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The effect of distance on maternal institutional delivery choice: Evidence from Malawi

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Abstract

In many low- and middle-income countries, geographical accessibility continues to be a barrier to health care utilization. In this paper, we aim to better understand the full relationship between distance to providers and utilization of maternal delivery services. We address three methodological challenges: non-linear effects between distance and utilization; unobserved heterogeneity through non-random distance "assignment"; and heterogeneous effects of distance. Linking Malawi Demographic Health Survey household data to Service Provision Assessment facility data, we consider distance as a continuous treatment variable, estimating a Dose-Response Function based on generalized propensity scores, allowing exploration of non-linearities in the effect of an increment in distance at different distance exposures. Using an instrumental variables approach, we examine the potential for unobserved differences between women residing at different distances to health facilities. Our results suggest distance significantly reduces the probability of having a facility delivery, with evidence of non-linearities in the effect. The negative relationship is shown to be particularly strong for women with poor health knowledge and lower socio-economic status, with important implications for equity. We also find evidence of potential unobserved confounding, suggesting that methods that ignore such confounding may underestimate the effect of distance on the utilization of health services.

KEYWORDS

dose-response function, generalized propensity score, health care demand, non-linear effects, utilization

1 | INTRODUCTION

Low- and middle-income countries (LMICs) continue to face problems of underutilization for basic health care (O'Donnell, 2007). The household cost of accessing health care can be broadly split into financial and time costs (Acton, 1973; Gertler & van der Gaag, 1990). Consequently, countries pursue two broad policies to improve utilization; reducing user fees, and setting geographical access policies. With an increasing number of LMICs removing pecuniary barriers to access, attention is switching to other determinants of healthcare utilization, such as travel distance. Despite many LMICs improving the physical access of health care, travel time/distance is still frequently cited as a significant barrier (Hjortsberg, 2003; Karra et al., 2017; Lohela et al., 2012; McLaren et al., 2014; Tegegne et al., 2018).

Previous literature has identified a "distance-decay rate," an inverse relationship between distance to health care and utilization (Borah, 2006; Lavy & Germain, 1994; Malqvist et al., 2010; Muller et al., 1998; Sarma, 2009; Shannon et al., 1969; Stock, 1983; Tanser et al., 2006; Wong et al., 1987). The association between distance and health care utilization has been found to be large relative to the effect of income, user fees and education (Buor, 2003; Thornton, 2008). Studies that examined the effect of travel time on health care utilization also found a negative relationship (Alegana et al., 2012; Blandford et al., 2012; Masters et al., 2013). It is well-established that distance can influence health care seeking behaviors in expectant mothers (Gabrysch & Campbell, 2009; Thaddeus & Maine, 1994). Specifically, distance is found to be a significant determinant of having a facility delivery, even at small distances in circumstances with poor transport (Chowdhury et al., 2006; Nesbitt et al., 2016; Yanagisawa et al., 2006). In the few studies which found distance to have no impact on utilization of delivery services (Duong et al., 2005; Paul & Rumsey, 2002), this might be explained with the relatively short average distances and high-quality transport infrastructure in the settings evaluated. Some qualitative evidence has identified a contradictory effect of distance on utilization of delivery services, with large distances stimulating women to seek facility deliveries due to the recognition of the impact of distance should complications arise during a home birth (Griffiths & Stephenson, 2001).

There is increasing recognition of the potential for unobserved confounding to bias estimates of the impact of distance on utilization and health outcomes. Manang & Yamauchi (2018) exploit the opening of new facilities in a differences-in-differences design, and find that increased access, measured by number of local public health facilities, increases the probability of having a facility delivery. In a study that focuses on facility deliveries in India, Kumar et al. (2014) attempt to address the possibility that distance may be endogenously determined by instrumenting distance to health facility with an index capturing distance to non-health "institutions of development." Their instrumental variable (IV) estimates are five times larger than their ordinary least squares (OLSs) estimates, with a 1 km increase in distance resulting in between 1.6 and 1.7 percentage point decrease in the probability of having a facility delivery. To the best of our knowledge, this represents the only current study examining the effect of distance on health care utilization that attempts to account for potential endogeneity.

In this paper, we investigate the impact of distance from the nearest health facility offering delivery services on the probability of having a facility delivery in rural Malawi. With a GDP per capita of US$338.50,[1] Malawi is one of the poorest countries in the world (World Development Indicators, 2019). Unlike many LMICs, Malawi has not seen a significant change in urbanization, with 84% of the population residing in rural households in 2018 (National Statistics Office, 2018). Further, there was in 2016 an average of 4.6 births per woman, one of the highest fertility rates in the world (World Development Indicators, 2019). Despite recent improvements, the country still suffers some of the highest rates of under-5 and neonatal mortality globally, 63/1000 and 27/1000 live births respectively in 2015/16 (Ministry of Health, 2017). The maternal mortality rate was 439/100,000 live births in 2016, a reduction from 675/100,000 in 2010 (Ministry of Health, 2017).

Like many LMICs, Malawi continues to aim to expand its health infrastructure and increase the physical access to health care services. However, despite the acknowledgment of a distance-decay effect, nuanced evidence to informatively guide infrastructure planning remains sparse. Distance is a continuous variable and populations are geographically distributed unevenly. Despite this, most studies treat the functional relationship between distance and utilization as linear, limiting the potential to explore variation in the relationship across distance levels. As efficient investment in health infrastructure relies on understanding the full relationship between access and utilization, it is important to identify differential impacts distance may have at different levels. Additionally, while many countries set minimum travel distance targets, it is unclear—equity arguments aside—whether such targets are appropriately set. Fundamentally, health systems have to provide a fair opportunity for populations to seek care. Therefore, from a health infrastructure planning perspective the effect of the minimum travel distance required to seek care on utilization remains an important issue. Information on this relationship can guide minimum access thresholds and infrastructure planning. In order to provide more nuanced evidence to inform policy-making, we adopt a continuous treatment approach, estimating a dose-response function (DRF) that relates each level of distance to the probability of having a facility delivery using generalized propensity scores (Hirano & Imbens, 2004). We also examine the potential modifying effects household socio-economic status (SES) and mother's health knowledge may have on the distance-utilization relationship. Additionally, we acknowledge that household and facility location may be strategically selected, and non-random sorting may result in distance to health facility being correlated with unobserved determinants of location of delivery such as health status or health-seeking preferences. To address this possibility, we employ an IV approach as an alternative estimation strategy. We view the methods applied as complementary, in that they address different challenges in estimating the distance-utilization relationship: potential nonlinearity in the relationship, potential heterogeneity according to pre-specified subgroups, and potential unobserved confounding. In our conclusions, we synthesize the results from these methods to provide comprehensive information on how distance may effect health care utilization and help inform policy decisions.

2 | METHODS

We briefly outline the contextual background and data used in the study before outlining a simple theoretical model of how distance impacts health care utilization and the identification strategies applied.

2.1 | Context

Primary health services in Malawi have been provided free at the point of access in public facilities since 1964. The services to which the population is entitled without user fees, including delivery services and maternal health care, were formalized with the introduction of the Essential Health Package (EHP) in 2004 (Ministry of Health, 2004). To further improve the utilization of maternal and child health services, service level agreements (SLAs) have been agreed with the Christian Health Association of Malawi (CHAM) since 2006. Under SLAs, CHAM facilities in catchment areas where no government facilities exist provide the EHP without charging user fees (Manthalu, 2019).

The Government of Malawi owns 48% of the health facilities within the country while the CHAM owns 17% of the countries facilities, with most located in rural areas. The remaining facilities are either private-for-profit (22%), NGO owned (6%) or company facilities (7%) (Ministry of Health & ICF International, 2014).

The national access policy seeks to ensure that all households live within 5 km of a health facility, reduced from a previous target of 8 km (Ministry of Health, 2017). From 2011–2016 12 new health facilities were constructed. Despite this, the proportion of the population living within 8 km of a health facility declined from 81% to 76% over the same period (Ministry of Health, 2017).

2.2 | Data

Our analysis combines data primarily from two key sources. The Demographic and Health Survey (DHS) 2015/16, a population-based household survey, provides data on births and health care utilization. It employs a two-stage cluster sampling design with 850 clusters identified in the first stage and approximately 30 households from each cluster selected in the second stage, resulting in a total sample population of 26,361 households. The survey provides self-reported birth histories for women up to 5 years before the survey.

We restrict analysis to rural households, as defined by the DHS. We focus on rural households because the determinants for health care utilization likely differ between urban and rural women, based on systematic differences in their characteristics and environment and they should be treated as different sample populations. Furthermore, distance is unlikely to present a significant barrier for urban households. Births which took place prior to the woman residing in her current location were excluded as observed distances are not related to these births. Caesarean deliveries are excluded as they all take place in health facilities. Lastly, the analysis includes women only if the household they were surveyed in was their usual place of residence. The final analytical sample consists of 11,881 births to 9250 women. See Appendix A for details on the construction of the analytical sample.

Facility data was obtained from the Service Provision Assessment (SPA) 2013/14, a census providing information on the availability and quality of health care services from all functioning health facilities within Malawi. The survey captures the geographic coordinates of all facilities. Of Malawi's 977 facilities in 2013/14, only 540 had basic delivery capacity and 71 had capacity to perform caesarean sections (Appendix B).

The outcome of interest is mother-reported location of delivery, indicating whether a birth occurred at a health facility with delivery services or at a location without appropriate services, predominantly home births. We cannot identify the specific facility at which deliveries occur, and do not assume it to occur at the nearest facility. Consequently, we measure the impact of distance to the nearest health facility with delivery services on utilization of any health facility with such capacity. In this sense, we examine the relationship between the minimum distance faced for the opportunity to access institutional delivery services and the fundamental decision of whether to utilize them or not. The DHS also provides information on reasons why women may not seek health care generally (Table 1). Distance is the second overall most cited problem in seeking health care. Unsurprisingly, a higher proportion of women residing at further distances cite distance as a significant problem.

We generated the explanatory variable of interest, Euclidean distance to nearest health facility with delivery capacity, by spatially linking household clusters with health facilities using QGIS (QGIS Development Team, 2009). Figure 1 shows the distribution of distance, with most women (62%) living within 6 km of the nearest health facility offering delivery services and a mean distance of 4.98 km. It should be noted that this represents the minimum distance women must travel in order to utilize an appropriate facility for delivery, not necessarily the facility in which the delivery ultimately took place.

The DHS geospatial data has geographic displacement procedures imposed to maintain respondent anonymity (Burgert et al., 2013). First, geographic coordinates are aggregated to a single point coordinate for each DHS cluster representing the cluster centroid. Second, a geo-masking process displaces the aggregated cluster by a random-angle, random-distance process whereby 99% of rural clusters are uniformly displaced up to 5 km and a further 1% are uniformly displaced up to 10 km. Consequently, as geocoordinates are at DHS cluster centroids, distance is measured at the cluster-level. This results in the loss of within-cluster variation. Additionally, the displacement process introduces a random measurement error in the geographic coordinate data, biasing estimates towards zero (see Appendix C; Arbia et al., 2015; Carroll et al., 1995; Goodchild et al., 1992; Perez-Heydrich et al., 2013).

Table 2 provides summary statistics for the outcome and control variables for both the full analysis sample and across distance tertiles. On average, women in the sample had 1.5 births within the 5 year sample period. Ninety-two percent of births take place at a health facility. Women who have a home birth on average reside further from a facility (6.2 km) than those having facility deliveries (4.8 km).

Figure 2 displays the observed locations of delivery, the mean outcome for 10 equally sized bins according to observed distances, and an unadjusted OLS line of distance on individual's probability of having a facility delivery,[2] showing a clear negative association.

2.3 | Empirical strategy

2.3.1 | Motivating model

Conventional models of demand view health care as an input in the health production function, influencing individuals' health (Fuchs, 1968; Grossman, 1972). The demand for health care is based on comparison of the relative costs and benefits of utilization. Underutilization is, therefore, a manifestation of the expected costs of utilization exceeding perceived expected benefits. We outline a conceptual model of location of delivery choice based on mother and facility characteristics. We assume maternal utility is a function of what we call "maternal capital," C, which can be thought of as wealth, and the outcome of the pregnancy, Y. That is, for woman $i = 1, \ldots, N$:

$$U_i = U(C_i, Y_i)\ ;\ \frac{\partial U}{\partial C} \geq 0;\ \frac{\partial U}{\partial Y} \geq 0 \tag{1}$$

Capital is depleted by an amount dependent on the distance traveled to the location of delivery j, which includes all facilities with delivery capacity and home. Thus:

$$C_i^j = f\left(C_i^0, d_{ij}\right)\ ;\ \frac{\partial f}{\partial C_i^0} \geq 0\ ;\ \frac{\partial f}{\partial d_{ij}} \leq 0 \tag{2}$$

where C_i^0 is the initial capital of mother i, C_i^j is the capital after delivery at location j and d_{ij} is the distance to location of delivery j. The outcome Y_i^j for mother i associated with delivery location j is assumed to be:

TABLE 1 Self-reported reasons for not seeking health care (proportion citing reason)

	Full analysis sample	First tertile (0.07–3.4 km)	Second tertile (3.4–5.8 km)	Third tertile (5.9–23.6 km)
Permission	0.17	0.16	0.18	0.17
Financial	0.55	0.50	0.57	0.58
Distance to facility	0.61	0.47	0.65	0.72
Going alone	0.31	0.23	0.33	0.37
Concerned no female provider	0.26	0.21	0.28	0.28
Concerned no provider	0.53	0.50	0.53	0.56
Concerned no drugs	0.70	0.65	0.71	0.72

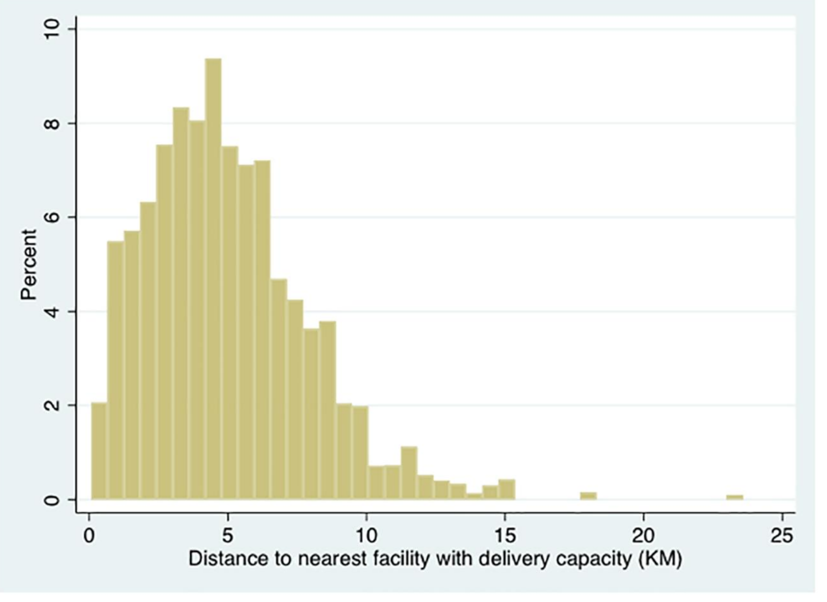


FIGURE 1 Distribution of treatment variable

$$Y_i^j = g\left(Q^j,\ H_i^0, x_i\right)\ ;\ \frac{\partial g}{\partial Q} \geq 0\ ;\ \frac{\partial g}{\partial H_i^0} \geq 0 \tag{3}$$

$g(.)$ can be thought of as the health production function of location of delivery j perceived by the mother, which depends on the quality of services, Q, the mother's underlying health, H^0, and a vector of individual characteristics x_i, which may include factors such as birth order, education level and health knowledge. By substituting Equations (2) and (3) into Equation (1), the utility V_i^jderived from delivery at location j can then be written as:

$$V_i^j = V\left(d_{ij}, Q^j,\ H_i^0,\ C_i^0, x_i\right)\ ;\ \frac{\partial V}{\partial d} \leq 0\ ;\ \frac{\partial V}{\partial Q} \geq 0 \tag{4}$$

Equation (4) is woman i's conditional indirect utility function for choice j which can be rewritten:

$$V_i^j = V\left(d_{ij}, Q^j, z_i\right) \tag{4.1}$$

where z_i is a vector of mother and household characteristics, including "maternal capital" and health status. Thus we implicitly compare the utility associated with delivery at each feasible location, assuming women choose the location maximizing V_i^j. Our dataset is at birth level, accordingly this optimization problem occurs at each birth and woman i's

TABLE 2 Summary statistics

	Full analysis sample	First tertile (0.07–3.4 km)	Second tertile (3.4–5.8 km)	Third tertile (5.9–23.6 km)
Number of deliveries	11,881	3907	4062	3912
Outcome variables				
Had facility delivery	0.92	0.96	0.92	0.89
Mother characteristics				
Age at delivery	26.5 (6.9)	26.3 (6.8)	26.6 (6.9)	26.7 (6.9)
Number of births in 5 years	1.5 (0.6)	1.5 (0.6)	1.5 (0.6)	1.5 (0.6)
Education level	1.0 (0.6)	1.1 (0.6)	1.0 (0.5)	1.0 (0.5)
Literacy	1.2 (0.9)	1.3 (0.9)	1.1 (0.9)	1.2 (0.9)
Health knowledge index	3.1 (0.8)	3.1 (0.8)	3.1 (0.8)	3.1 (0.8)
Gestation period	9.0 (0.5)	9.0 (0.5)	9.0 (0.5)	9.0 (0.5)
Frequency listen to radio[a]	0.7 (0.9)	0.8 (0.9)	0.7 (0.8)	0.7 (0.9)
Frequency read newspaper[a]	0.2 (0.5)	0.2 (0.5)	0.2 (0.5)	0.2 (0.5)
Frequency watch TV[a]	0.1 (0.5)	0.2 (0.6)	0.1 (0.4)	0.1 (0.4)
Years at current residents[a]	66 (41)	68 (40)	68 (40)	63 (41)
Have health insurance	0.00	0.00	0.00	0.00
Single child birth	0.96	0.97	0.95	0.97
2 years since previous birth	0.91	0.92	0.90	0.90
First child	0.21	0.23	0.21	0.20
Had caesarean-section in last 5 years	0.01	0.01	0.01	0.01
HIV positive[a]	0.07	0.08	0.08	0.07
Always lived at current residents	0.66	0.68	0.68	0.62
Child characteristics				
Birth year	2012.9 (1.4)	2012.9 (1.5)	2012.9 (1.4)	2013.0 (1.4)
Mother reported child birth size	2.8 (0.9)	2.8 (0.9)	2.8 (0.9)	2.8 (0.9)
Household characteristics				
Wealth index	2.8 (1.4)	2.9 (1.4)	2.7 (1.4)	2.7 (1.3)
Health care decision maker	2.2 (0.7)	2.1 (0.7)	2.2 (0.7)	2.2 (0.7)
Have bicycle	0.45	0.42	0.45	0.47
Have motorcycle	0.02	0.02	0.02	0.03
Have car	0.01	0.01	0.02	0.01
Female head of household	0.25	0.27	0.24	0.24
Environment characteristics				
Region	2.3 (0.7)	2.3 (0.8)	2.4 (0.7)	2.3 (0.8)
Rainy season birth	0.27	0.26	0.26	0.27
Number of HSAs in 1 km	0.34 (0.57)	0.33 (0.56)	0.33 (0.56)	0.34 (0.57)
Facility characteristics				
Facility type	4.7 (1.0)	4.7 (1.0)	4.7 (1.1)	4.6 (1.0)

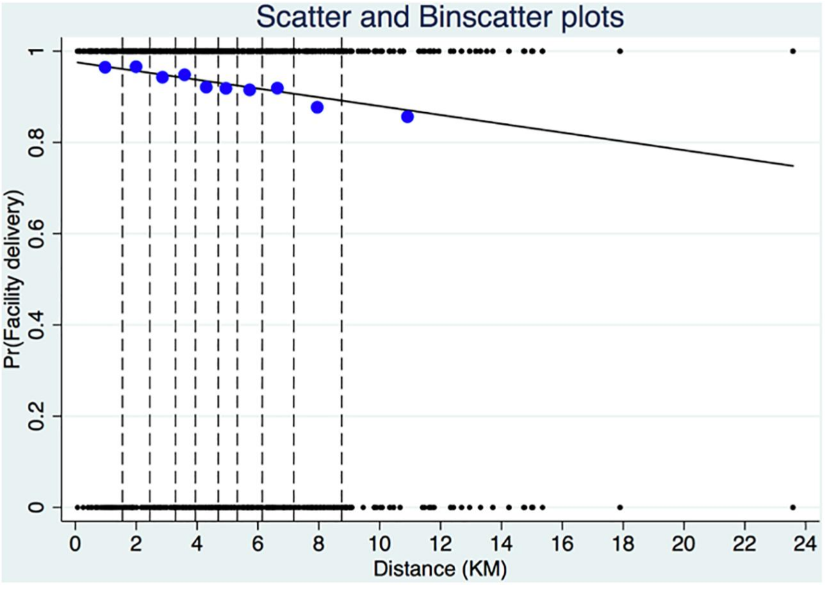
TABLE 2 (Continued)

	Full analysis sample	First tertile (0.07–3.4 km)	Second tertile (3.4–5.8 km)	Third tertile (5.9–23.6 km)
Managing authority	1.4 (0.8)	1.5 (1.0)	1.5 (0.9)	1.3 (0.6)
Other				
Bypassed nearest facility[a]	0.41	0.44	0.43	0.34

Note: Years at current residents is skewed upwards by the number representing "always." HSAs stands for Health Surveillance Assistant, Malawi's cadre name for community health workers.

[a]Variables are not included in main specifications for inference for a variety of reasons but provide descriptive insight.

FIGURE 2 Non-parametric and parametric association of distance and facility delivery



strategy maximizing utility may vary by birth. Empirical strategies and model specification choices derive from this simple theoretical model. Despite a set of j realizable utilities from alternative facility choices, we observe only the singular preference choice. The observed V_i^j is the revealed preference which can be formulated as a probabilistic choice model. Our first empirical strategies assume all elements of $V_i^j = V(d_{ij}, Q^j,\ H_i^0,\ C_i^0, x_i)$ are captured, while our second acknowledges aspects of H_i^0 and x_i may be unobservable.

2.3.2 | Identification strategy 1: Selection on observables

Linear probability model

We assume the linear predictor of the model to be additive separable and linear in its inputs, which relates to the conditional probability of the outcome with the link function $G(.)$:

$$\Pr(FD_B = 1) = G(\beta_0 + \beta_1 DIST_M + \beta_2 SES_M + \beta_3 HH_M + \beta_4 CB_B + \beta_5 FC) \tag{5}$$

where FD_B is a binary outcome indicating whether the birth occurred in a health facility or at home. $DIST_M$, the treatment, is distance to the nearest health facility from the woman's household. SES_M is a vector of socio-economic variables that may be related to women's choice of place of delivery such as age at delivery, education, literacy, health insurance, health knowledge and wealth index. HH_M includes household variables such as bicycle, motorcycle and car ownership. CB_B includes characteristics of the birth such as the gestation period, whether it was a single child birth and if it was the woman's first birth. Finally, FC includes facility characteristics such as the type of facility and the managing authority of the facility. A potential determinant of location of delivery is past exposure to the health care system, such as ante-natal care (ANC) visits. However, ANC visits may themselves be affected by distance, and adjusting for it would cause bias in estimator of the treatment effect (Gelman & Hill, 2007), hence we do not include it as a covariate.

The causal interpretation of β_1 and the corresponding marginal effects hinge on two key conditions: exogeneity of distance and overlap. The former relies on including all confounders—variables that predict both distance and the location of delivery—in the regression model. Should a factor that influences a woman's decision to have a facility delivery (distance) not be observed, it must be assumed that this factor is independent of distance (choice of location of delivery). In the context of a continuous treatment such as distance, the latter condition, implies that for each level of treatment and combination of covariates, there is some non-zero probability that the treatment will be received (Cattaneo, 2010). The probability of poor overlap increases with the number of covariates adjusted for, and when the variable of interest is continuous, such as distance.

A problem with regression methods is that lack of overlap leads to a strong reliance of the specification of the regression model which extrapolates to regions with poor overlap (Ho et al., 2007). In our context, this involves correctly modeling the complex process that determines a woman's choice of birth location (Seljeskog et al., 2007). Specifically, correctly modeling the relationship between the distance and the outcome, as well as the relationship between the covariates and the outcome, through a linear predictor and the $G(.)$ link function. We first implement this regression approach, with main terms only in the linear predictor, and alternative (linear, probit and logit) link functions. Next, as a more flexible method, we implement a generalized propensity score (GPS) approach, which moves the model specification task from the outcome regression function to the treatment assignment mechanism.

DRF estimation

To relax the parametric assumptions of the regression function and flexibly explore the relationship between distance and the probability of having a facility delivery we treat distance as a continuous "treatment," and estimate a DRF. We follow the GPS approach by Hirano and Imbens (2004).[3] The attractive features of the GPS method relative to regression methods are that it requires only adjusting for a scalar variable to control for imbalance in observed covariates, and—in the more recent proposals implemented here—it is possible to use the GPS as a weight, without having to specify a parametric relationship between the treatment variable and the outcome.

We briefly outline the GPS method within the potential outcomes framework (Rubin, 1974). Given a random sample of individuals $i = 1, 2, \ldots, N$, for each unit i there exists a set of individual potential outcomes $Y_i(j)$ capturing i's response to treatment level j, known as the individual DRF. $j \in \mathfrak{J}$ denotes the treatment level—distance to nearest facility—where $\mathfrak{J}$ is the interval $[j_{min}, j_{max}]$, in this case $\mathfrak{J}$ is the interval $[0.07km, 23.58km]$. For every individual only one treatment J_i and one potential outcome is observed, $Y_i = Y_i(J)$. The causal effect of individual i moving from j to Δj is defined as, $Y_i(j) - Y_i(j + \Delta j)$ is unobservable. However, an estimate of the population average effect $E[Y_i(\Delta j)] - E[Y_i(j)]$ can be obtained. Calculated over the range of values $\mathfrak{J}$ this is known as the DRF, given as $\mu(j) = E[Y_i(j)]$ for all $j \in \mathfrak{J}$, measuring the relationship between the treatment, distance from the nearest health facility as the cause, and potential utilization outcomes as the effect. The DRF, therefore, signifies the average response in the population if all women were at distance $J = j$. The marginal treatment effect estimation with respect to treatment level j is given as:

$$ATE = E[Y_i(j) - Y_i(j - \Delta j)] = \frac{E[Y_i(j)] - E[Y_i(j - \Delta j)]}{\Delta j}$$

The approach relies on the weak unconfoundedness assumption, stating that, conditioned on the observed covariates, there is pairwise independence of the treatment level received with each of the potential outcomes: $Y_i(j) \perp J_i \mid X_i$ for all $j \in \mathfrak{J}$ (Hirano & Imbens, 2004). In our setting, this implies that distance to nearest facility is unrelated to unobserved covariates that themselves affect the probability of facility utilization. For adjustment, we use the same covariates we used in the regression adjustment, specified in the previous section. Similar to the regression approach, identification with GPS relies on good overlap. This requires that the conditional density of the treatment is positive for any covariate values, $\Pr(r(j,x) > 0) = 1$, where $r(j,x) = f_{J|X}(j|x)$, is the conditional density function of the treatment given the covariates. However, an advantage of the GPS method is it enables a relatively straight-forward process, outlined below, of identifying women for whom it is difficult to construct counterfactual outcomes, allowing estimation to be restricted to comparable individuals.

The GPS is defined as $r(J, X)$, the probability that individual i belongs to the distance at which they are observed. Assuming the conditional distribution of treatment has been correctly specified, the GPS has a balancing property:

within strata with the same value of the GPS evaluated at a given treatment level, $r(j, X)$, the probability that the treatment received equals this treatment level, $J = j$, does not depend on the values of the covariates.

Informed by statistical tests (Akaike information criteria, Bayesian information criteria and Modified Park tests), we estimate the GPS using GLM with Gamma distribution and log link function for the conditional distribution of distance. Following Hirano and Imbens (2004), we perform balance checks on the estimated GPS, dividing the sample into three mutually exclusive intervals according to the 33rd and 66th percentile of the distribution. Within each interval the GPS is computed at the median distance. Each interval is divided into five blocks by the quintiles of the GPS evaluated at the median. Within each block, covariates difference in means are calculated for individuals who have a GPS such that they belong to that block but belong to a different treatment interval. T-statistics are used to assess the differences in the GPS-weighted means between each treatment interval and the pooled means of the remaining two intervals.

To estimate the DRF without the need to specify an outcome regression as a function of the GPS (Bia et al., 2011; Bia & Mattei, 2012) we implement a non-parametric inverse-weighting (IW) estimator (Flores et al., 2012). The approach corresponds to implementing a local linear regression of the outcome on the treatment levels, using a global bandwidth that is chosen data-adaptively (Fan et al., 1996). More detail on the IW estimation approach is outlined in the Appendix D.

We restrict estimation to areas of common support with respect to the estimated GPS, using a method proposed by Flores (2007): again we split the treatment at the 33rd and 66th percentile, and evaluate the GPS at the median treatment of each group for the whole sample, we then compare the distribution of the GPS for observations that belong to one group versus the other two groups pooled, doing this for all three groups.[4]

Heterogeneity analysis

Studies indicate that health knowledge and SES affect engagement with health systems, particularly in LMICs (Budhathoki et al., 2017; Van Doorslaer & Masseria, 2004; Wagstaff & van Doorslaer, 2000). The effect of distance may also vary along these dimensions. Households with higher SES may mitigate the impact of distance with their ability to pay for public transport. Greater health knowledge may reduce the disincentive effect of distance through better awareness of the benefits of health care. We generate a measure of mother's health knowledge through the cumulative score of a set of questions including whether the mother has heard of oral rehydration solution, Tuberculosis and natural birth complications and whether they know that HIV is spread by sexual activity. DHS rural-specific wealth index is used creating wealth quintiles. We adapt Equation (5) to estimate the average marginal effects of distance across these subgroups. We undertake sub-group analysis using a regression approach due to the larger sample requirements of the GPS framework.

2.3.3 | Identification strategy 2: Selection on unobservables

If mother- or community-specific unobservable characteristics are correlated with distance to health facility and health care utilization, this would bias the estimated effect of distance on utilization (Schultz, 2004). Several mechanisms may result in such a scenario arising. Selective migration may lead individuals with stronger need or preferences for health care to relocate to communities with better access to health facilities. HIV positive individuals in rural Malawi have over two times greater odds of migration than HIV negative individuals (Anglewicz et al., 2016). Furthermore, placement of facilities may be influenced by lobbying from local communities or other political pressures (Todd, 2007). Rosenzweig & Wolpin (1986) showed endogeneity in development program placement can be a source of significant bias. Such targeting has been identified for reproductive health services (Schultz, 2005; Strupat, 2017). The number of health facilities has expanded in Malawi, with 575 facilities in 2003, rising to 606 in 2010 (Ministry of Health 2010). Should facility placement be linked to health care demand, this would violate the assumption of exogeneity of distance. Finally, facilities may be located in areas of higher population density. Such areas may suffer higher rates of communicable disease or other risk factors—the HIV prevalence rate was 17.4% in urban settings compared to 8.9% in rural areas in 2010 (National Statistics Office. Malawi Demographic and Health Survey 2010/2011)—resulting in lower health status and increased need for health care utilization. It has been noted generally that the argument for exogeneity is weak in cases where distance is not fixed, but responsive to incentives (Basker, 2007).

To attenuate concerns about potential endogeneity, we also employ an IV approach. The candidate IVs for distance must meet the standard conditions; (a) they have a strong correlation with distance to health facility, and (b) they do not have any effect on location of delivery, other than through their relationship with distance to health facility. Several studies have used instruments based on distance to other infrastructure when concerned about the endogeneity of distance to a specific service (Kumar et al., 2014; Lavy, 1996; Mukhopadhyay & Sahoo, 2016). Kumar et al. (2014) use distance to "non-health institutions of development"[5] as an instrument for distance to health facility. Following this approach we first use (a) distance to nearest school and (b) distance of nearest school to closest trading center, as instruments.

However, distance to other types of institutions may be correlated with community-level variables, which in turn, may influence the demand for health care. Lavy et al. (1996) suggests a community's local infrastructure may measure the degree to which the village leadership supports public service provision and, generally, the degree of community "progressivity." Therefore, institutions, health-related or otherwise, may be subject to the same non-random sorting, bringing into question the credibility of distance to other infrastructure as a valid instrument. Hence, we identify two instruments that we believe more appropriate than distance from other infrastructure: (c) number of qualified teachers at nearest school (d) number of students at nearest school.

Local context underpins our rationale for why these instruments (c) and (d) are potentially less likely to suffer from violations of the exclusion restriction. We contend that local institution quality—proxied by number of qualified teachers—is less under the direct control of communities than access, and should be less related to unobserved community heterogeneity which may also influence distance to health facility. In Malawi, remote schools often face difficulty recruiting and retaining qualified teachers. Teachers themselves are important decision makers, using formal and informal channels to influence placement to avoid remote schools, where there are also high teacher attrition rates (Asim et al., 2017). Therefore, while "progressive" communities may increase public service delivery in their locality, they may have less influence on the quality of those services, in this case number of qualified teachers. Hence, while number of qualified teachers captures an aspect of remoteness, this aspect is less directly related to the factors that jointly determine distance to health facility/public infrastructure and health care utilization. Likewise, the number of students at the nearest school will generally capture "remoteness" of households with schools in more remote communities having less students. However, as households may be located close to or far from the nearest school, we expect it to be a measure of "remoteness" less related to preferences than distance measures. Because the household may in fact be located close to or far from the nearest school (and health facility), we expect that this instrument captures a measure of distance isolated from preferences which may also drive utilization. Additionally, we contend these instruments are unrelated to selective migration due to the high informational requirements and the localized nature of migration in Malawi (Anglewicz et al., 2017).

We extract data on the instruments from a comprehensive World Bank dataset on teachers and schools. This dataset included information on the placement of all teachers in Malawi's 5700 schools, linked with data on school facilities and locations and geo-spatial coordinates of commercial centers.

We implement several alternative IV approaches: 2SLS, Ivprobit and two-stage residual inclusion (2SRI). The latter, 2SRI approach is our preferred specification, due to its relatively good performance in non-linear models (Terza, 2018; Terza et al., 2007; Wooldridge, 2014). In all specifications, we use the following linear model to estimate the first stage:

$$DIST_M = \beta_0 + \beta_1 Z + \beta_2 SES_M + \beta_3 HH_M + \beta_4 CB_B + \beta_5 FC + \varepsilon_B \tag{6}$$

where Z is a vector of each pair of the above specified instruments. For the 2SRI method, we use the predicted residuals ($\hat{\varepsilon}_B$), and include them in the regression of distance on place of delivery in addition to the original endogenous variable using the following regression model:

$$\Pr(FD = 1) = \Phi\left(\beta_0 + \beta_1 DIST_M + \beta_2 SES_M + \beta_3 HH_M + \beta_4 CB_B + \beta_5 FC + \beta_6 \widehat{\varepsilon_B^{2SRI}}\right) \tag{7}$$

where Φ is a probit link function. The β_1 coefficient and corresponding marginal effect in the second-stage equation reflects the causal effect of distance. Following Hausman (1978), we test the coefficient of the first stage residuals to test for the presence of endogeneity. We obtain corrected standard errors in the second stage via bootstrapping.

2.4 | Robustness checks

In addition to varying specifications of our primary models, we undertake robustness checks examining a different measure of distance and a more detailed metric capturing facility quality. Euclidean distance may not always best represent the realistic travel distance women travel in order to reach the nearest health facility (Guagliardo, 2004; Nesbitt et al., 2016). Therefore, we also calculate the road-network distance to test the robustness of the results to alternative distance measures.

Poor service quality or perceptions of quality also play a role in utilization decisions (Macarayan et al., 2018; Mwabu et al., 1993). Further, quality may be associated with distance, with more remote facilities being of worse quality on average, which could inflate the estimated impact of distance if not adequately controlled for. Our baseline specifications included facility type and ownership which are frequently used proxies for facility quality. However, the SPA captures more detailed facility information allowing us to better control for potential variation in relevant aspects of facility quality.

3 | RESULTS

3.1 | Linear probability model results

Estimation of Equation (5) by OLS shows a significant inverse relationship between distance and the probability of having a facility delivery (Table 3). Comparing the unadjusted correlations with those including the full set of controls the relationship remains almost unchanged. This can be explained by the small and insignificant coefficients of the covariates in the outcome model with few variables strong predictors of location of delivery. A kilometer increase in distance to nearest facility reduces the probability of having a facility delivery on average by between 1.1 and 1.3 percentage points significant at the 1% level.

Results remain largely unchanged when using non-linear model specifications and when run on several relevant sub-samples (Appendix E).

3.2 | DRF results

Table 4 shows the improvement in balance of the covariates once they have been adjusted by the calculated GPS using the procedure outlined above. There is an initial lack of balance with 31 of 66 t-statistics greater than |1.96|, indicating significant differences in means between treatment intervals. After adjusting for the GPS this is reduced to 22 of 66. Further, balancing for the GPS causes the average absolute t-statistic to decrease from 2.63 to 1.89.[6] Although not achieving perfect balance, adjusting for the GPS does improve comparability across distance.

Assessment of overlap in the distribution of the estimated GPS among individuals in the three treatment tertiles shows a high level of common support (Appendix F). We restrict DRF estimation to observations within the common support for all three treatment groups simultaneously.[7]

We estimate the effect of distance at values between 1 and 20 km, as small samples at the extreme distances prevent meaningful estimates being obtained at the largest distances observed. We present estimates with 95% confidence bands obtained by 1000 bootstrap replications. While the confidence bands grow after 10 km, from the DRF it is clear the probability of having a facility delivery is a negative function of distance, with a 96.9% probability of facility delivery at 1 km, falling to 74.1% at 20 km (Figure 3). We find clear non-linearities in the marginal effect of a 1 km increment in distance on the probability of having a facility delivery at different distance exposures (Figure 4): the estimated treatment effect of an additional kilometer appears, largely, to increase with the level of distance. A movement from 1 to 2 km leads to a fall of 0.9 percentage points in the probability of having a facility delivery, while moving from 14 to 15 km, the furthest distance for which we have a statistically significant effect, causes the probability to fall by 2.9 percentage points. Table 6 in Appendix G shows estimates and confidence bands relating to figures.

To check the robustness of our estimates we also follow Hirano and Imbens (2004) in estimating the DRF. This approach estimates the conditional mean of the outcome given the observed treatment level and the probability of receiving that value by parametrically fitting a linear regression function on the treatment and the estimated GPS: $E[Y_i \mid J_i, \hat{GPS}_i] = \beta_0 + \beta_1 J_i + \beta_2 \hat{GPS}_i$ (Appendix H). All specifications gave results similar to our IW estimates.

TABLE 3 Regression of location of delivery (home vs. facility)

	LPM (1) Coeff	LPM (2) Coeff	LPM (3) Coeff
Distance to nearest relevant facility	−0.011***	−0.013***	−0.013***
	−0.002	−0.002	−0.002
Number of observations	11,881	11,375	11,375
Number of clusters	677	676	676
Mother, household, environment controls	-	X	X
Facility characteristics	-	X	X
Birth year trend	-		X
District fixed effects	-	X	X

Note: Controls refers to the inclusion of the full set of mother, child, household, environment controls as well as regional fixed effects. Average marginal effects are calculated following probit and logit specifications.

Abbreviation: LPM, linear probability model.

Statistical significance levels are denoted by *** $p < 0.01$, ** $p < 0.05$ and * $p < 0.10$. Robust standard errors clustered as the DHS cluster level and reported with estimated coefficients.

3.3 | Heterogeneity analysis results

While distance has a significant negative effect on the probability of having a facility delivery across all levels of health knowledge, as expected, there is evidence that distance has a smaller reductive effect on the probability of having a facility delivery for women with higher health knowledge (Figure 5). There appears to be a threshold level of health knowledge at which the modifying effect disappears.

Similarly, the effect of distance is largest for the poorest households and smallest for the richest (Figure 6).

3.4 | IV results

All proposed instruments have statistically significant predictive effects on distance to health facility (Table 5). These first-stage partial correlations are in line with anticipated effects of the excluded instruments on distance to health facility. The Kleinbergen-Paap rk Wald F-statistics exceed the instrument relevance rule of thumb >10 for all instruments individually. Tests checking the endogeneity of distance validating the IV approach and tests for the exogeneity of the proposed instruments further validate the IV approach and instruments (Appendix I).

Table 6 shows the results of our IV estimates. Using the distance-based instruments, the estimates suggest the impact of distance to be similar to those estimated using the linear probability model (LPM)/GLMs. However, using our preferred instrument specification, it appears previous estimates underestimate the effect. The LPM-IV and 2SRI estimates suggest a kilometre increase in distance reduces the probability of having a facility delivery by between 2.3 and 2.5 percentage points.

When including residuals from the first-stage equation in the second-stage, the positive sign suggests individuals who reside at distances further from facilities have unobservable characteristics which increase the probability of having a facility delivery.

3.5 | Robustness check results

The effect of a change in road-network distance on the probability of having a facility delivery is smaller than that of Euclidean distance (Appendix J). That the size of the relationship between road-network distance and the utilization of facility delivery services is smaller than that of Euclidean distance suggests the former may be less representative of true travel distances. This is highly possible due to the number of informal paths and roads and travel habits in Malawi. Therefore, we view this as a validation of the use of Euclidian distance as the preferable measure of travel distance.

TABLE 4 Balance given GPS: t-statistics for equality of means

Variable	Unadjusted			Adjusted for GPS		
	First tertile (0.07–3.4 km)	**Second tertile (3.4–5.8 km)**	**Third tertile (5.9–23.6 km)**	**First tertile (0.07–3.4 km)**	**Second tertile (3.4–5.8 km)**	**Third tertile (5.9–23.6 km)**
Mother characteristics						
Mother age at delivery	**2.1**	−0.3	−1.8	1.5	−0.6	−0.7
No. of births in last 5 years	**6.2**	**−2.9**	**−3.2**	**2.7**	**−4.9**	**2.3**
Education level	**−7.3**	**2.2**	**5.1**	**−2.1**	**4.0**	−1.2
Literacy	**−5.9**	**3.2**	**2.8**	**−2.6**	**4.5**	−1.3
Mother health knowledge	**−4.2**	**2.3**	1.9	−1.6	**3.3**	−1.4
Gestation period	−1.3	0.8	0.5	−1.6	0.7	1.0
Health insurance	0.1	−0.3	0.2	0.4	−0.3	0.4
Single child birth	−1.2	**2.8**	−1.6	−1.1	**2.8**	−1.5
2 years since previous birth	**−3.9**	0.7	**3.2**	−1.8	**2.3**	−0.7
First child	**−3.1**	0.7	**2.4**	−0.9	1.3	−0.4
C-section in last 5 years	−0.8	1.5	−0.6	−1.1	1.4	−0.4
Child characteristics						
Birth year	0.3	0.9	−1.2	0.0	0.6	−0.7
Mother reported child birth size	−0.8	1.6	−0.8	−1.2	1.5	0.0
Household characteristics						
Wealth index	**−8.4**	**4.0**	**4.4**	**−3.7**	**5.3**	−0.8
Bicycle	**3.9**	−0.2	**−3.7**	1.1	−1.4	−0.4
Motorcycle	1.5	−0.2	−1.3	0.9	−0.5	−0.5
Car	0.8	**−2.4**	1.5	1.2	**−2.3**	1.1
Female headed household	**−3.5**	1.3	**2.2**	−1.2	**2.2**	−0.9
Environment characteristics						
Region	**2.5**	**−10.2**	**7.6**	**6.1**	**−9.1**	**2.5**
Rainy season birth	−0.1	1.8	−1.7	−0.6	1.6	−1.1
Facility characteristics						
Facility type	0.5	−1.8	1.3	−0.8	**−2.7**	**3.3**
Managing authority	**−8.1**	**−4.1**	**12.2**	**−2.6**	**−4.4**	**8.2**

Note: T-statistics greater than 1.96 bolded to signify a statistically significant difference in characteristic between treatment groups.
Abbreviation: GPS, generalized propensity score.

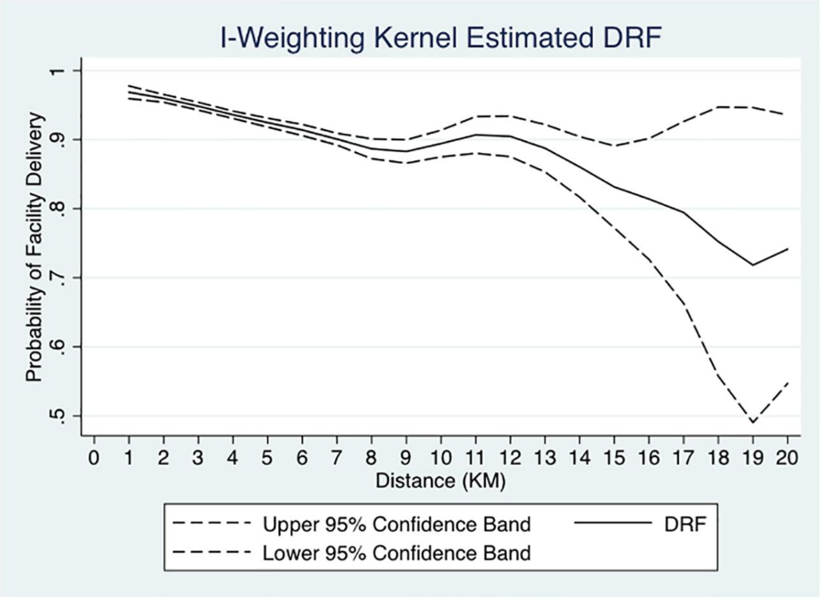


FIGURE 3 Dose response function

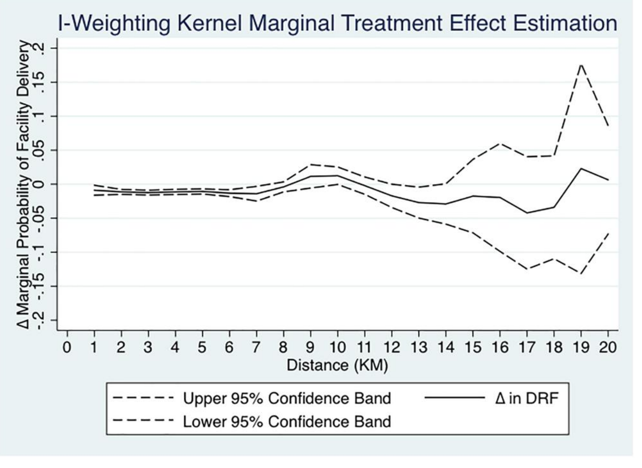


FIGURE 4 Derivative of dose response function

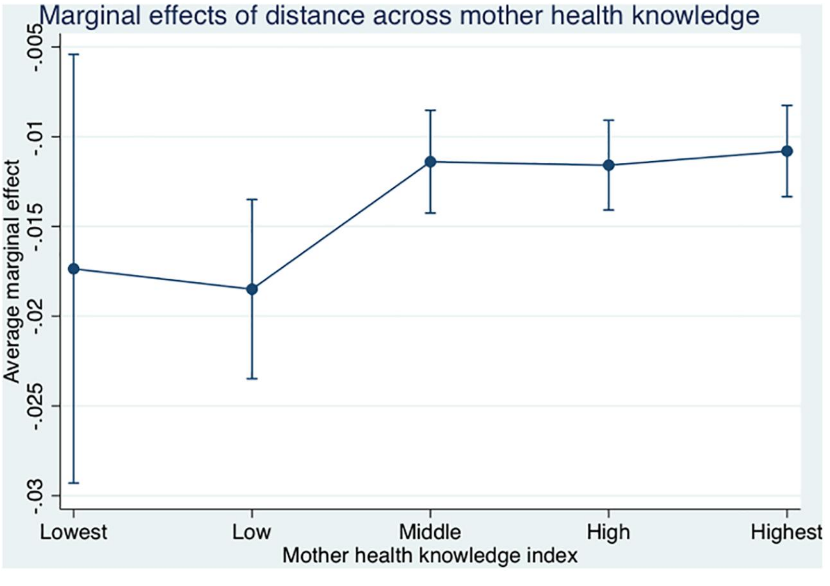
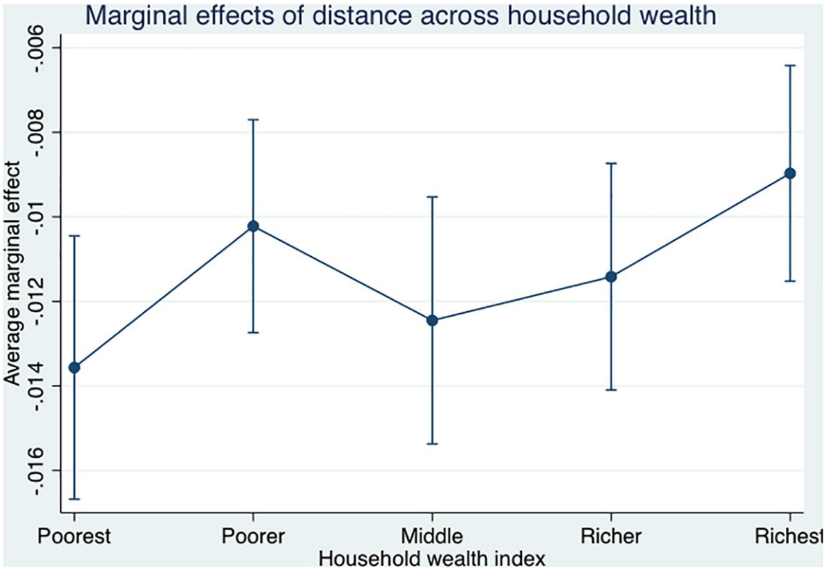


FIGURE 5 Heterogeneous effect of distance across levels of mother health knowledge

FIGURE 6 Heterogeneous effect of distance across levels of household wealth



We use principal component analysis to create a composite quality index and categorize facilities by level of quality. We then divide the sample according to the quality category of the nearest health facility offering delivery services (low, medium, high). Our results are unchanged when controlling for the quality of the nearest facility with this more detailed measure of quality (see Appendix K; MacQueen, 1967).

4 | DISCUSSION

This paper examines the effect of geographical access to health care, measured by distance to nearest health facility, on the utilization of delivery services. The results suggest that distance to health care still represents a significant constraint to utilizing maternal health care services in Malawi. Importantly, our findings go beyond previous studies which have also identified similar negative distance-utilization relationships. Unlike previous models which have parametrically constrained the impact of distance, our DRF estimates allow full exploration of heterogeneity in the effect of distance on facility delivery along the values of distance observed. The expected probability of having a facility delivery falls with distance: from 96.9% at 1 km, to 74.1% for women residing at 20 km from their nearest facility. We find non-linearities, with the marginal effect of distance increasing at greater distance levels. Ceteris paribus, this suggests targeting health infrastructure development towards households at marginally further distances will result in larger utilization gains. Crucially, such information can be combined with population distribution data to significantly improve evidence-based infrastructure planning. Additionally, we find that distance has a more adverse effect on the utilization rates of women with lower levels of health knowledge and household wealth. Hence, even in circumstances where the direct money price of health care is zero, such as in our setting, heterogeneous responses to distance may maintain inequities in access. This suggests that population characteristics should also be considered in both infrastructure development and attempts to increase utilization rates and improve equity. Finally, we find the estimated impact of distance on the probability of facility delivery substantially increases when accounting for the endogeneity of distance, with estimates over twice as large as when not accounting for unobserved differences in women across distance. The finding that distance is endogenous with respect to utilization suggests the results from the LPM and DRF models should be interpreted as lower bounds of the impact of distance.

Although the models utilized should be considered as complementary, the DRF is our preferred model specification due to the valuable information provided beyond an average effect, which can be readily used to guide health infrastructure development. The findings suggest that health infrastructure policy may benefit from considering factors beyond counts of populations within distance thresholds. Non-linearities in the effect of distance should be considered in facility openings/closings, and can be used with population distribution data to model potential utilization impacts. Information on population background characteristics can also be used to target health infrastructure towards localities

TABLE 5 LPM-IV results

	IV: Distance to nearest school Linear IV model	IV: Number of qualified teachers at nearest school Linear IV model	IV: Number of students in nearest school Linear IV model	IV: Distance of nearest school to trading center Linear IV model	IV: All Linear IV model
First-stage					
Distance to nearest school	0.057***	-	-	-	0.042***
	0.017				0.016
Number of qualified teachers at nearest school	-	−0.082***	-	-	−0.005
		0.012			0.022
Number of students in nearest school	-	-	−0.001***	-	−0.001*
			0.00		0.00
Distance of nearest school to trading center	-	-	-	1.666***	0.257***
				0.276	0.042
Number of observations	11,375	11,375	11,375	11,375	11,375
Number of clusters	676	676	676	676	676
Mother, household, environment controls	x	x	x	x	x
Facility controls	x	x	x	x	x
Birth year trend	x	x	x	x	x
District fixed effects	x	x	x	x	x
Post-estimation results					
Kleibergen-Paap rk Wald F statistic	11.3	34.2	32.2	36.6	23.74
Prob > K-P F	0.00	0.00	0.00	0.00	0.00
Effective F statistic (Olea & Pflueger, 2013)	11.3 < 37.4	34.2 < 37.4	32.2 < 37.4	36.6 < 37.4	25.3 > 23.6
Partial R-squared	0.025	0.049	0.044	0.099	0.177

Note: Robust standard errors clustered as the DHS cluster level in parentheses. All model specifications include the full set of covariates as in specification three of Table 5. All effective F-stats are compared to the critical value given for 5% of the "worst-case" bias and for 5% significance levels. Both first- and second-stage equations include the full set of control covariates. In specifications with one instrument the effective F-stat collapses to the K-P F-stat.

Abbreviations: DHS, Demographic and Health Survey; IV, instrumental variable; LPM, linear probability model.

*$p < 0.10$; **$p < 0.05$; ***$p < 0.01$.

TABLE 6 Instrumental variable estimation results

	IV: Distance to nearest school & Distance of nearest school to nearest trading center			**IV: Number of students at nearest school & number of qualified teachers at nearest school**		
	LPM-IV	**IVprobit**	**2SRI (Raw residuals)**	**LPM-IV**	**IVprobit**	**2SRI (Raw residuals)**
First-stage						
IV: Distance to nearest school	0.041***	0.041***	0.041***	-	-	-
	−0.016	−0.016	−0.016			
IV: Number of qualified teachers at nearest school	-	-	-	−0.057**	−0.055**	−0.057**
				−0.023	−0.023	−0.023
IV: Number of students in nearest school	-	-	-	−0.000	−0.000	−0.000
				0.000	0.000	0.000
IV: Distance of nearest school to trading center	0.283***	0.282***	0.283***	-	-	-
	−0.042	−0.041	−0.041			
Second-stage						
Distance to nearest relevant facility	−0.012***	−0.012***	−0.012***	−0.025***	−0.011***	−0.023***
	0.004	0.003	0.002	−0.006	−0.006	−0.005
Number of observations	11,375	11,456	11,375	11,375	11,456	11,375
Number of clusters	676	675	676	676	675	676
Mother, household, environment controls	x	x	x	x	x	x
Facility characteristics	x	x	x	x	x	x
Birth year trend	x	x	x	x	x	x
Region fixed effects	x	x	x	x	x	x

Note: 2SRI first-stages estimated by GLM and second-stage estimated via probit. AMEs for Ivprobit and 2SRI are reported. Standard errors are bootstrapped for 2SRI estimates to account for estimated residuals included in second-stages. Second-stage reported estimates are calculated average marginal effects and represent changes in the probability of having a facility delivery from a unit increase in distance.

Abbreviations: 2SRI, two-stage residual inclusion; IV, instrumental variable; LPM, linear probability model.

Statistical significance levels are denoted by ***$p < 0.01$, **$p < 0.05$ and *$p < 0.10$.

with populations for whom distance has a relatively larger reductive effect on utilization. Considering such information in health infrastructure development could not only result in greater utilization rate improvements than targeting solely based on population levels, but could also reduce within country utilization inequalities.

Understanding of the mechanisms through which distance reduces utilization is also of significant importance for designing effective policy to mitigate the impact. Policy responses to increase utilization rates may either be supply side, aimed at increasing the availability and quality of maternal health care services, or demand-side, aimed at increasing individuals' demand for services. A range of policies including travel vouchers (Ommeh et al., 2019), improving referral transport (Samai & Sengeh, 1997) and cash on delivery (Grepin et al., 2019) have been trialed in various LMICs to increase maternal health care utilization. In Malawi, a presidential initiative stated an intention to build 130 maternity waiting homes in Malawi (Presidential Initiative on Safe Motherhood, 2012). When the physical obstacle of distance is the primary disincentive to seek care, policy should focus on expanding access or improving transport. However, in circumstances where other factors, such as a baseline preference for a home delivery, are important, such policies might have less impact.[8] The hypothesized mechanisms behind the unobserved confounding and the higher utilization rates in women with greater health knowledge suggests the disincentive effect of the physical obstacle of distance may not be the primary issue. This suggests alternatives to increasing the physical accessibility of health facilities may be effective in reducing the impact of distance. General improvements in health information or facility quality should increase utilization among women not currently seeking facility deliveries. Therefore, although increasing health infrastructure will increase utilization rates, Malawi has a range of policy alternatives which should be considered. Further research on the factors mediating the effect of distance on utilization can provide useful insights to assist policy-makers in ensuring access policies target the specific factors dissuading women from seeking care.

Relatedly, additional research is required into the source of distance's endogeneity with respect to utilization. Kumar et al. (2014) speculate that residing closer to health facilities results in improved health behaviors. Individuals residing further from facilities may, therefore, have worse health status inducing individuals to seek delivery in a health facility to offset higher risks of complications. An alternative explanation is that women at further distance differ in the information and treatment by health workers. As almost all women in our sample attend ANC visits, some exposure to health care during pregnancy is consistent across distances. Pressure may be put on women who live in remote communities by health workers who understand the consequences of complications in remote settings. This is similar to the qualitative findings of Griffiths & Stephenson (2001) who found remote women understood the extra importance of preventive action. This could be through strategic relocating during the final stages of pregnancy or simply extra effort to ensure a facility is reached. The different mechanisms suggest differential appropriate policy responses.

Finding ideal instruments for a variable such as distance—which is related to remoteness—is inherently difficult, due to the relation of remoteness with a large number of other factors. One alternative strategy, and an approach for consideration in future research, could be to exploit facility openings and closings. However, to date data limitations have precluded this approach. A complicating factor of utilizing panel data on this topic is that in the presence of measurement error it can significantly magnify attenuation bias (Griliches & Hausman, 1986). Therefore, IV approaches may represent the optimal strategy without access to more accurate spatial data. However, exploration with alternative methods could also shed light on whether local average treatment effects (LATE) of IV estimates are closer to the policy relevant parameter than OLS (Heckman et al., 2006). Future research would also benefit from data providing measures of distance to health facility at household level. This would allow for controlling of unobserved village differences that are common to women within a village that may be correlated with health facility accessibility and utilization rates (Kondylis & Manacorda, 2012). Methods which could account for such unobserved heterogeneity should be combined with models allowing the exploration of the heterogeneity in the effect of distance to provide the best information to inform health infrastructure planning.

Like any study, we faced several limitations. We are unable to identify the specific facility women utilized. This constraint partially informed our research question as, had we observed delivery location, it would be possible to construct a full patient choice model, mapping women's preferences among the full set of alternative health care providers (McFadden, 1973). In the absence of this information, we examine the impact of distance to the nearest health facility on the utilization of any health facility for delivery services. A distinction has been made between "passive" and "active" patients in LMICs, where unlike the former, the latter do not necessarily seek health care at the lowest distance/cost provider (Leonard, 2014). While this article does not attempt to address issues surrounding facility choice, our data suggests that a non-trivial proportion of women in Malawi may bypass the nearest health facility (Table 5 and Appendix E). Future research would benefit from data that definitively matched individuals with where care was sought, allowing for the development of accurate facility choice models. To date, this has only been examined in an urban environment where distance is a much weaker determinant of facility choice (Cronin et al., 2017). Such research would allow for the examination of the impact of distance compared to other facility-level characteristics and how these are traded-off. Additionally, use of administrative data linking individuals to facilities where care was sought would also circumvent the potential for recall bias faced when using mother-reported historical birth location.

We rely on having adequately controlled for all observable confounders. It is likely that rurality, to which distance is related, is highly correlated with factors that may also impact utilization, for example SES. The DHS does not contain information on income or consumption expenditure, therefore, we use proxy variables to capture variation in SES. Our primary specifications include measures of women's education and literacy and a household wealth index. While this is standard practice, the veracity of the use of wealth indices to proxy for income is debatable (Filmer & Prichett, 2001). We also checked specifications including further information on the characteristics of women's husband which may have further captured variation in household income (husband's occupation, husband age, husband educational level, woman's earning relative to husband etc.) with the effect of distance unchanged by their inclusion.[9] Further, contextual factors reduce concerns about missing variation in SES and its potential importance in modeling health care utilization in Malawi. Work has examined the income/expenditure distribution in Malawi to identify households in need of targeted cash transfers (International Labour Organisation, 2016). This work has exposed the difficulty in identifying households due to a lack of variation in many common measures of SES. Given this high degree of homogeneity in income and expenditure in the rural population, this reduces the risk of variation in income/expenditure explaining different in health care utilization in our sample. The absence of user fees also reduces the role of income in determining utilization. Finally, in addition to the use of variables proxying for SES, the IV approaches should alleviate concerns of confounding from this source.

For most household surveys collecting sensitive information and geographic data, some form of “geo-scrambling” is undertaken to maintain individual “anonymity.” In our context, two distinct geographic displacement procedures introduce measurement error to the constructed distance variable. First, due to the aggregation of households located within the same cluster to a single point coordinate representing the DHS cluster centroid results, we are unable to measure within-cluster distance to health facility variation. However, this within cluster variation is unlikely to be substantive. DHS clusters are related to Enumeration Areas (EA) defined for the Population and Housing Census in Malawi. EAs are the lowest administrative area within Malawi and therefore represent small geographic areas: “Since the EAs are delineated for the purpose of census enumeration, they generally have a relatively small number of households (e.g., between 80 and 120 households, which is a practical size for the listing operation. It is important that the EAs have well-defined boundaries, which are generally defined on census maps.” (Department of Economic and Social Affairs: United Nations, 2016). Second, the displacement of cluster centroids results in random noise being added to the measure of distance. We contend that both procedures bias our estimates of the causal effect of distance towards 0 (Appendix C; Arbia et al., 2015; Carroll et al., 1995; Goodchild et al., 1992; Perez-Heydrich et al., 2013) effect. Simulation work attempting to quantify the impact of such displacement on empirical estimates has suggested that the coefficient on distance may be 36% smaller for the circumstances most similar to ours faced (Elkies et al., 2015). Therefore, the implications of this measurement error imparted from the “geo-masking” are predictable and can be accounted for in the interpretation of our results. Acknowledging these effects of the measurement error (in addition to the dissection of the endogeneity) we interpret our estimate as a lower bound of the effect of distance on utilization. On the other hand, a strength of our study is that we avoid another sources of measurement error, such as expert elicitation or household estimates of distance, or only using a sample of health facilities. These approaches have been shown to introduce relatively more severe effects than cluster displacement, as they have an ambiguous effect on the sign and size of the bias compared to measurement error originating from known geographic displacement formulae (Schoeps et al., 2011, Skiles et al., 2013).

There is a growing debate about the perceived trade-off between increasing health care accessibility and improving the quality of health care (Kruk et al., 2018). Improvements in access to and utilization of health care services have not always translated into improved health outcomes. This has led some to suggest LMICs should consider relocating certain health care services—including delivery services—to higher levels of care, such as specialist hospitals (Gage et al., 2019). Given that such policies would result in longer travel distances to utilize services, the potential benefits of improved quality must be considered in the context of potentially significant reductions in utilization, as suggested by our findings. Our results can provide important inputs to this quality-access trade-off debate in order to model welfare changes from different policy choices.

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CONFLICT OF INTEREST

No conflict of interests are present to declare.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are openly available at https://urldefense.com/v3/__https://dhsprogram.com/__;!!N11eV2iwtfs!4mdvHDRgNduxVujlFyA29YeCfV5_TBTyS07m8mmAVSnfE3l38a3h4jafuDPObTGx$

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ENDNOTES

[1] 2017 US dollars.
[2] 0 indicates a home birth and 1 a facility delivery. Binscatter plot produced from Cattaneo et al. (2019).
[3] See also Kluve et al. (2012), Flores & Mitnik (2013), Egger & Ehrlich (2013).
[4] DRF analyses are implemented using the STATA packages GPS score, dose response and DRF by Bia et al. (2008, 2014).
[5] Non-health institutions of development include towns, district headquarters, railway stations, and bus stops.
[6] We also perform a likelihood-ratio test to check balance reaching similar conclusions. Table available upon request.
[7] This drops only 16 observations.
[8] In addition to likely not being cost-effective in high baseline utilization contexts such as Malawi.
[9] These results are available upon request.

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SUPPORTING INFORMATION

Additional supporting information may be found online in the Supporting Information section at the end of this article.

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