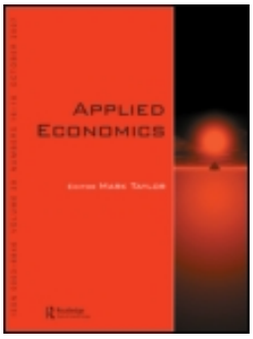

Applied Economics

ISSN: 0003-6846 (Print) 1466-4283 (Online) Journal homepage: https://www.tandfonline.com/loi/raec20

Does distance matter for institutional delivery in rural India?

Santosh Kumar, Emily A. Dansereau & Christopher J. L. Murray

To cite this article: Santosh Kumar, Emily A. Dansereau & Christopher J. L. Murray (2014) Does distance matter for institutional delivery in rural India?, Applied Economics, 46:33, 4091-4103, DOI: 10.1080/00036846.2014.950836

To link to this article: https://doi.org/10.1080/00036846.2014.950836

© 2014 The Author(s). Published by Taylor & Francis.

Published online: 30 Aug 2014.

Submit your article to this journal

Article views: 4145

View related articles

View Crossmark data

Citing articles: 26 View citing articles

Full Terms & Conditions of access and use can be found at
https://www.tandfonline.com/action/journalInformation?journalCode=raec20

Applied Economics, 2014
Vol. 46, No. 33, 4091–4103, http://dx.doi.org/10.1080/00036846.2014.950836

Does distance matter for institutional delivery in rural India?

Santosh Kumar[a,*], Emily A. Dansereau[b] and Christopher J. L. Murray[b]

[a]*Department of Economics and International Business, Sam Houston State University, Huntsville, TX 77341-2118, USA*
[b]*Institute for Health Metrics and Evaluation, University of Washington, Seattle, WA 98121, USA*

This article estimates the causal effect of distance to health facility on in-facility birth in rural India, taking into account the endogenous placement of the health facility. We find that women living farther away from the health facilities are less likely to give birth at a health facility. Each additional kilometre from the nearest health facility is associated with a 4.4% decline in the probability of in-facility birth. Policy simulation results indicate that providing access to a health facility within 5 km would increase institutional delivery by 10%. Overall, our findings confirm that distance is an important barrier to in-facility births in rural India.

Keywords: in-facility birth; access; distance; India

JEL Classification: I1; I18; 012

I. Introduction

The aim of Millennium Development Goal (MDG) 5 is to reduce the maternal mortality ratio (MMR) by three-quarters between 1990 and 2015. One of the important indicators that this goal is on track is safe delivery. Progress on this front has advanced quickly as MMR has declined by almost 50% between 1990 and 2005, from 520 to 290 deaths per 100 000 live births (Hogan *et al.*, 2010). However, this decline in mortality has not been uniform. There are still many countries, particularly in Africa and South Asia, where the incidence of maternal deaths is still unacceptably high. India in particular faces one of the greatest burdens of maternal and neonatal deaths.

Safe delivery is also hypothesized to improve health-seeking behaviour and health care practices related to post-natal care. Children born at health facility are more likely to be vaccinated and breastfed (Odiit and Amuge, 2003). Properly vaccinated and adequately breastfed children are less likely to be malnourished and have better health. There is a growing literature on the interaction between early-life health and human capital accumulation (Bleakley, 2010). Bleakley (2010) discusses that poor childhood health might depress the formation of human capital, which in turn could affect lifetime income through either schooling or labour-market productivity channels. Therefore, institutional delivery can also be thought of as an investment in human capital and can play an important contributory role in the development process of an economy.

In 2008, more than 63 000 maternal deaths and 1 million neonatal deaths occurred in India, a number that represents 20% and 30% of the global burden (World Health Organization *et al.*, 2010). Most of these deaths occur in situations where the mother must deliver in a risky environment, one that lacks life-saving equipment, hygienic conditions and supervision by skilled attendants. It is estimated that nearly 60% of all births in rural parts of

*Corresponding author. E-mail: skumar@shsu.edu
An earlier version of the article was circulated as 'Geographic Constraints to Institutional Delivery in Rural India: An Instrumental Variable Approach'.

© 2014 The Author(s). Published by Taylor & Francis.

This is an Open Access article distributed under the terms of the Creative Commons Attribution License (http://creativecommons.org/licenses/by/3.0/), which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited. The moral rights of the named author(s) have been asserted.

India still occur at home without the benefit of skilled birth attendants (International Institute for Population Sciences (IIPS), 2010).

There are three primary types of barriers to health care service utilization: (1) delays in deciding to seek care, (2) delays in reaching an adequate health care facility and (3) delays in receiving adequate care at health care facilities. This is cited as the 'three delays' model in the literature (Thaddeus and Maine, 1994). The first delay stems from the lack of health-related knowledge; the second delay is caused by physical inaccessibility (distance) of facilities, lack of transportation, difficult terrain and high travel costs; and the final delay is caused by inadequate availability of equipment, drugs and medical staff.

Poor identification of the danger signs and failure to recognize symptoms delay decision-making to seek care. Poor health decision-making depends on many factors such as lack of health knowledge, unsupportive spouse, lack of autonomy, etc. Many studies have shown that patients' limited health knowledge has a substantial negative effect on the use of health services (Hsieh and Lin, 1997; Parente *et al.*, 2005; Waiswa *et al.*, 2010). In the Indian context, Bhargava *et al.* (2005) and Kumar and Dansereau (2014) found that health infrastructure, availability of drugs and the quality of care are important predictors of health care utilization.

In this article, we focus on the second delay, which is related to access and distance to health facilities. Distance is known to be one of the most important nonmonetary barriers that impede access to health care, especially in rural areas. Large geographic distances to a health care provider coupled with a lack of transportation facilities can adversely affect the utilization of health services and health outcomes (Sarma, 2009). Despite the importance of access to health care usage, very little evidence is available on the *causal* impacts of distance to health facility on health care utilization. The objective of this article is to explore this relationship in a causal framework in a resource-constrained country like India, which relies heavily on a decentralized public health system.

The extent to which distance to health facilities may affect utilization of health services and health outcomes is an empirically open question and depends greatly on contextual factors. For instance, geographic distance may become irrelevant in a setting with high-quality health and transport infrastructures (Matthews *et al.*, 2005). Some studies have shown that households are keen to travel longer distances for high-quality care, and there is some evidence of a trade-off between distance and quality of care (Collier *et al.*, 2002).

However, these findings may not apply in a setting plagued with limited health services, inadequate transport infrastructure and poor populations, such as rural India. In such a setting, physical access often presents a fundamental and insurmountable barrier to accessing adequate care at birth and therefore plays a central role in causing high maternal mortality (Gething *et al.*, 2012).

Furthermore, rural households are particularly deprived as they often lack efficient means of transportation. Even among women who do reach a facility, some are beyond help by the time they arrive (Ronsmans and Graham, 2006). Some research (including on India) has found that geographic access is more important than socio-economic factors for the usage of maternal health services, particularly in rural areas with limited health services (Elo, 1992; Sawhney, 1993). Another study found that the distance to the nearest hospital was an important determinant of institutional delivery in rural India, although they identified wealth status as the most influential factor (Kesterton *et al.*, 2010). While estimating the demand for outpatient care, Sarma (2009) found that distance to formal health care facilities negatively impacted the health care demand and the effect was modified by access to transport. In a similar study in Zambia, distance was found to have a negative impact on the probability of seeking professional care (Hjortsberg, 2003).

Against this background, the primary aim of this study is to assess the importance of the distance to the nearest health facility in determining the place of delivery (facility versus home) after controlling for the influence of confounding factors, such as socio-economic status, mother's age, mother's education, mother's religion and region. We also consider factors that may modify the impact of distance, such as access to roads and motorized vehicles.

Due to a lack of suitable data, very few studies that are nationally representative have examined the effect of distance on maternity care after controlling for individual and household-level variables. The majority of health surveys do not contain information on the distance to health facilities. The recent Demographic and Health Surveys have collected geographic coordinates, but the scrambled nature of geographic information systems coordinates makes their use prone to errors and inconsistent. Fortunately, we have access to data that provide more reliable information on the distance between a village cluster and the nearest health facilities. Specifically, we use the District Level Household Survey (DLHS-3), implemented in 2007–2008 in all Indian districts, to test our hypothesis that better access to health facilities improves the probability of in-facility delivery (IFD).

This study contributes to the existing literature on barriers to access to health care and utilization of health services. This is especially relevant in a resource-constrained setting where access to health care is not universal. This article has four main strengths and differs from previous studies on these four dimensions. First, the data used in this study measure distance well, while very few other household data have distance measures. Second, the strength of this article also lies in the large sample size. Most of the previous studies are either case studies or

focused on one particular region of a country. In contrast, our study uses a recent nationally representative survey and includes close to 200 000 births. The most similar national analysis for India was conducted using National Family Health Survey 1 and 2 data collected in 1992 and 1998, respectively (Kesterton *et al.*, 2010). The sample size in this study was less than 22 000 births, significantly less than the sample size of our study. Third, to the best our knowledge, this is the first study that tackles the endogeneity issue head on and provides a robust causal relationship between distance to facility and IFD. Finally, the study also contributes to the debate on the relative importance of access versus the quality of care. Policymakers in developing countries are stuck in policy dilemmas on whether to spend resources in increasing the density of facilities or improving the quality of care in existing facilities and findings of our study can help them make an informed decision.

The remainder of this article is organized as follows: Section II lays the conceptual framework while Section III presents the empirical methodology adopted in this article. Section IV describes the data, Section V presents the main results and finally Section VI concludes and discusses policy implication of the findings.

II. Conceptual Framework

The health care demand model that we estimate in this study is similar to Borah (2006). Consider a representative consumer i who derives utility from consumption of medical and non-medical goods. The utility maximizing behaviour of the individual is represented by the utility function $U(C,H)$, where C is the consumption of nonmedical goods and H is the expected level of improvement in health after receiving care. The usual assumptions are made about the utility function: $U_c > 0$, $U_{cc} < 0$, $U_h > 0$, $U_{hh} < 0$.

The model also assumes that an individual faces J alternative health care providers. However, for simplicity, we assume that the individual has two options: (1) seek modern care ($J = 1$) or (2) use home-based treatment ($J = 2$). The level of improvement in health (H) after receiving treatment from provider j is $H_j(X, Z_j)$, where X is observed attributes of the individual or household and Z_j is a set of provider j attributes. For simplicity, assume that this consumer spends her income only on the consumption of goods and health. Therefore, combining all these information, consumer i's utility maximization problem can be written as:

$$\max_{C_{ij}, j\in(1,2)} U(C_{ij}, H_{ij}) \tag{1}$$

subject to the budget constraint:

$$C_{ij} + P_{ij} = Y_i, \text{where } P_{ij} = p_{ij} + d_{ij} \tag{2}$$

where Y is the income of an individual, C_{ij} is the amount spent on consumption goods, P_{ij} is the total amount spent on seeking care from provider j. P_{ij} is the sum of direct (p_{ij}) and indirect costs (d_{ij}). d_{ij} may be the transport cost or foregone wages due to the time spent on travelling to the provider j.

The consumer will choose provider j that gives her the highest expected utility. Giving birth in a health facility will certainly provide higher utility; however, it involves cost as well (both direct and indirect). The consumer will choose to deliver in a health facility only if the expected benefit of in-facility birth is higher than the total cost. One prediction of this model is that the utility of consumer i from choosing provider j will be lower as the distance to provider j increases because greater distance implies increased travel time and that in turn results in higher transport cost and forgone wages (d_{ij}). The following section shows the empirical specification used to test this prediction.

III. Empirical Framework

This section describes the econometric methodology used to empirically investigate the model laid out in the previous section, which is to estimate the causal effect of distance to closest health facility on IFD. Since our main outcome variable IFD is binary, we first estimate the following probit model:

$$\begin{aligned} P(IFD_{ivd} = 1) = \phi(&\alpha + \beta_1 DIST_v + \beta_2 X_{ivd} \\ &+ \theta YOB_{ivd} + \mu_d + \varepsilon_{ivd}) \end{aligned} \tag{3}$$

where IFD_{ivd} is a binary variable indicating whether women i delivered in a health facility, DIST is the distance to nearest health facility in kilometres, X_{ivd} is a vector that includes household and village-level variables as described below, YOB is the year of birth dummies capturing the time trend and μ_d is a fixed effect unique to a district that captures the time-invariant differences across districts. Finally, ε_{ivd} is the error term that captures the impact of all other unobserved variables that vary across individuals, villages and districts, and ϕ is the standard normal cumulative distribution. All models use survey weights to account for sample design and population weighting, and SEs are adjusted for clustering at the village level.

X_{ivd} represents characteristics of women, households and villages, such as mother's age at birth; mother's education; whether the household belongs to scheduled caste/tribe;

religion; household wealth quintile; whether the household possesses motorcycle/car/truck; Janani Suraksha Yojana (JSY) payment; and finally whether the village is connected to an all-weather road.[1] IFD includes births in private as well as in public health facilities. Equation 1 is estimated in STATA/SE 11 using the 'probit' command, and marginal effects (ME) are estimates using the 'margins' command.

DIST in Equation 3 is a continuous variable and is measured in kilometres. The village module of the DLHS-3 survey reports the distance from the village to each type of facility in kilometres,[2] and the DIST variable has been generated as the shortest distance to one of these six facilities. For some households, DIST could be distance to a primary health centre (PHC), while for other households, it could be distance to a district hospital (DH). We also estimate a variant of Equation 3 that uses distance as a categorical rather than continuous variable. DIST is divided into three categories: less than 5 km, between 5 and 10 km and greater than 10 km, with less than 5 km as the reference category.

Our preferred model is probit; nevertheless for comparison, we also estimate a linear probability model (LPM) wherever possible. Previous studies have shown that if the goal of the study is to estimate the average effect, which we often are interested in, then LPM and probit provide qualitatively similar results.[3]

Under the assumption that distance to the nearest health facility is purely exogenous, the probit estimates in Equation 1 provide the causal estimate of access on IFD. However, this assumption is unlikely to be true as facility placement may not be random. Although many previous studies have assumed distance to be an exogenous variable, one could still argue that the placement of health facilities may be nonrandom. Health facilities may have been set up in areas that have poor health outcomes and high morbidity burdens. Endogeneity of DIST may also be due to measurement error and unobserved heterogeneity.[4] There could be unobserved omitted variables that may affect the outcomes and placement of the health facilities. For example, a village with a larger, educated and political active population could attract health facilities and may also have better outcomes due to higher health knowledge and better health behaviour of the population. This will bias the estimates in Equation 1.

This discussion suggests that the exogeneity assumption for DIST in Equation 3 may not be true. Therefore, we attempt to deal with this concern by employing instrumental variable (IV) estimation to consistently estimate the causal impacts of DIST on IFD. Instrumental variables are (1) correlated with the endogenous variable (distance to the nearest health facility) and (2) not correlated with the error term in Equation 3. If these two conditions are satisfied, then one can identify and estimate a consistent estimate of the causal effect of distance on IFD.

There are many variants of IV estimation for binary-dependent variable, including two-stage residual inclusion (2SRI), IV-probit, IV-LPM and full-information maximum likelihood (FIML) bivariate probit. Bhattacharya *et al.* (2006) reviewed the latter three estimators and showed that in a test on simulated data, the IV-probit and IV-LPM estimators exhibited greater bias than the 2SRI and FIML estimator even in the presence of misspecification of the distribution of the error terms. Thus, the 2SRI estimator appears to be a good choice for this analysis; however, as a robustness check, we also estimate IV-probit and IV-LPM.

We estimate 2SRI model as suggested by Terza *et al.* (2008). The basic empirical model for our analysis is:

$$DIST_v = \alpha + \beta_1 Z_v + \beta_2 X_{ivd} + \theta YOB_i + \mu_d + \varepsilon_{ivd} \tag{4}$$

$$IFD_{ivd} = \alpha + \beta_3 \widehat{DIST}_v + \beta_4 X_{ivd} + \theta YOB_{ivd} + \mu_d + \varepsilon_{ivd} \tag{5}$$

Equation 4 is the first-stage regression where the endogenous variable, DIST, is regressed on the instrument (Z) and other exogenous variables. In the second stage (Equation 5), the outcome IFD is regressed on the predicted value of the endogenous variable DIST from the first stage (Equation 4) along with other exogenous variables. For 2SRI, the endogenous DIST variable and the predicted residuals from the first-stage estimations are included in the second stage.[5]

X_{ivd} in Equations 4 and 5 is the same set of controls used in Equation 3 that are assumed to be exogenous. The parameters in Equation 5 are identified uniquely by the assumption that the instrument Z does not belong to Equation 5, that is assumption (2) above. The excludability of the instrument is an assumption that is inherently un-testable since one can never observe the error term, and so researchers often have to rely on *a priori* reasoning to

[1] JSY is a conditional cash transfer scheme to promote birth in a health facility.

[2] The village questionnaire reports distance to 10 types of health facilities. For the purpose of our analysis, we only considered the types of facilities that accounted for at least 1% of all births. These included PHC, block PHC, community health centre (CHC), DH, private clinic and private hospital/nursing homes.

[3] Angrist and Pischke (2008, Chapter 3) show that LPM is a good option for different kinds of limited dependent variables. Hellevik (2009) also makes a compelling case for choosing LPM over logit or probit.

[4] Distance was not measured by the survey or rather it was subjectively reported by the village head. In the absence of actual measurement, we believe that DIST is prone to measurement error.

[5] We use 'IVPROBIT and IVREG2' command, respectively, in STATA/SE 11 to estimate the IV-probit and IV-LPM models.

justify the excludability condition. A few statistical tests are available to indirectly test the excludability condition if the model is over-identified; however, it cannot be tested in a just-identified model like ours.[6]

The bias in the OLS estimates is very difficult to establish and can go in either directions. For instance, an area with higher density of facilities (less distance) may also have better health behaviour. In this case, the actual effect of distance will be underestimated. By contrast, if facilities were placed in areas with high disease burden, then the actual effect of distance will be overestimated. Consequently, it is not easy to correctly estimate the effect of distance on IFD by using OLS regression model.

Instrument

Finding good instruments for DIST is key for our empirical approach. A valid instrument should be correlated with DIST but not with IFD. We chose an instrument based on the prior studies in which DIST is an endogenous variable. In the development economics literature, a widely used instrument for distance to school is distance to other village-level infrastructures. For example, while examining the effect of school supply constraints on educational outcomes in Ghana, Lavy (1996) used distance to public telephone and post office as instruments for distance to middle school. Similar in spirit, Mukhopadhyay and Sahoo (2012) constructed an index variable by principal component analysis (PCA) that includes distance to the nearest telephone booth, police station, public distribution shop and bank and used this index to instrument the distance to nearest primary school.

Following this strand of literature, we use 'distance to non-health institutions of development' to instrument the endogenous variable. Specifically, we construct an index using PCA that includes distance to the nearest town, distance to the district headquarter, distance to the nearest railway station and distance to the nearest bus stop.[7] The implicit assumption is that improving access to village facilities is correlated with the opening of health facilities but has no direct effect on IFD once we have controlled for other regressors.

IV. Data

We use data from the third wave of the DLHS-3, which is a nationally representative health survey covering maternal and child health, reproductive health and use of maternal and child health care services. DLHS-3 was carried out during 2007 and 2008, interviewing 643 944 ever-married women between 15 and 49 years of age in 601 districts from 28 states and 6 union territories of India. Every woman was asked about her fertility history since 1 January 2004. Of the 643 944 ever-married women interviewed, 504 272 (78%) resided in rural areas and only 177 294 women had given birth since 2004. After dropping observation with missing values, our final analytical sample comprises of 158 897 women. The survey also has village and facility survey corresponding to each household.

In the women module, for the last live/still births born since 2004, women are asked where (place) their children were born, who assisted during the delivery, characteristics of delivery and any problems that they faced during the delivery. We use the information on place of the last delivery to construct our main outcome variable IFD. It includes births either at public or at private health facilities. The reference category is out-of-facility delivery which includes noninstitutional births mainly at home. We exclude births in sub-centres, Ayush clinics and non-governmental organization/trust clinics, as less than 1% of births were recorded in these facilities.

The main independent variable is the distance to the nearest public or private health facility. We use information on the distance to different types of health facilities collected in the village survey, including PHC, block PHC, CHC, DH, private clinic, and private hospital/nursing home. The distance is measured from the village centre and is reported in kilometres. The average distances to the nearest PHC, CHC and DH are 9.06, 17.66 and 32.57 km, respectively. The average distances to the nearest private clinic and private hospital are 10.38 and 18.69 km, respectively. The identifying assumption in our article is that women visit the nearest health facility for delivery care or that access to a nearby facility helps with referral to a higher level facility.

Furthermore, we additionally control for potential confounders that may affect IFD. In India, utilization of health services varies greatly by social groups and caste, so we include household caste and religion as other explanatory variables. Previous research has also shown that mother's age and education are dominant predictors of facility delivery. To capture this, we add mother's age at birth and mother's education in our model. An asset-based wealth index is also included to capture the importance of financial resources in delivery care. Finally, we also include access to a drivable road and ownership of a car or

[6] Angrist and Pischke (2008) provide an excellent review of the IV model.

[7] We preferred to use an index rather than the distances to nonhealth infrastructures as multiple instrument because too many instruments can overfit instrumented variables, failing to expunge their endogenous components and biasing coefficient estimates towards those from noninstrumenting estimators (Roodman, 2009).

motorcycle to capture the effect of transport barriers on IFD. Sampling weights are used in the regression models to account for sampling design.

V. Results

Summary statistics

Table 1 provides the means and SDs for the variables used in the analysis. The institutional delivery rate is 36%, implying that 64% of births occur at home under risky and unsafe environments. The mean distance to the nearest health facility is 4.94 km (this includes public as well as private facilities). About 58% of the women in rural India live within 5 km of health facility and a quarter of women live between 5 and 9 km. For 18% of women, the nearest health facility was located beyond 10 km.

The IFD delivery rate is highest in the 0–4 km category. About 42% of women living within 5 km of a health facility gave birth at the facility while the IFD rate was 32% and 26% for women living between 5 and 9 km and more than 9 km away from the nearest facility, respectively. The average distance to PHC is 8.70 km and the mean distance to the district hospital is 34 km.

The average age at birth is 25 years and about 34% of the women have completed primary school, while only 7% of the women have completed secondary school (more than 10 years of schooling). The majority of the women are Hindu (79%) and many belong to disadvantaged social groups (SC/ST, 40%). Very few households have access to either a car or a motorcycle (2%), but the majority live in villages connected by an all-weather drivable road (85%). About half of the sample (50%) belongs to the bottom two wealth quintile categories, implying that poor women constitute the majority of the sample.

Table 1. Descriptive statistics, *N* = 158 897

	Mean	SD
	(1)	(2)
In-facility delivery	0.36	0.48
Distance to nearest health facility (km)	4.94	6.08
Women living in 0–4 km	0.58	0.49
Women living in 5–9 km	0.24	0.43
Women living in >9 km	0.18	0.38
In-facility delivery (0–4 km)	0.42	0.49
In-facility delivery (5–9 km)	0.32	0.47
In-facility delivery (>9 km)	0.26	0.43
Distance to nearest PHC (km)	8.70	7.97
Distance to nearest block PHC (km)	11.70	10.63
Distance to nearest CHC (km)	17.64	15.46
Distance to nearest DH (km)	34.07	23.83
Distance to nearest private clinic (km)	10.06	12.49
Distance to nearest private hospital (km)	18.67	17.49
Mother's age at birth	25.08	5.36
Mother's education (primary = 1)	0.34	0.47
Mother's education (secondary = 1)	0.07	0.26
Scheduled caste/tribe (SC)	0.40	0.49
Other backward caste (OBC)	0.41	0.49
Below poverty line (BPL)	0.34	0.47
Hindu	0.79	0.41
Muslim	0.12	0.32
Wealth quintile (1, poorest)	0.25	0.43
Wealth quintile (2, poor)	0.25	0.43
Wealth quintile (3, middle)	0.22	0.42
Wealth quintile (4, rich)	0.19	0.39
Wealth quintile (5, richest)	0.10	0.30
JSY payment	0.10	0.31
All-weather road in the village	0.85	0.36
Owns car/motorcycle	0.02	0.12

Notes: Means are reported for the continuous variables, and proportions are reported for categorical variables with the SDs. PHC refers to primary health centres, CHC refers to community health centres and DH refers to district hospitals. Primary schooling means completion of more than 5 years of school while secondary schooling means completion of more than 10 years of school. Distance to nearest health facility is the shortest distance to one of six types of facilities.

Regression results

Table 2 presents results from two models where probability of IFD is the main outcome and DIST is the main covariate of interest. The first model is the LPM and the second model is the standard probit model. Results in Table 2 do not correct for endogeneity of the DIST variable. In addition to the possible confounding variables, columns (2) and (4) include district fixed effects to account for time-invariant district characteristics.[8] ME are reported in columns (3) and (4). In all four columns, the coefficients for distance are negative and statistically significant, suggesting that distance to the nearest health facility is negatively associated with the probability of IFD.

As per the results in column (1), a 1-km increase in the DIST results in a 0.5 percentage point reduction in the probability of IFD; the coefficient is statistically significant at the 1% level. Given that the mean IFD is 36%, this means a decrease in IFD by 1.4% (0.005/0.36). The coefficients on road access and ownership of a car/motorcycle are positive and statistically significant at 1% level (column (1)).

Inclusion of district fixed-effects reduces the coefficient almost by half, indicating that district-level characteristics are also important in explaining the variation in IFD (column (2)). The probability of IFD deceases to 0.2 percentage points in column (2) and is statistically different from zero at the 1% level. Columns (3) and (4) report ME from the

[8] We do not report the coefficients for such variables to keep the presentation simple.

Table 2. Effect of distance on institutional delivery in rural India

	In-facility births			
	LPM	LPM	Probit ME	Probit ME
	(1)	(2)	(3)	(4)
DIST (km)	−0.005***	−0.002***	−0.005***	−0.003***
	(0.0006)	(0.0005)	(0.0007)	(0.0005)
Access to road	0.035***	0.019***	0.038***	0.019***
	(0.004)	(0.003)	(0.008)	(0.007)
Own motorized vehicle	0.068***	0.057***	0.066***	0.053***
	(0.012)	(0.010)	(0.012)	(0.011)
District fixed-effect	No	Yes	No	Yes
Observations	158 897	158 897	158 897	158 897

Notes: Robust SEs, clustered by village, are presented in parentheses. Columns (1) and (2) report coefficients from linear probability model (LPM), while columns (3) and (4) report marginal effects (ME) from probit model. All regressions adjust for caste, religion, mother's age at birth, mother's education, wealth quintile, JSY receipt and year of birth dummies. Distance is continuous and is measured in kilometres. All results are adjusted for population weighting and survey design.
***$p < 0.01$.

probit model and results are not very different from the results in first two columns in Table 2. However, since our dependent variable is binary, our preferred specification is probit with district fixed-effects (column (4), Table 2).

Our preferred model in column (4) shows that the probability of IFD decreases by 0.3 percentage points as the distance to health facility increases by 1 km. This means a reduction in IFD by 0.8% at the mean delivery rate of 36%. Ownership of car or motorcycle and access to a road have positive effects on IFD, and the effects are statistically significant at the 1% level. Access to all-weather road increases the probability of IFD by 1.9 percentage points, while ownership of motorized transport increases the probability of IFD by 5.3 percentage points (column (4), Table 2).

The point estimates in column (4) in Table 2 may seem small; however, they are not. The mean distance to the nearest PHC, which is the lowest tier of health care in India, is 8.7 km (Table 1). This implies that if a household lives 8.7 km away from the nearest PHC, the IFD probability decreases by 2.7 percentage points ($0.003 \times 8.7 = 0.026$). This translates into 7.3% decline in IFD $\left(\frac{0.026}{0.36}\right)$ which is quite sizable. At the mean distance to the nearest health facility of 5 km, this effect translates to 1.5 percentage points reduction in the probability of IFD. This result is consistent with the theoretical prediction of distance being an important constraint to seeking care and utilization of health services.

Heterogeneous effects. Next, we examine whether the effect of distance varies by the poverty status of the household and by mother's education level. Poverty status of the household is measured by possession of the government-approved below poverty line (BPL) card by the households. As mentioned before, financial constraints could limit seeking of delivery care as households may not have enough resources to spend on medical fees or transport. In this scenario, we should be able to see a bigger effect of distance on poor households compared to rich households. In Table 3, we run the regressions separately on households that are below the poverty line (BPL = 1) and households that do not belong to the BPL category (BPL = 0). BPL is a government-recognized classification of poverty status and most government-sponsored social programmes are run on the basis of the BPL classification.

Comparing the results in columns (1) and (2) in Table 3, it seems that distance does not have a differential effect on IFD by the poverty status of the household. Though the effects are statistically significant in each group, they are statistically not different across the poverty groups. The probability of IFD decreases by 0.3 percentage points for BPL women, while it is 0.2 percentage points for non-BPL women; however, the difference is statistically insignificant (column (1) versus column (2)).

Columns (3) and (4) explore the heterogeneous effect of distance on IFD by mother's education. Column (3) presents the result for mother with less than 5 years of schooling while column (4) shows the results for mother with more than 5 years of schooling. We chose 5 years as the cut-off point because this is the primary level of schooling in India. The results suggest that effects are not statistically different across columns (3) and (4), though the baseline differential in the IFD rate across the groups is substantial. The IFD rate among primary-schooled women is 58%, while it is only 25% among women that are not primary-schooled.

Table 3. Probit estimates of institutional delivery – by poverty status and mother's education

	In-facility births			
	BPL		Mother's education	
	No	Yes	<5	>5
	(1)	(2)	(3)	(4)
DIST (km)	−0.002***	−0.003***	−0.002***	−0.003***
	(0.0003)	(0.0005)	(0.0003)	(0.0005)
Access to road	0.021***	0.018***	0.022***	0.010
	(0.006)	(0.006)	(0.005)	(0.006)
Own motorized transport	0.058***	0.071***	0.021	0.073***
	0.011	(0.029)	(0.018)	(0.013)
District fixed-effect	Yes	Yes	Yes	Yes
Observations	104 608	54 289	104 948	52 288

Notes: Robust SEs, clustered by village, are presented in parentheses. All columns report marginal effects (ME) from probit model. All regressions adjust for caste, religion, mother's age at birth, mother's education, wealth quintile, JSY receipt and year of birth dummies. Distance is continuous and is measured in kilometres. BPL is below poverty line. All results are adjusted for population weighting and survey design.
***$p < 0.01$.

Instrumental variable results

The results presented so far show that distance is an important barrier to maternity care in India. Women living farther away from health facilities have a lower probability of institutional delivery. These results are consistent with the previous findings on the negative effects of distance on utilization of health services (Currie and Reagan, 2003; Sarma, 2009; Kesterton *et al.*, 2010). However, for several reasons, these results may not be interpreted as the causal estimates of distance on IFD. For example, nonrandom placement of facilities, unobserved heterogeneity and measurement error may make the DIST variable endogenous, thereby rendering the estimates biased. So we want to be sure that endogeneity in the key independent variable is not driving our results. To address this concern of endogeneity due to distance not being truly exogenous, we provide additional evidence on the causal effects in Table 4 by estimating an IV model. Specifically, we estimate two-stage residual inclusion (2SRI), IV-probit and IV-LPM. As stated above, we used DIST_INDEX as the instrument for the DIST variable.

First, we check whether DIST is really an endogenous variable. To check this, we perform Wu–Hausman F-test (Cameron and Trivedi, 2009). It should be noted that this is a test for the exogeneity of the regressor DIST and not for the exogeneity of the instrument. Based on this test, the null that DIST is exogenous is rejected implying that OLS estimates are not consistent, and IV approach would provide a consistent and efficient estimate of the parameter. The F-statistic is 638.63 with p-value <0.0001.

The first panel in Table 4 reports the results from the first-stage estimation. As defined in the previous section, the instrument is a summary index of distance to nonhealth infrastructures in the village. This index varies at the village level. Specifically, the index consists of distances to various nonhealth institutions of development. The first-stage results in Table 4 suggest that the instrument, DIST_INDEX, positively and significantly affects the availability of health facilities (DIST). This means that if the DIST_INDEX variable increases by 1 km, the DIST increases by 1.34 km. This satisfies the relevance condition of the IV model, that is, the instrument should be correlated with the endogenous variable. Note that the validity of the exclusion restriction cannot be tested since our model is just identified.

We also perform several weak-IV identification tests to ensure that the instrument does not suffer from weak-IV problem. Weak-IV test results are reported in column (1). The Cragg–Donald Wald F-statistics is 10 689.56 and Kleinbergen–Paap Wald rk F-statistic is 238.34, rejecting the null hypothesis of weak instrument. These results suggest that the instrument is strongly related to the endogenous variable and the instrument does not suffer from weak-IV problem. The tests for weak-instrument-robust inference are also statistically different from zero, indicating that the estimated effects are robust to weak instrument problem if there is any.

In the second panel of Table 4, results from IV-LPM, IV-probit and 2SRI models are reported. The first column shows the results from IV-LPM model. As predicted, the naive LPM/probit models have seriously underestimated the effect of distance on IFD. The 2SRI and IV estimates are about five times larger than the LPM/probit estimates. For instance, according to IV-LPM model, a 1-km increase in DIST results in 1.6 percentage points reduction in the probability of IFD; the coefficient is statistically

Table 4. Marginal effects on institutional delivery from 2SRI, IV-probit and IV-LPM

	In-facility births		
	IV-LPM	IV-probit	2SRI
	(1)	(2)	(3)
Panel A			
First-stage	1.34***	1.34***	1.34***
	(0.076)	(0.076)	(0.076)
Panel B			
DIST (km)	−0.016***	−0.016***	−0.017***
	(0.003)	(0.002)	(0.002)
Road access	0.001	0.004	0.005
	(0.002)	(0.005)	(0.002)
Own motorized vehicle	0.057***	0.054***	0.055***
	(0.010)	(0.009)	(0.011)
Weak IV identification test			
Cragg–Donald Wald F-statistic	10 689.56		
Kleibergen–Paap Wald rk F-statistic	238.34		
Weak-instrument-robust inference			
Anderson–Rubin Wald test, $F(1,588)$	175.72($p < 0.000$)		
Stock–Wright LM S-statistic, $\chi^2(1)$	129.43($p < 0.000$)		
District fixed-effect	Yes	Yes	Yes
Observations	158 897	158 897	158 897

Notes: Robust SEs, clustered by village, are presented in parentheses. Columns (1) and (2) report predicted probabilities. Panel A reports the coefficient from the first-stage regression, while panel B reports results from second-stage regression. In the IV-LPM and IV-probit models, DIST is instrumented by PCA index of distances to nonhealth infrastructures (defined in text). All regressions adjust for caste, religion, mother's age at birth, mother's education, wealth quintile, JSY receipt and year of birth dummies. All results are adjusted for population weighting and survey design.
***$p < 0.01$.

significant at the 1% level. Given that the mean IFD is 36%, this means a reduction of 4.4% in the sample mean $\left(\frac{0.017}{0.36}\right)$. The coefficients on road access and ownership of car/motorcycle are positive; however, the effect of connectivity to road loses statistical significance.

The second and third columns in Table 4 report the results from the IV-probit and the 2SRI models, respectively. The IV-probit estimate in column (2) is negative and statistically significant, indicating that living farther away from a health facility decreases the probability of IFD. The point estimate is identical to the IV-LPM model. Results are similar in our preferred specification of 2SRI model. The 2SRI results in column (3) show that the probability of IFD is 1.7 percentage points lower for every 1 km of distance. Overall, estimates from all the three models in Table 4 suggest that distance is a significant burden on households for IFD. The magnitude of the effect in column 3 is large in the sense that households living 8.7 km away (mean distance to PHC) are 41% less likely to deliver in health facility $\left(\frac{(0.017\times 8.7)}{0.36}\right)$.

As a robustness check, we reconstructed the DIST_INDEX by including a few additional distance variables in the principal component model. For example, the new index additionally includes distance to telegraph service, distance to railway station, distance to phone and distance to bank. We re-estimate the same specification with this new instrument. Results are essentially unchanged (not reported but available upon request). We came to a similar conclusion, though the point estimate is slightly lower than the results presented in Table 4.

Nonlinear effects of distance

In order to investigate the nonlinearities in the effects of distance on IFD, we estimate Equation 3 with distance as categorical variable. This specification would be useful in capturing any threshold effect. Distance is included as dummies for households at different distances (less than 5 km, 5–10 km and more than 10 km, with less than 5 km being the reference category). This specification ignores the concern for endogeneity since we do not have as many instruments as the number of endogenous variables, so results reported are from noninstrumented models.

Results are reported in Table 5. The first two columns report the results from the LPM estimation, while columns (3) and (4) report MEs from probit model. Columns (1) and (3) consist of estimates without district fixed effects, while columns (2) and (4) include district fixed effects.

Table 5. Effect of distance dummies on institutional delivery in rural India

	In-facility births			
	LPM	LPM	Probit (ME)	Probit (ME)
	(1)	(2)	(3)	(4)
Distance (0–4 km)(Ref)				
Distance (5–9 km)	−0.042***	−0.012***	−0.041***	−0.012***
	(0.007)	(0.004)	(0.007)	(0.002)
Distance (>9 km)	−0.075***	−0.038***	−0.078***	−0.039***
	(0.007)	(0.005)	(0.007)	(0.006)
Road access	0.037***	0.020***	0.039***	0.020***
	(0.007)	(0.004)	(0.008)	(0.005)
Own motorized vehicle	0.069***	0.057***	0.066***	0.053***
	(0.011)	(0.010)	(0.011)	(0.010)
District fixed-effect	No	Yes	No	Yes
Observations	165 949	158 897	158 897	158 897

Notes: Robust SEs, clustered by village, are presented in parentheses. Columns (1) and (2) show results from linear probability model (LPM) while columns (3) and (4) reports marginal effects from probit. All regressions adjust for caste, religion, mother's age at birth, mother's education, wealth quintile, JSY receipt and year of birth dummies. All results are adjusted for population weighting and survey design. Distance is a categorical variable.
***$p < 0.01$.

Results in column (1) show that the probability of IFD decreases by 4.2 percentage points if the nearest health facility is between 5 and 9 km, compared to the reference category of a facility within 5 km. This translates to a 10% reduction in IFD $\left(\frac{(0.042)}{0.42}\right)$. When the distance to the nearest health facility is greater than 9 km, the probability of IFD reduces by 7.5 percentage points compared to the reference group, which translates to a reduction in IFD by 18%, relative to the mean IFD of 42% in the reference group (column (1)).

Coefficient estimates of distance are smaller in magnitude in columns (2) and (4), relative to results in columns (1) and (3). Including fixed effects reduces the magnitude of the coefficients by more than half, suggesting that cross-district variations are also important in explaining the variation in IFD (column (2)). With the district fixed effect, the probability of IFD is 1.2 and 3.8 percentage points lower for the 5–9 km and >9 km categories, respectively. We obtain extremely similar results using probit models. Coefficient estimate is 1.2 percentage points for 5–9 km category, while it is 3.9 percentage points for >9 km category. Coefficient estimates for road access and motorized transport continue to be positive and statistically significant. The magnitude of the transport coefficient is 3.3 percentage points larger than the road access coefficient, indicating ownership of car or motorcycle is a more important predictor than road connectivity. In summary, we obtain very similar results in LPM and probit models. To sum up, consistent with the theoretical prediction, we find that distance to the nearest health facility appears to impose a binding constraint on utilization of health services in rural parts of India.

Policy simulation

In this section, we discuss the results from a policy simulation exercise. We simulate the effect of increasing the density of facilities or decreasing the distance to the nearest health facility on IFD. The counterfactual question we would like to answer is 'What would be the IFD rate if all the sampled women live in a 5 km radius of a facility?' We attempt to answer this question by replacing greater than 5 km values of DIST by 5 km. Now, the maximum value of DIST is 5 km and the distance to closest facility is between 0 and 5 km.

The simulation exercise follows these three steps. First, we estimate the baseline probabilities of IFD by averaging the individual predicted probability of IFD from the IV-LPM model. Second, a simulated IFD probability for each woman is predicted using the coefficients derived from the IV-LPM and altering the DIST variable, and then the average IFD rate of the sample is calculated. Third, simulated policy effects are estimated by comparing the simulated probability values with the baseline probability values (simulated *minus* baseline).

The simulated results show that increasing the density of the health facilities, that is constructing more health facilities, would improve the IFD rate and the effects are sizeable. For instance, the predicted baseline probability of IFD is 36.27%. If we restrict the maximum DIST to be 5 km, the simulated probability based on IV-LPM coefficients is 39.72%, suggesting an increase of 3.45 percentage points, which is an approximate improvement of 10% over the current baseline probability.

VI. Conclusions

This study shows that distance is a significant barrier to institutional births in India. We use an instrumental variable model to estimate the causal effect of distance to the closest health facility on in-facility birth. We find that distance to the closest health facility has a negative effect on the probability of giving birth in health facilities. Without accounting for endogeneity, the probability of IFD decreases by 0.8% due to an increase in distance by 1 km. However, results from IV estimation show that the true causal impact of distance on institutional delivery is 4.4–4.7%. We also find that access to road and transport infrastructure positively affects the delivery care.

To the best of our knowledge, this is one of the few studies that provide the causal impacts of distance on institutional births in India. Previous studies on the effect of distance on formal care in India are mainly from epidemiological literature, and due to lack of appropriate econometric models, the causal interpretation is weak in these studies. However, the significance of distance has been established in these studies as well. Many of these studies have demonstrated that access to health services within 5 km of the village or higher density of health facilities has a statistically significant effect on institutional delivery, though the effect of access varies by state (Stephenson and Tsui, 2003).

Previous evidence on the impact of distance on health outcomes, such as child mortality, has been mixed. For example, geographic access was not a significant barrier to infant and child mortality in Kenya (Moïsi *et al.*, 2010) or in Gambia (Rutherford *et al.*, 2009). In contrast, many studies have found a strong association between child mortality and physical access to health care in Tanzania (Schellenberg *et al.*, 2008), the Democratic Republic of Congo (Broeck *et al.*, 1996) and Burkina Faso (Becher *et al.*, 2004). The mixed evidence suggests that the effect of distance could depend on the country context, the density of health facilities and the outcome of interest.

Limitations

Although the reported measure of distance in this article is an improvement over other studies, it still is an imperfect proxy for travel time and cost. Additionally, the distances are estimated based on the village centre, while women may reside some distance from that location. Our controls for all-weather road access and vehicle ownership address this issue somewhat, but ideally these estimates should be household specific, and include information about the topography of the area and local travel costs. Our study also assumes that women deliver at the closest facility or at least that this facility helped them access care through a referral or otherwise. Furthermore, future work should continue to address the possibility of a quality-distance trade off by incorporating the quality of maternity care available at each facility. Due to unavailability of data, this study did not include any supply-side variable that may explain the variation in the quality of care.

Our study has important policy implications. Our study findings suggest that in a country like India, where physical distance to health facilities is quite large in rural areas, access is a significant barrier to institutional delivery. The significant effect of distance suggests that increasing the density of health facilities and providers in rural areas may improve maternal and neonatal care; however, a comprehensive cost-effective analysis should be performed to demonstrate that benefits of institutional delivery outweigh the cost of building new facilities.[9] Another important finding is that reducing transport barriers may also help reduce the inequity in geographic access to health facilities, and it would likely improve institutional delivery coverage. Our findings may assist health policymakers in Indian and other resource-constrained countries to understand the likely impact of health infrastructure on health care utilization.

However, merely increasing the number of health facilities may not be sufficient to promote health service utilization as poor quality of care and high cost may inhibit the uptake of the services. The wealth gradient found in this study also emphasizes the importance of financial resources in a household's choice of IFD. Therefore, in addition to increasing access, further improvements in institutional delivery can be met by improving the quality of care and easing financial constraints. The Government of India has implemented the conditional cash transfer scheme JSY to promote institutional delivery. This scheme has been successful in improving the IFD rate (Lim *et al.*, 2010) to some extent. However, to meet the target of the fifth MDG by 2015 and provide universal coverage, the Government of India would have to undertake a series of supply- and demand-side interventions, ranging from increasing access to addressing cultural beliefs.

Acknowledgements

We thank Abhiroop Mukhopadhyay, Edward Hoang, Emmanuela Gakidow, Mike Hanlon, two anonymous referees and conference participants at the University of Washington, CUGH, IHEPA, PAA, iHEA and ACEGD

[9] Conducting a cost-effectiveness analysis is beyond the scope of this article.

for helpful comments. We thank Kelsey Moore for project management and Nisha Sinha for outstanding research assistance. We are responsible for any errors that may remain and bear sole responsibility for the content of this article.

Funding

This project was funded by the Disease Control Priorities Network grant to the Institute for Health Metrics and Evaluation from the Bill and Melinda Gates Foundation.

References

Angrist, J. D. and Pischke, J. S. (2008) *Mostly Harmless Econometrics: An Empiricist's Companion*, Princeton University Press, Princeton, NJ.

Becher, H., Muller, O. and Jahn, A. *et al*. (2004) Risk factors of infant and child mortality in rural Burkina Faso, *Bulletin of the World Health Organization*, **82**, 265–73.

Bhargava, A., Chowdhury, S. and Singh, K. K. (2005) Healthcare infrastructure, contraceptive use and infant mortality in Uttar Pradesh, India, *Economics and Human Biology*, **3**, 388–404. doi:10.1016/j.ehb.2005.09.001

Bhattacharya, J., Goldman, D. and McCaffrey, D. (2006) Estimating probit models with self-selected treatments, *Statistics in Medicine*, **25**, 389–413. doi:10.1002/sim.2226

Bleakley, H. (2010) Health, human capital, and development, *Annual Review of Economics*, **2**, 283–310. doi:10.1146/annurev.economics.102308.124436

Borah, B. (2006) A mixed logit model of health care provider choice: analysis of NSS data for rural India, *Health Economics*, **15**, 915–32. doi:10.1002/hec.1166

Broeck, J., Eeckels, R. and Massa, G. (1996) Maternal determinants of child survival in a rural African community, *International Journal of Epidemiology*, **25**, 998–1004. doi:10.1093/ije/25.5.998

Cameron, C. A. and Trivedi, P. K. (2009) *Microeconometrics Using Stata*, Stata Press, College Station, TX.

Collier, P., Dercon, S. and Mckinnon, J. (2002) Density versus quality in health care provision: using household data to make budgetary choices in Ethiopia, *The World Bank Economic Review*, **16**, 425–48. doi:10.1093/wber/lhf003

Currie, J. and Reagan, P. B. (2003) Distance to hospital and children's use of preventive care: is being closer better, and for whom?, *Economic Inquiry*, **41**, 378–91. doi:10.1093/ei/cbg015

Elo, I. T. (1992) Utilisation of maternal health-care services in Peru: the role of women's education, *Health Transition Review*, **2**, 49–69.

Gething, P. W., Johnson, F. A. and Frempong-Ainguah, F. *et al*. (2012) Geographical access to care at birth in Ghana: a barrier to safe motherhood, *BMC Public Health*, **12**, 991.

Hellevik, O. (2009) Linear versus logistic regression when the dependent variable is a dichotomy, *Quality and Quantity*, **43**, 59–74. doi:10.1007/s11135-007-9077-3

Hjortsberg, C. (2003) Why do the sick not utilise health care? The case of Zambia, *Health Economics*, **12**, 755–70. doi:10.1002/hec.839

Hogan, M. C., Foreman, K. J., Naghavi, M. *et al*. (2010) Maternal mortality for 181 countries, 1980–2008: a systematic analysis of progress towards Millennium Development Goal 5, *The Lancet*, **375**, 1609–23. doi:10.1016/S0140-6736(10)60518-1

Hsieh, C. R. and Lin, S. J. (1997) Health information and the demand for preventive care among the elderly in Taiwan, *The Journal of Human Resources*, **32**, 308–33. doi:10.2307/146217

International Institute for Population Sciences (IIPS). (2010) *District Level Household and Facility Survey (DLHS-3*), IIPS, Mumbai.

Kesterton, A. J., Cleland, J., Sloggett, A. *et al*. (2010) Institutional delivery in rural India: the relative importance of accessibility and economic status, *BMC Pregnancy and Childbirth*, **10**, 30. doi:10.1186/1471-2393-10-30

Kumar, S. and Dansereau, E. (2014) Supply-side barriers to providing maternity-care in India: a facility-based analysis, *PLoS ONE*, **9**, e103927. doi:10.1371/journal.pone.0103927

Lavy, V. (1996) School supply constraints and children's educational outcomes in rural Ghana, *Journal of Development Economics*, **51**, 291–314. doi:10.1016/S0304-3878(96)00416-6

Lim, S. S., Dandona, L., Hoisington, J. A. *et al*. (2010) India's Janani Suraksha Yojana, a conditional cash transfer programme to increase births in health facilities: an impact evaluation, *The Lancet*, **375**, 2009–23. doi:10.1016/S0140-6736(10)60744-1

Matthews, Z., Ramakrishna, J., Mahendra, S. *et al*. (2005) Birth-rights and rituals in rural south India: care-seeking in the intrapartum period, *Journal of Biosocial Science*, **37**, 385–411. doi:10.1017/S0021932004006911. Available at http://www.ncbi.nlm.nih.gov/pubmed/16082853 (accessed 13 August 2014).

Moïsi, J. C., Gatakaa, H., Noor, A. M. *et al*. (2010) Geographic access to care is not a determinant of child mortality in a rural Kenyan setting with high health facility density, *BMC Public Health*, **10**, 142. doi:10.1186/1471-2458-10-142

Mukhopadhyay, A. and Sahoo, S. (2012) Does access to secondary education affect primary schooling? Evidence from India, IZA DP No. 6507.

Odiit, A. and Amuge, B. (2003) Comparison of vaccination status of children born in health units and those born at home, *East African Medical Journal*, **80**, 3–6.

Parente, S. T., Salkever, D. S. and DaVanzo, J. (2005) The role of consumer knowledge of insurance benefits in the demand for preventive health care among the elderly, *Health Economics*, **14**, 25–38. doi:10.1002/hec.907

Ronsmans, C. and Graham, W. J. (2006) On behalf of the lancet maternal survival series steering group: maternal mortality: who, when, where and why, *The Lancet*, **368**, 1189–200. doi:10.1016/S0140-6736(06)69380-X

Roodman, D. (2009) A note on the theme of too many instruments, *Oxford Bulletin of Economics and Statistics*, **71**, 135–58. doi:10.1111/j.1468-0084.2008.00542.x

Rutherford, M. E., Dockerty, J. D. and Jasseh, M. *et al*. (2009) Access to health care and mortality of children under 5 years of age in the Gambia: a case-control study, *Bulletin of the World Health Organization*, **87**, 216–24. doi:10.2471/BLT.08.052175

Sarma, S. (2009) Demand for outpatient healthcare: empirical findings from rural India, *Applied Health Economics and Health Policy*, **7**, 265–77. doi:10.1007/BF03256160

Sawhney, N. (1993) Management of family welfare programmes in Uttar Pradesh: infrastructure utilisation, quality of

services, supervision and MIS, in *Family Planning and MCH in Uttar Pradesh (A Review of Studies*), Premi, M. (Ed), Indian Association for the Study of Population, New Delhi, pp. 50–67.

Schellenberg, J. R. M. A., Mrisho, M., Manzi, F. *et al*. (2008) Health and survival of young children in southern Tanzania, *BMC Public Health*, **8**, 194. doi:10.1186/1471-2458-8-194

Stephenson, R. and Tsui, A. (2003) Contextual influences on reproductive wellness in northern India, *American Journal of Public Health*, **93**, 1820–29. doi:10.2105/AJPH.93.11.1820

Terza, J., Basu, A. and Rathouz, P. (2008) Two-stage residual inclusion estimation: addressing endogeneity in health econometric modeling, *Journal of Health Economics*, **27**, 531–43. doi:10.1016/j.jhealeco.2007.09.009

Thaddeus, S. and Maine, D. (1994) Too far to walk: maternal mortality in context, *Social Science and Medicine*, **38**, 1091–110. doi:10.1016/0277-9536(94)90226-7

Waiswa, P., Kallander, K., Peterson, S. *et al*. (2010) Using the three delays model to understand why newborn babies die in eastern Uganda, *Tropical Medicine and International Health*, **15**, 964–72. doi:10.1111/j.1365-3156.2010.02557.x

World Health Organization, UNFPA and the World Bank. (2010) *Trends in Maternal Mortality: 1990 to 2008 Estimates Developed by WHO, UNICEF, UNFPA and the World Bank*, World Health Organization, Geneva.