over the country (Figure 2). There are three central hospitals and 8 provincial hospitals. Rural health centers and health posts account for nearly about 90 percent of the facilities (Table 1). Although

![Figure 1. Malaria cases and deaths in Mozambique](image1)

Sources: WDI, WHO (2019).

![Figure 2. Health facilities in Mozambique](image2)

Source: Based on Maina et al. (2019).

| Type                  | Number of facilities |
|-----------------------|----------------------|
| Hospital Central      | 3                    |
| Hospital Provincial   | 8                    |
| Hospital Distrital    | 16                   |
| Hospital Geral        | 5                    |
| Hospital Rural        | 29                   |
| Centro de Saude Urbano A | 39               |
| Centro de Saude Urbano B | 56               |
| Centro de Saude Urbano C | 49               |
| Centro de Saude Rural I | 130              |
| Centro de Saude Rural II | 982              |
| Posto de Saude        | 262                  |
| **Total**             | **1579**             |

Source: Based on Maina et al. (2019).
Mozambicans are still lacking access to health care services, particularly in rural areas. While health infrastructure is limited, medicine stockouts are common (USAID 2020). Transport connectivity is also a matter of concern. In rural Mozambique, more than 60 percent of the population lacks access to health services because of high transportation costs and long travel distance (Schiwitters et al. 2015). Geographically, about 90 percent of Mozambique is considered as unserved areas, in which 67 percent of the total Mozambican population lives (Luis and Cabral, 2016). Moreover, access to socioeconomic facilities seems to have deteriorated in recent years (Figure 3).

Figure 3. Distance to facilities by walking time in Mozambique

Source: World Bank (2019).

About three-quarters of Mozambicans do not have access to health facilities by walking. There is no universally accepted notion to allow people to travel for health care. Following the literature (e.g., Luis and Cabral, 2016), two thresholds are examined: 1-hour walking distance and 1 hour driving distance. The share of the total population who live within the 1 hour walking distance is estimated to have increased from 19.8 percent in 2010 to 24.8 percent in 2017 (Figure 4). On the other hand, the 1-hour connectivity by vehicle slightly declined from 68.1 percent to 64.1 percent during the same period (Figure 5). One of the interpretations is that accessibility improved within the close areas to health facilities, while very remote areas are left less connected. This looks consistent with the fact that the quality of the rural road network worsened in recent years.
By region, health care access varies across areas considerably. While the accessibility is relatively good around urban areas and along the main corridors, rural areas are lagging behind, particularly in Niassa, Tete, Gaza and Inhambane Provinces. There were some minor improvements in different places, but the regional inequality remains persistent over the period between 2010 and 2017. The areas that had poor accessibility in 2010 are still poorly connected to health facilities.

Figure 4. Health access by district: Share of population within 1 hour walking distance (2010)
In the transport sector, rural accessibility has long been a challenge in Mozambique. Mozambique has a road network of about 29,800 km of classified roads, out of which about 8,300 km or 27 percent of roads are paved (Figure 6). The road network broadly covers the entire country, however, road density remains low at 3.8 km per 100 km² of land, which is among the lowest in the region and unfavorably compared with its neighboring countries (for example, 11 km in Kenya and 6 km in Tanzania). This means that a lot of feeder roads remain unclassified, for which the government does not have the responsibility to rehabilitate or maintain. Even if they are classified, many secondary and tertiary roads, particularly, unpaved ones are in poor condition. As a result, many Mozambicans presumably have difficulty in their last mile connectivity, even though primary paved roads were improved substantially in recent years and are relatively well maintained (Figure 7).

In 2017, about 16 million people were estimated to live without access to the good road network, which translates into a rural access index (RAI) of 19.3 percent, a slight improvement from 20.4 percent in 2010. Within the country, rural accessibility varies substantially depending on location, and regional inequality has been widened in recent
years. At the district level, the RAI is, for instance, high at 60.8 percent in Chokwe, followed by about 45 percent in Manhica, Bilene and Maputo. In most of the rural areas, however, the RAI is estimated at less than 10 percent (Figure 8). There is no doubt that the people’s health care access is influenced depending on their connectivity.

Figure 6. Road and population distribution

Figure 7. Road condition by road class

Figure 8. Rural Access Index (2010) (2017)

Sources: WorldPop, ANE.

Source: ANE
III. Methodology and data

To examine the impact of transport connectivity on health care access, the current paper is focused on the following particular question: Do people choose to visit a health facility and seek medical advice or treatment when they have a fever? This is such an important question in the Mozambican context. As discussed above, malaria is still a life-threatening serious disease in Mozambique, which accounts for 29 percent of all deaths and 42 percent of deaths in children less than five years old (USAID 2018). In 2018 about 40 percent of children age 6-59 months were tested positive. Whether or not children are protected from malaria is crucially dependent on their parents’ decision on whether to take them to a health facility as soon as possible. It is well known that preventive measures and early stage treatments are much better and cost effective than treating more severe complications of malaria. Importantly, there is wide regional variation in the malaria prevalence rate, from less than 1 percent in Maputo City to 57 percent in Cabo Delgado. This seems to be attributable to the difference in health care accessibility among regions. Of course, however, there are also other factors that may explain such differences.

To identify different effects, the following probability model is considered: Suppose that individual $i$ decides to seek advice at health facility $j$ at time $t$, depending on transport connectivity from her house to the nearest health facility ($Z_{it}$), other individual and household characteristics ($X_{it}$), and the nearest health facility-specific attributes ($V_{jt}$):

$$Y_{ijt} = \begin{cases} 1 & \text{if } Y_{ijt}^* = Z_{it}' \alpha + X_{it}' \beta_1 + V_{jt}' \beta_2 + c_t + \epsilon_{ijt} > 0 \\ 0 & \text{otherwise} \end{cases}$$

where $Y^*$ is a latent value. In our data, there is a wide variation in transport connectivity $Z$ across locations as well as over time. This constitutes the basis of empirical identification. $c_t$ is the time-specific fixed-effect.
Note that the data are not panel but two cross-sectional data at two points of time, i.e., 2011 and 2018. These two rounds are selected because the transport connectivity variables are available for 2010 and 2017. To avoid potential complexity of endogeneity between infrastructure placement and health outcomes, some time lag is preserved between transport data and health data.

The two surveys have different focuses. The former surveyed about 9,800 individuals, and the latter covered about 29,000 individuals. However, it is found that both data sets covered the entire country geographically (Figure 9). The reported health conditions and behavior when people have a fever are also broadly similar between the two surveys. About 13 percent of people reported in 2011 that they had a fever in the last two weeks. This ratio slightly increased to 17 percent in 2018. For both years, however, slightly more than half of those who had a fever visited a health facility (Figure 10). The share of those who consulted looks indifferent between 2011 and 2018.

Figure 9. Clusters surveyed by two DHS data

Source: Based on DHS data.
By region, the probability of a person visiting a hospital looks substantially different. The probability tends to be high around urban areas and along the main corridors but remains less than 10 percent in certain rural areas, particularly in Niassa, Tete and Gaza Provinces. (Figure 11). Note that the DHS surveys are not designed to be statistically representative at the detailed subnational level. However, the regional difference in the people’s likelihood to visit a hospital appears broadly consistent with the above-mentioned spatial difference in rural accessibility in the previous section.

Not surprisingly, the simple correlation analysis already indicates that people who live closer to a health facility are twice more likely to visit a health facility for seeking advice or treatment for fever (Figure 12). Of course, other factors may also matter. But on this basis, if a health facility is available in less than 20 minutes, 70 percent of people would seek advice at a health facility. If it is more than 2 hours away from home, only 40 to 50 percent would visit.
To estimate Equation (1), there are at least two empirical challenges. First, there may be sample selection bias. As shown above, only 13-17 percent of the sampled households or individuals reported that they had a fever in the last two weeks and therefore were asked whether or not they visited a health facility. Thus, the probability regression with data from those who had a fever could potentially lead to sample selection bias. To deal with this problem, the probit model with sample selection is considered, for which the following selection equation is assumed:
\[ D_{ijt} = \begin{cases} 1 & \text{if } D_{ijt}^* = W_{it}' \gamma_1 + X_{it}' \gamma_2 + c_t + u_{ijt} > 0 \\ 0 & \text{otherwise} \end{cases} \] (2)

where \( D \) is set to one if the dependent variable for observation \( i \) is observed, that is, individual \( i \) had a fever, and zero otherwise. Both error terms, \( \varepsilon \) and \( u \), are distributed according to \( N(0,1) \) and \( \text{corr}(\varepsilon, u) = \rho \). When \( \rho = 0 \), the standard probit regression can be applied to Equation (1). Otherwise, the result would be biased.

In our context, whether an individual had a fever may be particularly dependent on household sanitary conditions and hygiene practices, including availability of piped water and flush toilets and application of mosquito nets. These are included in \( W \) in the equation. The transport connectivity variables \( Z \) can also potentially be included. However, the ex post test statistics indicate that they are not statistically relevant to this sample selection. That is, whether people have a fever or not does not depend on transport connectivity. See more details in the following section.

The second empirical challenge is that there might be unobserved household or individual characteristics, which may lead to omitted variable bias. For example, those who live in warm and humid areas may be more exposed to higher risk of mosquito-borne diseases, such as malaria, than those who live in dry and cool areas. Recall that our data are two cross-sectional data sets. Thus, it is impossible to control for these unobservables at the individual or household level. To address this problem, the district fixed effects are used, taking advantage of available spatial information of households in the DHS data. This may not be able to remove unobservables completely but can control for unobserved characteristics to a large extent. The number of district dummy variables that can be included is about 120, depending on specification. Statistically, the hypothesis that there are no district fixed effects can be easily rejected, as will be seen in the following sections.
On the health side, the sample data come from the two DHS data in 2011 and 2018. After data with missing values are excluded, data for about 38,000 individuals are used, of which about 5,800 people reported that they had a fever within the last two weeks. On the transport side, travel time is estimated by using spatial analysis based on the underlying road conditions. Using road condition data (i.e., road roughness), network analysis was carried out to estimate the shortest travel time required to visit a health facility. In general, it takes more time to drive on roads in poor condition. Other connectivity variables, such as estimated transport costs and road distance, which are used in the robustness discussion, are also calculated in the same manner. These variables are all related to the underlying road conditions but different. The average travel time to visit a health facility is 0.14 hour i.e., about 10 minutes (Table 2). However, there is a substantial variation from nearly zero minutes to more than 2 hours.

The information on whether a household owns transport means is also included in the model. In general, transport means are conducive to better access of households to health facilities. In our data, about 38 percent of households possess bikes or motorcycles. There are only a few households that own cars.

Whether people visit a health facility may also depend on what kind of facility exists around them. The model includes the type of health facility, following Mozambique’s health system classification: Hospital, urban and rural health centers, and health posts. Since remoteness may be a general disadvantage of health facilities in terms of medical supplies and availability of doctors and nurses, the distance from each facility to the nearest major city is calculated and included in the model. The major cities with more than 100,000 population are considered, and the distance is measured by travel time by car.

In addition to traditional individual and household characteristics, such as household head’s age and sex, the analysis uses a set of household characteristics related to sanitary conditions and hygiene practices for the selection equation. These are particularly important in our health or malaria context. While 35 percent of households have access to electricity,
33 percent have access to piped water. Flush toilets are less available. Most households have at least one mosquito net. However, only 45 percent of households own mosquito nets used for kids. These characteristics are considered to be important to determine if people are likely to be affected by disease, having a fever.

**Table 2. Summary statistics**

|                        | Obs  | Mean  | Std. Dev. | Min  | Max  |
|------------------------|------|-------|-----------|------|------|
| **Dependent variable:**|      |       |           |      |      |
| Y: Visit a health facility | 5,778 | 0.60  | 0.49      | 0    | 1    |
| **Transport connectivity variable:** |      |       |           |      |      |
| Travel time to HF (hours) | 36,134 | 0.14  | 0.22      | 0.00002 | 2.67 |
| Transport cost to go to HF ($) | 36,397 | 0.38  | 0.56      | 0.00011 | 6.34 |
| Distance to HF (km) | 36,570 | 5.46  | 7.86      | 0.00239 | 66.11 |
| Bike/Motorcycle owned | 38,115 | 0.38  | 0.49      | 0    | 1    |
| Car owned | 38,115 | 0.07  | 0.25      | 0    | 1    |
| **Health facility characteristics:** |      |       |           |      |      |
| Rural health center | 38,092 | 0.64  | 0.48      | 0    | 1    |
| Urban health center | 38,092 | 0.17  | 0.38      | 0    | 1    |
| Hospital | 38,092 | 0.09  | 0.29      | 0    | 1    |
| Health post | 38,092 | 0.09  | 0.28      | 0    | 1    |
| Remoteness of HF (hours to the nearest city with 100,000 population or more) | 37,533 | 1.81  | 2.08      | 0.0010 | 16.35 |
| **Individual characteristics:** |      |       |           |      |      |
| Age | 38,115 | 16.74 | 18.42     | 0    | 95   |
| Female | 38,115 | 0.51  | 0.50      | 0    | 1    |
| **Household characteristics:** |      |       |           |      |      |
| HH size | 38,115 | 6.14  | 3.00      | 1    | 33   |
| Female HH head | 38,115 | 0.31  | 0.46      | 0    | 1    |
| Age of HH head | 38,115 | 42.68 | 14.47     | 14   | 97   |
| No of bedrooms | 38,115 | 2.35  | 1.30      | 0    | 22   |
| Wealth index | 38,115 | 3.25  | 1.41      | 1    | 5    |
| Access to power | 38,115 | 0.35  | 0.48      | 0    | 1    |
| Piped water | 38,115 | 0.33  | 0.47      | 0    | 1    |
| Flush toilet | 38,115 | 0.12  | 0.33      | 0    | 1    |
| Solid roof | 38,115 | 0.51  | 0.50      | 0    | 1    |
| Mosquito net | 38,115 | 0.84  | 0.36      | 0    | 1    |
| Mosquito net for kids | 38,115 | 0.45  | 0.50      | 0    | 1    |
| **Time fixed effects:** |      |       |           |      |      |
| t=2011 | 38,115 | 0.25  | 0.43      | 0    | 1    |
| t=2018 | 38,115 | 0.75  | 0.43      | 0    | 1    |
IV. Main estimation results

First, the probit regression with sample selection is performed. As discussed, there is a possibility that the sample selection matters. That is, people’s decision on whether to visit a health facility, $Y$, is conditional on people having a fever. With the sample selection controlled, it is found that the probability of visiting a health facility decreases with required travel time, as expected. The coefficient is significantly negative at -0.563 (Table 3). In addition, people are more likely to go to the hospital when they own bikes or motorcycles. This is also consistent with prior expectation.

Compared with rural health centers (baseline), urban health centers and hospitals are more attractive, holding other conditions constant. This follows the literature: People prefer to visit a well-equipped health facility, indicating that rural health facilities are disadvantageous. The remoteness of health facilities also has a negative and significant coefficient, evidencing their general disadvantages. While many individual and household characteristics are found to be irrelevant to the decision of whether to visit a health facility, the wealth index has a strong impact. It means that the richer tend to visit to health facilities more frequently. The wealth index is a composite measure (quantile) of a household’s cumulative living standard estimated by the DHS Program.

In the selection equation, three household-specific variables related to sanitary and dwelling conditions are found to be significant: Access to power, piped water and flush toilet. If a household has access to these facilities, its household members are less likely to have a fever, holding other conditions constant. This can be interpreted as a positive impact of good sanitary conditions and hygiene practices at the household level.

From the statistical point of view, the exclusion restriction of these sanitary and dwelling condition variables is supported by our data. When the probit model is applied to the health access equation including these variables (as shown in the last column model of the table),
the hypothesis that their coefficients are all zero cannot be rejected. The chi-square test statistic with a degree of freedom of 6 is estimated at 7.19. Thus, these sanitary and dwelling conditions can be excluded from the health access equation.

On the other hand, one may wonder if the transport related variables, i.e., travel time and ownership of transport means, should be included in the selection equation. Technically, it is possible to include them, but conceptually, it is unlikely that whether or not people have a fever is directly related to transport connectivity. Statistically, this is supported by the chi-square test when these three variables are included in the selection equation. The test statistic is estimated at 2.76, which is far from significant, validating our specification of the probit model with sample selection.

While our sample selection probit model is shown to be valid to generate a consistent estimation result, it is also found that the standard probit techniques applied to the health access equation does not yield biased results. The correlation between the two error terms is estimated to be negative, meaning that those who reported that they had a fever are less likely to visit a health facility. This may be an anticipated result: Holding everything else constant, people living in poor sanitary and general living conditions may be more likely to have a fever but less likely to visit a health facility, possibly because they are poor or live in remote areas. But the estimated correlation coefficient $\rho$ is statistically indifferent from zero. The coefficient is estimated at -0.366 with a standard error of 0.317. The Wald chi test statistic is 1.10. Therefore, the sample selection hypothesis can be rejected, meaning that whether or not having had a fever is random conditional to the adopted control variables.
Since it is found that the sample selection bias is not severe, the standard probit regression can also be applied (Table 4). Not surprisingly, the results remain broadly similar to the above. The coefficient of travel time to visit a health facility is -0.59, which is statistically significant. Owning bikes or motorcycles is found to be useful to promote people’s access to health care services. Health facilities in rural and remote areas are less attractive: The quality of health care services provided may be low. Younger people, essentially children, are more
likely to be treated at health facilities when they have a fever. This is because they are more vulnerable to health risk. The rich tend to benefit more from health care services.

The results are robust to other different transport variables. The proximity to a health facility can be measured by transport costs based on road user costs as well as road distance. No matter how it is measured, transport connectivity is among the most important determinants of the people’s decision of whether to go to the hospital. The year effect is also found to be strongly positive after all other observables are controlled. Thus, it can be concluded that there was a general improvement in people’s access to health care services between 2011 and 2018.

The significant income effect is also found to be robust. A set of dummy variables associated with each quantile classification are included. It is clear that health access is disadvantageous to households in the first two quantiles. Households of which wealth is at the third to fifth quantile are particularly more likely to benefit from health care services. Thus, transport connectivity is important to promote people’s health care access, but other complementary policies are also necessary, such as income support and improvement of health care service quality in remote areas.
Table 4. Probit regression with different specifications

|                                | Probit Health access (Y) | Probit Health access (Y) | Probit Health access (Y) | Probit Health access (Y) |
|--------------------------------|--------------------------|--------------------------|--------------------------|--------------------------|
|                                | Coef.                    | Std. Err.                | Coef.                    | Std. Err.                | Coef.                    | Std. Err.                | Coef.                    | Std. Err.                |
| Travel time to HF              | -0.590 (0.153) ***       |                         | -0.584 (0.153) ***       |                         |
| Transport cost                 | -0.239 (0.059) ***       |                         | -0.012 (0.004) ***       |                         |
| Road distance                  | 0.105 (0.042) **         | 0.098 (0.042) **         | 0.098 (0.042) **         | 0.109 (0.042) ***       |
| Bike/Motorcycle                | -0.027 (0.086)           | -0.028 (0.086)           | -0.013 (0.086)           | -0.033 (0.089)           |
| Car                            |                          |                          |                          |                          |
| Type of HF:                    |                          |                          |                          |                          |
| Urban health center            | 0.266 (0.081) ***        | 0.262 (0.081) ***        | 0.260 (0.080) ***        | 0.257 (0.082) ***        |
| Hospital                       | 0.305 (0.098) ***        | 0.303 (0.098) ***        | 0.309 (0.098) ***        | 0.295 (0.099) ***        |
| Health post                    | 0.027 (0.082)            | 0.025 (0.082)            | 0.071 (0.081)            | 0.021 (0.083)            |
| Remoteness of HF               | -0.118 (0.027) ***       | -0.115 (0.027) ***       | -0.125 (0.027) ***       | -0.116 (0.028) ***       |
| Age                            | -0.003 (0.001) ***       | -0.003 (0.001) ***       | -0.003 (0.001) ***       | -0.003 (0.001) ***       |
| Female                         | 0.040 (0.036)            | 0.038 (0.035)            | 0.039 (0.035)            | 0.040 (0.036)            |
| HH size                        | -0.002 (0.008)           | -0.003 (0.008)           | -0.002 (0.008)           | -0.002 (0.009)           |
| Female HH head                 | 0.008 (0.040)            | 0.003 (0.040)            | 0.003 (0.040)            | 0.006 (0.040)            |
| Age of HH head                 | -0.001 (0.001)           | 0.000 (0.001)            | 0.000 (0.001)            | -0.001 (0.001)           |
| No of bedrooms                 | -0.023 (0.021)           | -0.020 (0.021)           | -0.023 (0.021)           | -0.023 (0.021)           |
| Wealth index                   | 0.116 (0.021) ***        | 0.114 (0.021) ***        | 0.118 (0.021) ***        |                          |
| Wealth index: 2nd quantile     |                          |                          |                          | 0.050 (0.058)            |
| 3rd quantile                  |                          |                          |                          | 0.205 (0.062) ***        |
| 4th quantile                  |                          |                          |                          | 0.334 (0.071) ***        |
| 5th quantile                  |                          |                          |                          | 0.455 (0.094) ***        |
| t=2018                         | 0.155 (0.051) ***        | 0.151 (0.050) ***        | 0.133 (0.050) ***        | 0.155 (0.051) ***        |
| constant                       | 0.305 (0.216)            | 0.301 (0.215)            | 0.279 (0.213)            | 0.436 (0.212) **         |
| No. of obs.                    | 5766                     | 5792                     | 5819                     | 5766                     |
| Wald chi                       | 657.4                    | 656.99                   | 659.63                   | 658.56                   |
| No. of district dummies        | 113                      | 113                      | 113                      | 113                      |

Note: The dependent variable is $Y$. Robust standard errors are shown in parentheses. *, ** and *** indicate statistical significance at the 10, 5 and 1 percent level, respectively.

To interpret the results better, the marginal effects are computed by using the delta method (Table 5). By reducing the travel time required to visit a health facility by 1 percent, the probability of visiting a health facility could be increased by about 2.9 percent. Although the costs of improving transport connectivity vary depending on circumstances, this estimated increase in health care access could bring significant socioeconomic benefits to the country. Recall that Mozambique is estimated to spend nearly US$300 million or 2 percent of GDP for malaria treatment every year.
Not only transport infrastructure but also transport services can have a significant implication for health care accessibility. The estimated marginal effects indicate that if a household owns a bike or motorcycle, the probability increases by about 4 percent, holding everything else constant. This measured impact may not have to be limited to the means of transport that households own. The similar impact is plausible when motorized transport services are available in local areas, which is also often an important constraint in many developing countries.

It is also shown that the magnitude of the impacts on the probability is particularly large for the quantile dummy variables for the wealth index. The delta method is applied for the last column model of Table 4. Compared with the first two quantile groups, the probability of wealthy households visiting a health facility is 7-16 percent higher. This means that the poor need certain support by the government. Complementary policies, such as a health care subsidy and public insurance, are needed to ensure households’ equal access to health care services.

| Table 5. Marginal effects | Coef. | Std. Err. |
|---------------------------|-------|-----------|
| Travel time to HF         | -0.029| 0.007 *** |
| Bike/Motorcycle           | 0.038 | 0.015 *** |
| Car                       | -0.012| 0.031     |
| Urban health center       | 0.090 | 0.028 *** |
| Hospital                  | 0.103 | 0.034 *** |
| Health post               | 0.007 | 0.029     |
| Remoteness of HF          | -0.076| 0.018 *** |
| Age                       | -0.017| 0.006 *** |
| Female                    | 0.014 | 0.012     |
| HH size                   | -0.004| 0.017     |
| Female HH head            | 0.002 | 0.014     |
| Age of HH head            | -0.010| 0.021     |
| No of bed rooms           | -0.017| 0.016     |
| Wealth index: 2nd quantile| 0.018 | 0.021     |
| 3rd quantile              | 0.075 | 0.023 *** |
| 4th quantile              | 0.120 | 0.026 *** |
| 5th quantile              | 0.160 | 0.032 *** |
| t=2018                    | 0.054 | 0.018 *** |
V. Conclusion

Health care access is an important challenge in many developing countries. In particular in remote rural areas, it is not easy to access good quality health care services. Among others, transport connectivity is often an important constraint to rural dwellers. Particularly in Africa where rural connectivity is still limited, many people do not have access to health care services.

The paper estimated the impact of transport connectivity on access to health care services, using data from Mozambique, especially focused on people’s decision of whether to visit a health facility when they have a fever. In Mozambique, malaria is still a life-threatening serious disease, which accounts for 29 percent of all deaths and 42 percent of deaths in children less than five years old. About three-quarters of the total population does not have access to health facilities by walking.

It is found that transport connectivity is an important determinant of health care access. The marginal effect of travel time to the decision of visiting a health facility is estimated at -0.029, which is statistically significant. Owning transport means, such as a bike or motorcycle, is also found to be instrumental to promoting people’s access to health care services. Health facilities in rural and remote areas are relatively less attractive, possibly indicating the low quality of health care services provided there. Children are more vulnerable to health risk and thus more likely to be treated, holding everything else constant. The rich take advantage of and benefit more from health care services when they have a fever. The observed income effect suggests a need for other complementary policies, such as a health care subsidy and insurance.
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