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The effect of health facility births on newborn mortality in Malawi

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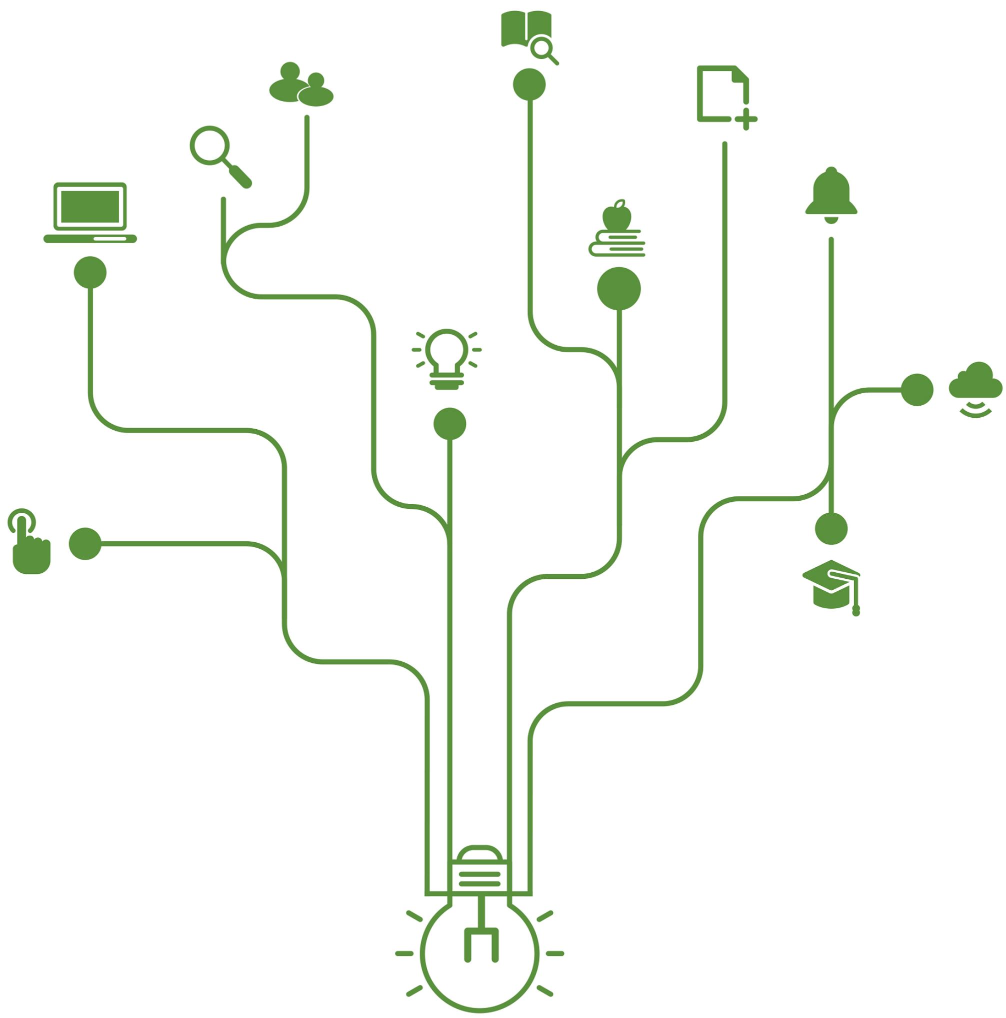

KDI SCHOOL
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The effect of health facility births on newborn mortality in Malawi

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Abstract

We examine the effect of health facility births on newborn mortality in Malawi using data from a unique survey of mothers in the Chimutu district, Malawi and data from the Malawi Demographic and Health Survey 2015. The study exploits two instrumental variables to overcome endogeneity of health facility births—labor contraction time and interaction of distance to health facilities and rainfall at birth. The results show that health facility births significantly reduce 7-day and 28-day mortality rates. We find suggestive evidence that readily available medical resources are the potential mechanisms through which health facility births reduce newborn mortality. (JEL I11, I12, J13)

Keywords

Corruption; Comparison of multiple theories; Determinants and cures for corruption

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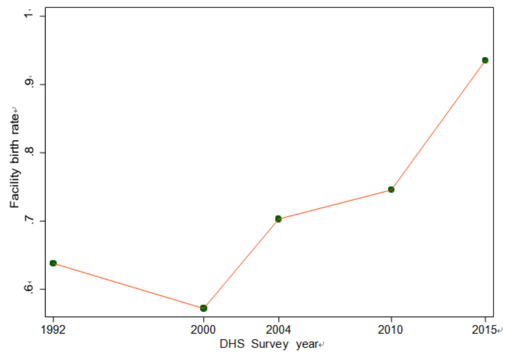
Reducing child mortality in developing countries has been an important part of the global health agenda for many years, as represented by Millennium Development Goal 4. In particular, the first 28 days of life—the neonatal period—represent the most vulnerable time for a child's survival; thus, the Sustainable Development Goals, which replaced the Millennium Development Goals, aim to reduce neonatal (28-day) mortality as low as 12 per 1,000 live births by 2030. Although the average global neonatal mortality rate decreased from 36 to 19 deaths per 1,000 live births between 1990 and 2015, the neonatal mortality rate in low-income regions in 2015 was still high, such as 28 and 24 deaths per 1,000 live births in Africa and South-East Asia, respectively. According to Global Health Observatory data published by the World Health Organization (WHO) in 2015, 4.5 million deaths occur within the first year of life. This accounts for 75 percent of all under-five mortality. Among them, approximately 2.7 million deaths (about 45 percent) occurred during the first 28 days of life while 1 million neonatal deaths occurred on the day of birth. Most of these deaths were observed in low-income countries located in sub-Saharan Africa and South Asia. The WHO (2016) finds that each year in Africa, approximately 1 million babies are stillborn and 300,000 die during labor, while 15 African countries have been ranked among the world's worst 20 countries with the highest risk of neonatal death. With help from improved access to medical resources in developing countries, opportunities to save children's lives continue to grow. However, given the fact that a large proportion of newborn births in low-income countries still occur outside health facilities (Darmstadt et al. 2009), evaluating the effect of improved access to medical resources on early childhood mortality is important for implementing the health policy. The underlying rationale for health facility births as opposed to home births is that emergency cases can be handled more safely and the right interventions can be properly offered during and after delivery (Pal 2015). The related literature documents associations between health facility births and newborn survival (Panis and Lillard 1994; Maitra 2004; Darmstadt et al. 2009; Goudar et al. 2015; Fink, Ross, and Hill 2015). However, it is not clear whether these associations represent causal relationships owing to endogenous choice of health facility births. Furthermore, the low quality of health facilities, measured by the shortage of electrical power, medicine, and medical personnel, might compromise the benefits of giving birth in health facilities.

In this study, we analyze the causal effect of health facility births on newborn mortality in Malawi. We provide consistent evidence of the impact of health facility births on early and infant mortality using two different data sets. The first comprises unique mother-level individual survey data collected in Chimutu area near Malawi's capital city, Lilongwe, in 2012 and 2013. The survey targeted current pregnant women to collect information of basic demographics, mothers' health, and children's health. The second data set is the Malawi Demographic and Health Survey (MDHS) 2015. The MDHS is a survey of nationally representative samples containing various information at the level of individual mothers and children.

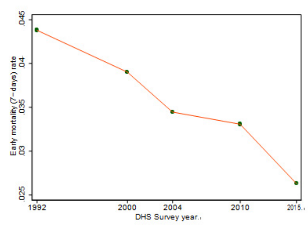
Malawi is an ideal setting to study the causal effect of health facility births on newborn survival in a low-income country for several reasons. According to the World Bank, the neonatal mortality rate in Malawi in 2015 was 22 per 1,000 newborn births, which is similar to other low-income countries, such as Bangladesh (23), Kenya (22), India (28), and Ethiopia (28).[2] And the health facility birth rate in Malawi has been rapidly increasing since 2000 and reached more than 90 percent in 2015, as shown in Figure 1 (a). Meanwhile, Figures 1 (b), (c), and (d) show the trend of early childhood mortality in Malawi calculated using information from multiple waves of the MDHS. Although the early childhood mortality rate in Malawi is still high, early, neonatal, and infant mortality has been decreasing dramatically since 1992. Linking Figures 1 (a) and (b)–(d) provides some insight into the relationship between health facility births and early childhood mortality. In Malawi, a negative correlation between the two is clearly observed. The negative correlation is also identified in several previous works, especially Fink, Ross, and Hill (2015) but also including Panis and Lillard (1994), Maitra (2004), Darmstadt et al. (2009), and Goudar et al. (2015).

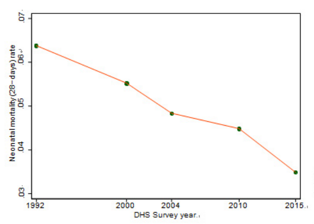
2) According to the World Bank, the infant mortality rate in Malawi in 2015 was 43 deaths per 1,000 newborn births. This number is relatively high compared to those in other low–income countries, such as Bangladesh (31), Kenya (38), and Ethiopia (41).

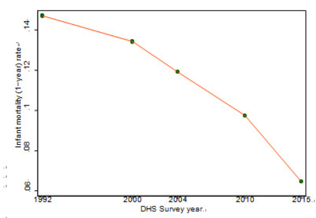
Figure 1 : Health facility births rate and Early childhood mortality rate-MDHS



(a) Health facility births trend







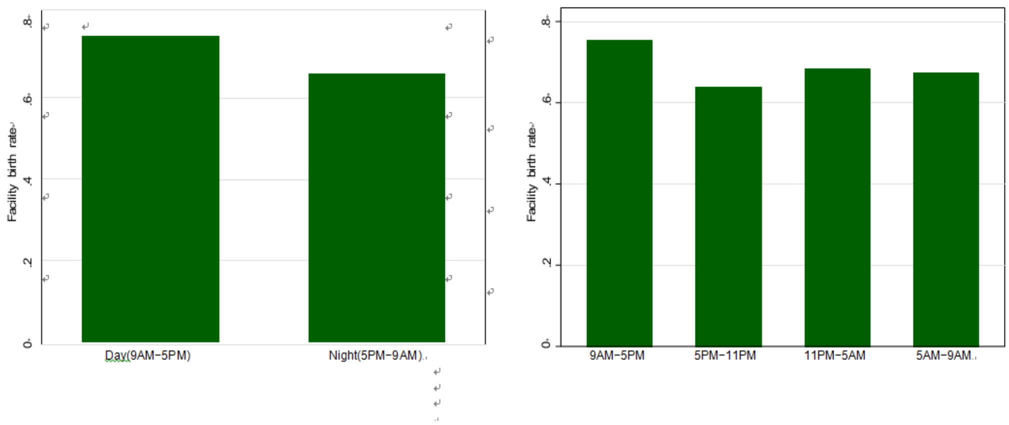
(b) Early mortality - 7 days (c) Neonatal mortality - 28 days (d) Infant mortality - 1 year

The main challenge in causal estimation of the effect is that individuals select healthcare use (Grossman 2000; Adhvaryu and Nyshadham 2015). Several previous studies on this topic have used instrumental variables (IVs) to estimate the causal relationship. For example, Daysal, Trandafir, and Van Ewijk (2015) estimated the causal effect of home births on infant outcomes using large samples of mothers in the Netherlands. The authors used distance to hospital from a mother's residence area as an IV to overcome the endogeneity of hospital choice for births. Pal (2015) used a similar approach by using access to local health facilities as an IV in Bangladesh. Both studies found a negative impact of health facility births on early childhood mortality. The logic behind using distance or access to health facility as an IV is related to the cost of demand for the health facility service, which is considered exogenously determined. As addressed in Gertler, Locay, and Sanderson (1987), the most salient cost of demand for a healthcare service is traveling cost, which is heavily dominated by distance to health facility, particularly in low-income countries. For example, it has been a trend to use distance to hospital to instrument the demand for health services (McClellan, McNeil, and Newhouse 1994; Gowrisankaran and Town 1999; Bowblis and McHone 2013; Anselmi, Lagarde, and Hanson 2015) assuming distance to hospitals is an excludable IV.

In our study, we use two different IVs for two different specifications with respect to each data set. For the unique survey data from Chimutu, we utilize information about the onset time of labor contractions. In the survey, respondents were asked to select from among the following ranges of onset time of labor contractions: 5am−9am (early morning), 9am−5pm (day), 5pm−11pm (night), and 11pm−5am (very late night). It is difficult and uncertain to predict the true timing of labor contractions (Witter, Rocco, and Johnson 1992; Iams 2003). According to McKinney et al. (2013), only 5 percent of women deliver on their due date and it is difficult even for clinicians to predict when women will give birth (American College of Obstetricians and Gynecologists 2014). Accordingly, labor-contraction timing would be unlikely to be correlated with mothers' characteristics and would occur only randomly. We use labor-contraction timing to predict the probability of health facility births. The main idea is that if labor contraction starts in the very late night, it is difficult to travel to health facilities to give birth owing to lack of available transportation or darkness and danger at night. Consequently, the labor-contraction timing IV satisfies the exclusion restriction and is closely related to our main regressor. On the other hand, we apply a different IV to examine the effect for the data set from the MDHS 2015. We exploit an exogenous variation in distance to health facility by rainfall at the time of birth. In the first stage of the regression, we interact the distance to the nearest health facility with rainfall at the month of birth to predict the health facility delivery. Our intuition is the same as that of Adhvaryu and Nyshadham (2015) in that rainfall provides more exogenous variation in the traveling cost to access the health facility. This interaction IV can overcome the weakness of the distance IV in that distance to health facility itself is likely to violate the exclusion restriction due to potential endogenous placement of the health facility (Kumar, Dansereau, and Murray 2014). The interaction of distance and rainfall IV satisfies the exclusion restriction while predicting the first stage of health facility births very well.

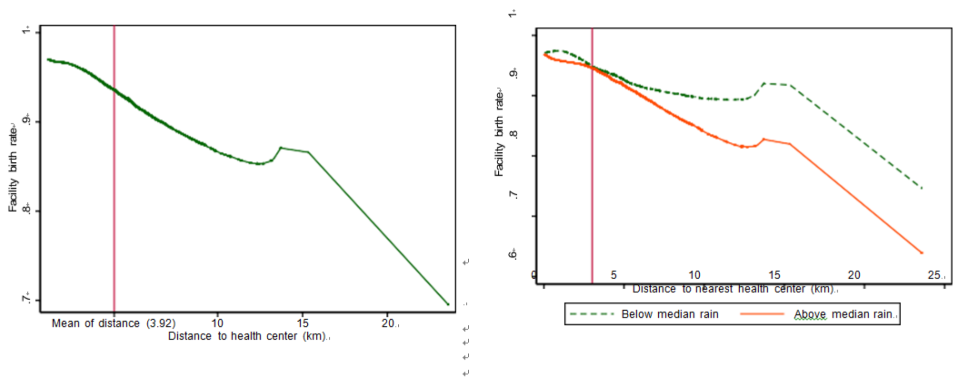
As Figure 2 shows, we find that labor timing at night (5pm−9am) compared to the day (9am−5pm) deters pregnant women from traveling to a health facility by approximately 10 percentage points (about 13 percent of the daytime standard). When pregnant women start labor contractions in the daytime, they are more likely to give birth in health facilities. In addition, using the interaction of distance to health facility and rainfall at birth shows a highly significant relationship with health facility births. Given the same distance to health facility, heavier rain at birth makes it more difficult to travel to the facility. Figure 3 (a) shows the negative correlation between distance to health facilities and health facility births, which shows the merits of using distance as an IV. In our study, as clearly shown in Figure 3 (b), rainfall at birth generates heterogeneity of the relationship between distance to health facility and probability of health facility births. Our identification strategy relies on the differences between the two lines presented in Figure 3 (b).

Figure 2 : Health facility birth rate and labor contraction timing



(a) Day and night (b) Four categories

Figure 3 : The association between health facility births and distance to the nearest health facilities



(a) Distance to health facilities

(b) Distance to health facilities by rainfall

Note: Median rain is the 30 years monthly average.

Using two IVs separately for the two different data sets, we consistently find a positive effect of health facility births on early childhood survival. Giving birth in health facilities causally decreases early mortality (7-day) by 14.6 percentage points in Chimutu 2013 while health facility births decrease early mortality by 13.4 percentage points in the MDHS 2015. Furthermore, we find a positive impact on infant survival (1-year) of 26.8 percentage points in Chimutu 2013. We also provide suggestive evidence by leveraging Malawi Service Provision Assessment (SPA) 2013-4 data where quality information on health facilities was available. Matching individual mothers' residence and health facility locations using global positioning system (GPS) information provided by MDHS, we explain how much health facility quality plays a role in reducing early childhood mortality. We conclude that health facility births are conducive to the survival of children because they benefit from readily accessible medicines and treatment.

Our contribution is mainly threefold. First, we estimate the causal effect of health facility births on early childhood mortality in the setting of a low-income country. Second, we improve IV specifications by using interaction of distance to health facilities and rainfall at birth. As mentioned earlier in the introduction, only a few studies have estimated the causal impact of health facility births on early childhood mortality, but the estimates might be confounded by unobservable factors that could be correlated with health facility location and household-level characteristics. In addition, since the two-stage least squares specification estimates only the local average treatment effect (LATE), we check whether our estimates are dependent on heterogeneous compliers by using two data sets with different IVs. We show that our estimates are consistent across different samples and compliers. Third, we provide a suggestive mechanism for how health facility births significantly impact low-income countries by examining health facility quality and individual behavior measures.

The remainder of the paper is organized as follows. Section I introduces the data. Section II explains our identification strategy and Section III interprets the empirical results. Section IV lists threats to identification. We conclude in Section V.

Data

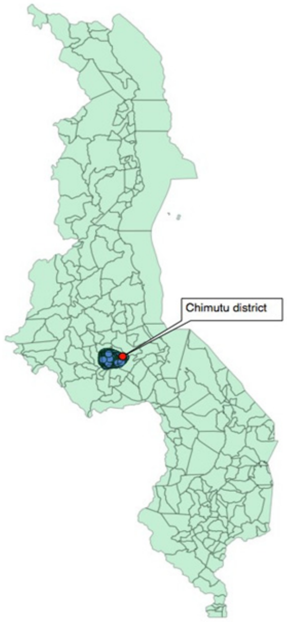
We use two main data sets, Chimutu 2013 and MDHS 2015. As mentioned in the introduction, we use distance to health facilities from residence and rainfall data to construct the IV. Malawi SPA 2013/2014 data collected by the MDHS are used to calculate the distance to health facilities. In addition, we calculate rainfall at birth using the Climate Prediction Center Merged Analysis of Precipitation (CPC CMAP) established by the National Weather Service.

Malawi Chimutu Survey 2013

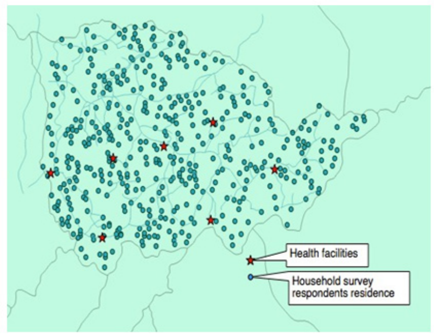
In July 2010, the Korea International Cooperation Agency granted the Africa Future Foundation (AFF) USD 2 million from Air-Ticket Solidarity Contribution Korea for health projects (HIV/AIDS prevention and mother and child health) in Malawi over a period of 3 years. In addition, the Ministry of Foreign Affairs and Trade granted another USD 1 million for the follow-up program for mother and child health project. AFF's implementing body is the Daeyang Luke Hospital, one of the main hospitals in Lilongwe. Daeyang Luke Hospital has been assigned the district of Chimutu located within the boundary of Lilongwe by the Malawian government. Chimutu is a rural area and had a population of 90,000 in 2010. Figure 4 shows the location of Chimutu. Figure 4 (b) shows the locations of our survey villages and seven health facilities in Chimutu. The baseline survey was completed in September 2013. The survey mainly focuses on women, including pregnant women, health information, household characteristics (assets and consumption patterns), children's demographic and health information, birth history, disease history (e.g., depression, HIV/AIDS, malaria, tuberculosis, diarrhea, cough, and fever), nutritional intake information, general health and treatment-seeking behavior, savings and entrepreneurship, HIV/AIDS knowledge, sexual behavior, and time/risk preferences. There are 311 questions in 31 sections. In our analysis, we choose samples of women born between 1973 and 1992.[3] We summarize several characteristics of our sample cohorts in panel A of Table 1. The mean age of sample mother cohorts is 30.4 years in of 2013. Most women have not completed primary school (only 19 percent attained education of primary school or above). More than 90 percent are Chewas (ethnicity, not displayed). The mean age of our sample children is 7.8 years. The early mortality rate is 13 per 1,000 new births while the neonatal and infant mortality rates are 17 and 39 per 1,000 new births, respectively. The survey's questions include information on place of birth and timing of labor contractions. The place-of-birth categories include home, government facility, and nongovernmental facility. In the empirical analysis, we define a health facility birth dummy as 1 if the respondent gave birth at a government or nongovernmental health facility, and 0 otherwise. As presented in Table 1, 68 percent of women gave birth in health facilities. The timing of labor contractions is categorized into four timing zones. The survey results show that 34 percent of women in Chimutu started labor contractions during 5pm−11pm followed by 24 percent during 9am−5pm, 23 percent during 5am−9am, and 19 percent during 11pm−5am.

3) Sample cohorts are trimmed at the 1 and 99 percentiles.

Figure 4: Survey area - Chimutu



(a) Malawi map



(b) Chimutu

Table 1—Summary statistics

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Pooled		Facility birth		Home birth		T-test
	Mean	S.D.	Mean	S.D.	Mean	S.D.	(P-value)
A. Chimutu 2013							
Facility birth	0.682	0.466					
7-day survival	0.987	0.115	0.986	0.117	0.988	0.111	0.83
28-day survival	0.983	0.130	0.980	0.139	0.988	0.111	0.36
1-year survival	0.961	0.194	0.957	0.202	0.968	0.176	0.37
Mother Age	30.39	4.718	30.01	4.798	31.20	4.439	0.00
Number of birth	3.153	1.434	2.983	1.409	3.516	1.422	0.00
Education: Primary school	0.196	0.397	0.228	0.420	0.128	0.335	0.00
Child Age	7.849	4.010	7.409	4.026	8.795	3.812	0.28
Child gender (1= Male)	0.498	0.500	0.517	0.500	0.457	0.499	0.05
Labor timing							
1. 11PM-5AM	0.200	0.400	0.200	0.400	0.200	0.400	0.99
2. 5AM-9AM	0.226	0.418	0.223	0.417	0.232	0.423	0.73
3. 9AM-5PM	0.235	0.424	0.259	0.438	0.183	0.387	0.00
4. 5PM-11PM	0.339	0.474	0.318	0.466	0.385	0.487	0.02
Observations	1,274		869		405		
B. MDHS 2015							
Facility birth	0.934	0.248					
7-day survival	0.981	0.137	0.982	0.134	0.970	0.172	0.01
28-day survival	0.977	0.151	0.977	0.149	0.966	0.181	0.04
1-year survival	0.966	0.181	0.967	0.180	0.956	0.205	0.11
Mother Age	28.48	5.895	28.42	5.865	29.38	6.245	0.00
Number of birth	3.563	1.952	3.512	1.927	4.271	2.160	0.00
Education: Primary school	0.292	0.455	0.302	0.459	0.159	0.366	0.00
Child Age	2.086	1.426	2.065	1.425	2.379	1.399	0.00
Child gender (1= Male)	0.505	0.500	0.507	0.500	0.471	0.499	0.05
Distance to health facilities (km)	3.922	2.648	3.830	2.590	5.221	3.089	0.00
Rainfall at birth month (mm)	66.81	83.91	66.18	83.4	75.81	90.09	0.00
Observations	12,465		11,642		823		
IV: Facility birth rate by distance*rain	Facility births rate						
<10 percentile	0.953						
<25 percentile	0.950						
<50 percentile	0.944						
<75 percentile	0.934						
>= 75 percentile	0.906						

Notes: MDHS 2015 collects information of children aged between 0 and 5. This causes difference in average age of children between Chimutu 2013 and MDHS 2015.

Demographic and Health Survey 2015

The other data set, the MDHS 2015, is a nationally representative household survey conducted every 5 years on average. The survey covers various topics, such as pregnancy, birth history, childcare, and health information at the individual mother level along with information on the place of birth. There are numerous place-of-births categories, such as home, government hospital, government health center, government health post, other public health center, mission hospital or health center, and private hospital or clinic. Similar to the Chimutu survey, we define a health facility birth dummy as 1 if respondents gave birth at a health facility, and 0 otherwise. In addition, we summarize the characteristics of our sample cohorts in panel B of Table 1. Our mother cohorts were born between 1973 and 1995.[4] The mean age of sample cohorts is 28.5 years old, slightly younger than the mother cohorts of Chimutu 2013. Most have not completed primary school, which is similar to Chimutu 2013. By contrast, however, the MDHS 2015 sample cohorts gave birth at health facilities (93 percent) more than Chimutu 2013 sample cohorts (68 percent). A possible reason is that the MDHS 2015 reports birth history only for those aged between 0 and 5 years in the survey year while the Chimutu 2013 survey collected all birth history information. Thus, the MDHS 2015 reflects the most recent upward trend in facility births, as observed in Figure 1 (a). Furthermore, given that Chimutu is a relatively poorer district, a lower health facility delivery rate compared to the national-level MDHS 2015 seems plausible. The mean age of sample children cohorts is 2.1 years, which is much lower than the sample age of children in the Chimutu 2013 survey. This is also due to the difference in sample selection in the MDHS 2015, which collected data only for children aged in the category between 0 and 5 years. The early childhood mortality rate of the MDHS cohort is 19 deaths per 1,000 new births, which is comparable to that of the Chimutu 2013 survey (13 deaths per 1,000 new births), while the neonatal and infant mortality in the MDHS 2015 are 23 and 34 deaths per 1,000 new births, respectively.

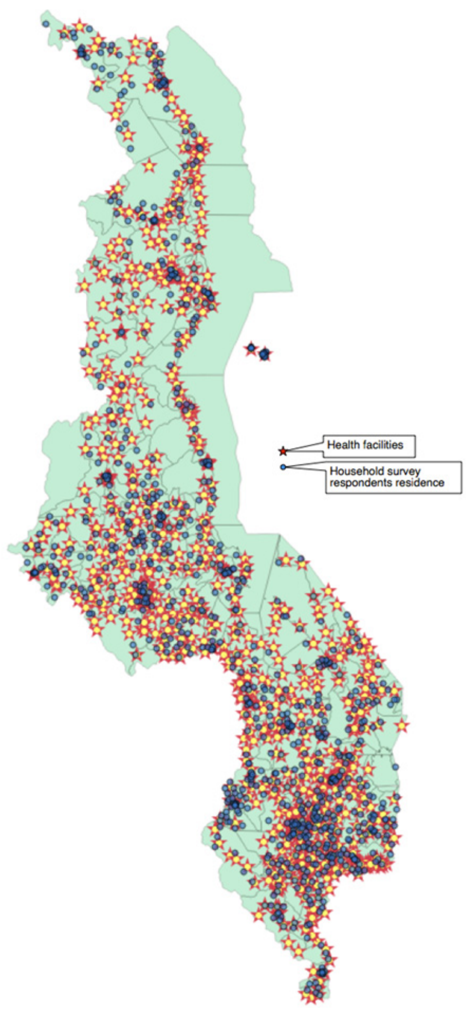
As discussed in the introduction, one of our main regressors is the interaction of distance to health facilities and rainfall at birth. To construct this, we make use of GPS data from the MDHS 2015, where latitudinal and longitudinal information of the MDHS cluster was recorded. In addition, we make use of the MDHS SPA, the first health facility assessment survey in Malawi, which was collected in 2013/2014 by the Malawi Ministry of Health with technical support from the MEASURE DHS program. The data are

4) Sample cohorts are trimmed at the 1 and 99 percentiles, as in Chimutu 2013.

designed to collect information of access to and quality of health services from 977 health facilities throughout Malawi. MDHS SPA provides information on the general performance or quality of health facilities in terms of childcare, maternal care, HIV/AIDS treatment, sexually transmitted infections, and malaria treatment along with health facilities' location latitudinal and longitudinal information.

We identify respondents' residences using GPS data from the main MDHS and nearest health facilities using GPS data from the SPA. Since we have latitudinal and longitudinal information of the DHS village cluster and health facilities, we can calculate the distance to the nearest health center from respondents' village of residence. The mean distance to nearest health facility is 3.9 km (Table 1 (b)). We map respondents' DHS cluster locations and 977 health facilities locations in Figure 5. Blue dots indicate DHS clusters in which the respondent households reside and red stars indicate 977 health facilities.

Figure 5: Location of DHS clusters and Health facilities



Rainfall Data

We use the CPC CMAP for rainfall data.[5] Monthly-level precipitation data have been collected from 1979 to 2017 using several satellite-based algorithms based on a 2.5 latitude by 2.5 longitude grid. The CPC CMAP data are consistent with the rainfall data collected by the University of Delaware Center for Climatic Research's "Terrestrial Precipitation: Gridded Monthly Time Series (1900–2014) (Version 4)," which uses an interpolation algorithm based on the spherical version of Shepard's distance-weighting method to combine data from 20 nearby weather stations for every 0.5 latitude by 0.5 longitude grid. The reason we choose the CPC CMAP over terrestrial precipitation data is that our sample children cohorts include those born in 2015. To include this cohort in the analysis, we use the CPC CMAP.[6]

We calculate DHS cluster-year specific rainfall by calculating the weighted average of rainfall across rainfall stations. We restrict weather stations located within 200 km of DHS clusters.[7] Then, the weighted average value is calculated by assigning larger weights to the closer weather stations and smaller weights to the farther weather stations. Finally, we assign rainfall quantity to each of the sample children according to their years of birth, months of birth, and places of birth. The mean rainfall per month is 66.8 mm (Table 1). As Figure 6 shows, rainfall is concentrated in January and February since the rainy season starts from November and continues to April in Malawi.

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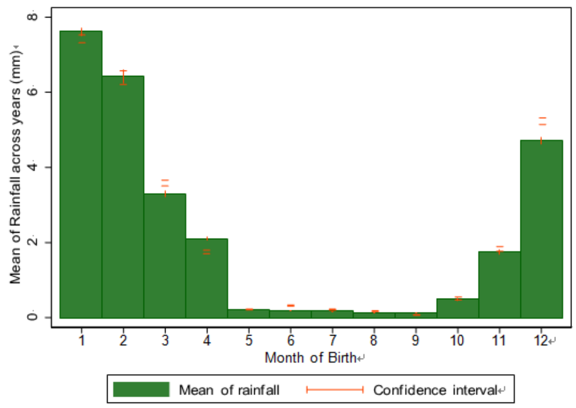
5) For more information, refer to http://www.cpc.ncep.noaa.gov/products/global_precip/html/wpage.cmap.html.

6) Since there are various ways to measure rainfall, rainfall information is likely to be subject to measurement error. Therefore, we check our results using terrestrial precipitation data. Still, we find consistent results.

7) The empirical findings are robust to a 100-km radius of rainfall data.

Figure 6: Distribution of rainfall by month of birth



Note: Rainfall by month of birth is calculated for our sample cohorts born between 2010 and 2015

Furthermore, we calculate the historical average and standard deviation of rainfall (10-year average and standard deviation before births) for each cluster and each month. Following Adhvaryu and Nyshadham (2015), we control for the historical mean and standard deviation of rainfall in all our MDHS regressions. If respondents can predict rainfall based on the historical information, the effect of rainfall at birth might be dependent on mothers' characteristics (e.g., information acquisition behavior) and this might compromise our main effect.[8)]

As already mentioned in the introduction, heavier rainfall makes it more difficult to travel to health facilities to give birth (Figure 4 (b)). Table 1 panel B shows that the health facility birth rate is highest (95 percent) in the lower percentile of value of the interaction term, distance to health center * rainfall (£10 percentile). As the value of the interaction term increases, the health facility birth rate decreases. The highest percentile group (³75 percent) shows the lowest health facility birth rate (90 percent).

Empirical Strategy

In this section, we describe our identification strategy and verify the validity of our IVs. As discussed in the introduction, ordinary least square (OLS) estimates are biased owing to self-selection into health services and unobservables in the regression error term. In order to overcome this endogeneity, we investigate the effect of health facility births using IVs. We propose two different exogenous variations as IVs for health facility births:

8) However, we do not find much difference before and after controlling for historical rainfall data.

labor contraction time and interaction of distance to health facilities and rainfall at birth. We exploit the same structure of equation for two specifications. In both specifications, we estimate the causal effect of health facility births on 7-day (early), 28-day (neonatal), and 1-year (infant) mortality.

We begin our empirical analysis by examining the Chimutu 2013 sample. The estimate is IV-2SLS specified in two stages:

(1) 1^{st} *stage:* $Birth_{imjt} = \alpha_1 \mathrm{Timing}_{imjt} + X_{imjt} + \omega_m + \mu_j + \tau_t + \epsilon_{imjt}$

(2) 2^{nd} stage: $\mathrm{Mortality}_{imjt} = \beta_1 \mathrm{Birt\hat{~}hi}_{mjt} + X_{imjt} + \omega_m + \mu_j + \tau_t + \nu_{imjt}$

where i indexes individual children, m mothers, *j* villages where the children and children's mothers have lived, and t the year of the child's birth. $\mathrm{Mortality}_{imjt}$ is the dependent variable of interest, early childhood mortality. In the first stage, Birth_{imjt}, an indicator variable that equals 1 if individual i was delivered in a health facility, is regressed on the IV Timing_{imjt}. Timing_{imjt} is a binary variable that equals 1 if the labor contraction starts during 5pm−9am (night). We compare this group to pregnant women whose labor contraction starts during 9am−5pm (day). For an additional check, we use three different timing dummies as IVs. In other words, we compare pregnant women whose labor timing is during 9am−5pm to pregnant women with timing during 11pm−5am, 5am−9am, and 5pm−11pm, respectively.[9] Ximjt includes a prenatal care dummy, birth-order fixed effect, twin dummy, and child gender. Ωm represents mother-level control variables, such as mother's year of birth fixed effect, mother's age at giving birth fixed effect, and dummies for ethnicity, migration, and primary school. μj is village fixed effect while τt absorbs the child's year of birth fixed effect and month of birth fixed effect. We cluster standard errors at the village level.[10]

The validity of our identification strategy relies on the assumption that the timing dummy is uncorrelated with any other unobservable factors affecting the child's mortality rate. However, there is no formal way to test this assumption. Instead, we validate the IV exclusion restriction by showing that certain characteristics of mothers and children are not correlated with labor-contraction timing. Table A.1 reports estimates of the effect of mother- and child-level observables on our IV. Column (1) reports the estimates on our

9) The empirical results are available upon request.

10) There are 84 villages in the Chimutu sample and 56 sampling units in the MDHS 2015, both of which are more than 40, a threshold of clusters below which standard error might be biased (Cameron and Miller 2015).

main IV and columns (2) to (5) present the results of indicators for each labor-timing category. As shown, we find no strong significant relationship between the observables and IV. Although this provides only suggestive evidence that our IV does not pick up any unobservable characteristics that might be closely related to both health facility births and child mortality, it is worth emphasizing that our IV seems to satisfy the IV exclusion restriction.

We next study the MDHS 2015 using a different IV: the interaction of distance to health facilities and rainfall at birth. The identification strategy is similar to the Chimutu 2013 sample, and is written as

$$(3)\ 1^{st}\text{ stage: } Birth_{imjt} = \alpha 1(d_{imjt} * R_{imjt}) + \alpha 3R_{imjt} + X_{imjt} + \omega_m + \mu_j + \tau_t + \epsilon_{imjt}$$

$$(4)\ 2^{nd}\text{ stage: } Mortality_{imjt} = \beta 1\hat{Birth}_{imjt} + \beta 3R_{imjt} + X_{imjt} + \omega_m + \mu_j + \tau_t + \nu_{imjt}$$

where subscripts i, m, j, and t are the same as in equations (1) and (2). Our main dependent variable of interest is the same as in the Chimutu 2013 sample, namely, early childhood mortality. In the first stage, we regress the health facility dummy on the interaction of dimjt, the distance to health facilities, and Rimjt, the rainfall at birth. Distance to health facilities is the distance from residence to the nearest health facilities and rainfall at birth is the weighted average of rainfall quantity across weather stations within a 200-km radius of the residence. Rimjt represents control variables in both the first and second stages of regression because rainfall around birth might have a direct impact on child mortality through the income-effect channel (Maccini and Yang 2009). Ximjt includes gestational age, caesarean section, birth order fixed effect, twin dummy, and child's gender. In addition, we include the average of historical rainfall and standard deviation of historical rainfall.[11] ωm represents mother level control variables, such as mother's year of birth, mother's age at giving birth, ethnicity, primary school dummy, ethnicity, religion, urban residence dummy, and household wealth. μj is a village fixed effect, which is defined in sampling units. τt is the child's year of birth fixed effect and month of birth fixed effect. Standard errors are clustered at the village level (sampling unit).

Similar to the Chimutu 2013 analysis, we provide suggestive evidence on the credibility of our IV. Daysal, Trandafir, and Van Ewijk (2015) and Pal (2015), who used distance to health facilities as an IV for health facility births, were subject to potential

11) Historical rainfall is calculated for each month of birth and year of birth using a 10-years average before birth.

bias due to endogenous health facility placement. In Table A.2, we run the regression of distance to health facility (column (1)), rainfall at birth (column (2)), and our IV (column (3)) on observable variables. As shown in column (1), distance to health facilities is correlated with most of the observables. For example, more educated mothers, wealthier mothers, and mothers with more educated husbands tend to live closer to health facilities. It is likely that either health facilities are constructed in wealthier areas or well-educated households move into areas near the health facilities. In column (3), our IV is not dependent on any observable variables except child gender (weakly significant). This lends support to our IV validity. Furthermore, we check whether rainfall at birth picks up the variation only around birth. If rainfall at birth is confounded by rainfall at other life periods, our IV estimate might be biased because rainfall at other periods could directly affect newborn mortality. Theoretically, rainfall at other periods should not affect health facility births. We check this possibility and find no effect of rainfall at other periods on health facility births.

Results

Main Results

We document that health facility births have a significant causal effect on newborn mortality (Table 2). The finding is consistent across two data sets with two different IVs. Before turning to the IV-2SLS results, we first investigate the OLS estimates. As already discussed in Section II, the OLS estimates are likely to be biased due to selection. There are two potential selections with regard to health facility births. It is possible that mothers who travel to health facilities to give birth already recognize their health problems and want to minimize the risk (adverse self-selection; Pal 2015). In this case, OLS estimates would underestimate the effect of health facility births. By contrast, it is possible that mothers who travel to health facilities might have strong preference for healthy children and are willing to invest more in their children's health than mothers who do not (favorable self-selection; Gortmaker 1979; Maitra 2004). In this case, OLS estimates would overestimate the effect. Consequently, OLS estimates compromise the true effect of health facility births on newborn mortality.

In panels A.a and B.a of Table 2, we examine the correlation between health facility births and newborn mortality. No significant relationship (but a negative sign) is found in the Chimutu 2013 analysis while a negative and weakly significant relationship is found in the MDHS 2015. We begin the discussion with the first-stage results in panels A.c and B.c of Table 2. In panel A.c, we use a labor contraction-timing dummy as an IV to predict the probability of health facility births. When a mother starts labor contractions during the night (5pm–9am), the chance of a health facility birth decreases by 9.7 percentage points (about 13 percent of the daytime standard). As most Malawians in rural areas rely on minibuses as a means of transportation, which constricts operating times to 6pm, labor-contraction timing at night is a critical factor for low accessibility to health facilities. In panel B.c of Table 2, we use interaction of distance to health facilities and rainfall at birth as an IV. The estimate is negative and significantly different from zero, suggesting that given the same distance to health facilities, heavier rainfall at birth makes it more difficult to travel to health facilities. Since we control for village fixed effect, our IV does not pick up geographic variation across regions (Adhvaryu and Nyshadham 2015). Instead, as shown in Figure 3 (b), our IV picks up the variation generated by heterogeneous rainfall level in the same village. The robust first stage F-statistic is 37.24 above the conventional threshold for weak instruments.

We next explain the main results. Panels A.b and B.b of Table 2 report the results of an IV method. In columns (1)–(3), we report the effect on early (7-day), neonatal (28-day), and infant (1-year) mortality, respectively. Using the Chimutu 2013 sample (panel A.b), the IV-2SLS estimates show that health facility births reduce early mortality by 14.6 percentage points, neonatal mortality by 16.4 percentage points, and infant mortality by 26.8 percentage points. In panel B.b of Table 2, we present the main effect of health facility births using the MDHS 2015 sample. Health facility births reduce early mortality by 13.4 percentage points and neonatal mortality by 12.4 percentage points but do not affect infant mortality significantly. Since our results are IV-2SLS, they estimate the LATE. Thus, they depend on samples and compliers of IVs. However, although we use two different data sets and different IVs, we obtain very similar results. While extreme caution should be applied in generalizing our results to other settings, two similar LATEs more strongly support the causal relationship between health facility births and newborn mortality.

The IV-2SLS coefficients are in fact much larger in magnitude than are the OLS estimates displayed in panels A.a and B.a of Table 2. We interpret the larger coefficients in the IV-2SLS specifications compared to the OLS specification as originating from two sources. First, IV-2SLS picks up only the local effect (LATE), while OLS captures the average effect of health facility births. If health facility births are correlated with health facility visits after giving birth, this might be picked up by OLS estimates leading to smaller direct effect of health facility births. In other words, if mothers' preference for health service is strong, self-selection into health facility births and health facility service use are likely to be closely interwound, which might compromise the true effect of health facility births. Second, as discussed in the empirical strategy section, self-selection into health facility births can contain two contradicting theories, that is, favorable or adverse self-selection. Since our IV-2SLS estimates are closer to the true effect of health facilities, we understand that the OLS specification is underestimated. Adverse selection into health service care is widely observed in both developing countries (Wang et al. 2006; Wagstaff et al. 2009) and developed countries (Savage and Wright 2003). Thus, it is unsurprising that adverse selection into health facilities compromises the true effect of health facility births in our setting.

Table 2—Main results: the effect of health facility births on child mortality

	(1) 7 days	(2) 28 days	(3) 1 year
A. Chimutu 2013 (sample: 1973-1992)			
a. OLS			
Facility birth	-0.001	0.004	0.005
	(0.008)	(0.009)	(0.013)
b. IV: labor timing dummy			
Facility birth	-0.146**	-0.164**	-0.268**
	(0.061)	(0.072)	(0.119)
c. First stage			
Labor timing (5PM-9AM)		-0.097***	
		(0.029)	
Observations		1,274	
First stage F-stat		11.17	
B. MDHS 2015 (sample: 1973-1995)			
a. OLS			
Facility birth	-0.012**	-0.010*	-0.008
	(0.005)	(0.006)	(0.008)
b. IV: Rain*Distance			
Facility birth	-0.134***	-0.124**	-0.061
	(0.050)	(0.059)	(0.074)
c. First stage			
Rain*Distance		-0.007***	
		(0.001)	
Observations		12,465	
First stage F-stat		37.24	

Chimutu 2013: We control for prenatal care dummy (four times or more), mother's education (primary school), mother's ethnicity, migration, child gender, and twin dummy. We include dummies for mother's year of birth, mother's age at birth, village fixed effect, child's month of birth fixed effect, year of birth fixed effect. Our sample cohorts are born between 1973 and 1992 (Sample cohorts are trimmed at one per- centile and 99 percentile). Standard errors are clustered at the village level (number of villages are greater than 40).
MDHS 2015: We control for mother's year of birth dummies, mother's age at birth, mother's education (primary school), ethnicity, religion, child's month of birth dummies, year of birth dummies, birth order, twin indicator, child gender, pregnancy duration, historical mean of rainfall historical rainfall standard deviation, whether the birth is done by caesarean, wealth and district fixed effect. We also choose sample of households who have not moved. Standard errors are clustered at the sampling district unit. Our sample cohorts are born between 1973 and 1995 (Sample cohorts are trimmed at one percentile and 99 percentile). Standard errors are clustered at the sampling unit (number of sampling unit is greater than 40).
*** p≤0.01, ** p≤0.05, * p≤0.1.

In summary, we find that health facility births causally reduce the newborn mortality rate using different samples and different IVs from two data sets. It is noteworthy that since the survey data were collected on the basis of respondents' recall, the empirical results might be biased owing to measurement error of health facility births and timing of newborn deaths. If a measurement error in health facility births were related to some unobservable factors determining newborn mortality, such as preference for health facility use, it would bias our estimate. This potential concern is minimized for the analysis using the MDHS 2015 because the survey collected information of children aged between 0 and 5 years. Thus, it is less likely that recall bias would confound our empirical findings in such a short time period. On the contrary, in Chimutu 2013 we use samples of children regardless of their ages if their health facility birth information is available. Although we control for a child's year of birth fixed effects and mother's year of birth fixed effects, a remaining concern could still be recall bias. We restrict our sample to children born during 2007–2012 and 2002–2012. In panel A of Table A.3, we estimate the effect of health facility births on newborn mortality using the sample of children born between 2007 and 2012. Compared to the main result in Table 2, we find a larger magnitude of effect, but the low first-stage F-statistics make it difficult to interpret the result precisely. In panel B of Table A.3, we use the sample of children born between 2002 and 2012, finding a similar magnitude effect of health facility births as the main result. However, the relatively low first-stage F-statistics also make it difficult to interpret the result precisely. We consider the insignificant effect and low first-stage F-statistics are because of sample size problems, as the implications and magnitude of the effect are similar across different samples. Thus, the concern for recall bias is minimized in the Chimutu 2013 data.

Heterogeneous Effect of Health Facility Births

We next expand the analysis to consider heterogeneous effects of health facility births. In Table 3, we estimate the effects by subsamples with respect to several observable characteristics, such as primary school completion, household wealth, mother's age, and child's birth weight. In panel A (Chimutu 2013 sample), we find a significant effect of health facility births on early mortality for those who did not complete primary school. We find a weak significant effect on infant mortality for mothers who completed primary school but the first-stage F-statistic is very low owing to small sample size. In addition, we find that health facility births significantly reduce early mortality by 13.7 percentage points for mothers whose age is above the median, although it is weakly significant. In panel B (MDHS 2015 sample), there is a substantial heterogeneous effect with respect to primary school completion, household wealth, mother's age, and child birth weight. We consistently find a significant effect on early mortality for mothers who did not complete primary school in the Chimutu 2013 sample. We find a significant and negative effect in both poorer and richer households but we find a significant effect on neonatal mortality only for poorer households. This is consistent with the findings of Gruber, Hendren, and Townsend (2014) and Daysal, Trandafir, and Van Ewijk (2015). In addition, similar to the Chimutu 2013 sample, we find that health facility births reduce early mortality by 12.8 percentage points for mother whose age is above the median. In addition, we check the heterogeneity by child's birth weight. Health facility births are conducive to children born with relatively lower birthweight.

Table 3— Heterogeneous effect of facility birth

	(1)	(2)	(3)	(4)	(5)	(6)
	7 days	28 days	1 year	7 days	28 days	1 year
Panel A. Chimutu 2013						
Primary School	Not complete primary school			Complete primary school		
Facility birth	-0.107**	-0.090	-0.132	-0.154	-0.243	-0.732*
	(0.048)	(0.062)	(0.105)	(0.212)	(0.236)	(0.415)
Observations	1,024	1,024	1,024	250	250	250
IV F-statistics	10.54	10.54	10.54	1.265	1.265	1.265
Mother's age	Below median			Above median		
Facility birth	-0.037	-0.132	-0.353	-0.137*	-0.100	-0.096
	(0.095)	(0.132)	(0.238)	(0.077)	(0.074)	(0.128)
Observations	631	631	631	643	643	643
IV F-statistics	3.358	3.358	3.358	6.591	6.591	6.591
Panel B. MDHS 2015						
Primary School	Not complete primary school			Complete primary school		
Facility birth	-0.103**	-0.079	0.019	-0.250	-0.329	-0.365
	(0.050)	(0.061)	(0.068)	(0.179)	(0.250)	(0.307)
Observations	8,822	8,822	8,822	3,643	3,643	3,643
IV F-statistics	29.54	29.54	29.54	2.621	2.621	2.621
Household Wealth	Below median			Above median		
Facility birth	-0.127**	-0.123*	-0.041	-0.204*	-0.193	-0.142
	(0.056)	(0.067)	(0.074)	(0.107)	(0.118)	(0.155)
Observations	6,307	6,307	6,307	6,158	6,158	6,158
IV F-statistics	22.83	22.83	22.83	14.31	14.31	14.31
Mother's age	Below median			Above median		
Facility birth	-0.135	-0.147	-0.066	-0.128**	-0.107	-0.036
	(0.111)	(0.134)	(0.164)	(0.063)	(0.068)	(0.074)
Observations	6,058	6,058	6,058	6,407	6,407	6,407
IV F-statistics	10.84	10.84	10.84	38.52	38.52	38.52
Child birth weight	Below median			Above median		
Facility birth	-0.593**	-0.549*	-0.066	0.349	0.513	0.315
	(0.276)	(0.307)	(0.355)	(0.592)	(0.675)	(0.897)
Observations	5,103	5,103	5,103	5,575	5,575	5,575
IV F-statistics	13.82	13.82	13.82	1.409	1.409	1.409

Note: We use same control variables as main results. Standard errors are clustered at the village level (Chimutu) and sampling unit level (MDHS 2015). *** p<0.01, ** p<0.05, * p<0.1.

Taken together, the results produce suggestive evidence that mothers from relatively poorer backgrounds experience more benefits by health facility births. Our LATEs pick up the effect mostly from mothers of poorer background, as addressed by Daysal, Trandafir, and Van Ewijk (2015). This pattern is clearly observed in developing countries (Cutler and

Lleras-Muney 2010) because people from poorer backgrounds are less likely to obtain access to health facilities.

Mechanisms of Impact

In this section, we examine potential mechanisms through which health facility births reduce newborn mortality. Due to a dearth of data to check the mechanisms, there is a lack of analysis of the mechanism in Daysal, Trandafir, and Van Ewijk (2015) and Pal (2015). However, we improve the mechanism analysis by leveraging the SPA data for which quality information of health facilities is available. Such quality information includes medicine storage, vaccination, malaria treatment, prevention of mother to child transmission (PMTCT), and HIV treatment service provision. By linking SPA data to individual-level data from the MDHS 2015, we can identify the nearest health facilities using such quality information.

Table 4 reports the mechanism results. In each potential mechanism check, we run a separate regression by health facilities with and without certain characteristics. For example, in the first row of the table, SPA provides information on whether health facilities are able to provide service for normal delivery. Normal delivery service refers to newborn care offered after normal delivery. Since we can identify whether health facilities provide normal delivery service, we can also identify whether the nearest health facilities from an individual mother’s residence provide this service. Based on this, we run two separate regressions of health facility births with and without normal delivery service on newborn mortality. Health facility birth with normal delivery service is an indicator variable if the mother gives birth at a health facility offering normal delivery service. In the same manner, health facility birth without normal delivery service is an indicator variable if the mother gives birth at a health facility without normal delivery service. Similarly, we use this specification for other mechanism checks. In all regressions, we use interaction of distance to health facilities and rainfall at birth as an IV.

In the first row of Table 4, we find that health facility births with normal delivery service and vaccine service reduce newborn mortality significantly. No significant or only a weak significant effect is found when mothers give birth at health facilities without these services. We find a very similar pattern for other quality measures of health facilities. In the second row, we find a significant effect of health facility births with a malaria cure and treatment system on newborn mortality. The magnitude of coefficients is greater than coefficients from normal delivery service and vaccine service. In the third and fourth rows of Table 4, we find very consistent results with regard to PMTCT service, HIV service, minor surgical service, and medicine provision. It is possible that these mechanism measures are strongly correlated to each other so that the pattern of mechanism analysis could be similar.

Table 4— Suggestive mechanism using MDHS 2015

	7 days	28 days	1 year	7 days	28 days	1 year
Obs (N) = 12,465						
	Normal delivery			**Vaccine**		
Facility birth with *	-0.024**	-0.027***	-0.022	-0.039**	-0.042**	-0.018
	(0.009)	(0.010)	(0.015)	(0.017)	(0.019)	(0.026)
Facility birth without*	-0.009	-0.005	0.005	-0.031*	-0.024	-0.009
	(0.008)	(0.012)	(0.020)	(0.019)	(0.024)	(0.031)
First stage F-stat with*	117.20	117.20	117.20	48.91	48.91	48.91
First stage F-stat without*	65.87	65.87	65.87	62.81	62.81	62.81
	Cure under ftve			**Malaria**		
Facility birth with *	-0.071**	-0.068**	-0.035	-0.070**	-0.063*	-0.028
	(0.031)	(0.034)	(0.040)	(0.031)	(0.035)	(0.041)
Facility birth without*	0.095	0.081	0.177	-0.009	-0.034	0.031
	(0.088)	(0.090)	(0.110)	(0.106)	(0.102)	(0.121)
First stage F-stat with*	45.62	45.62	45.62	44.07	44.07	44.07
First stage F-stat without*	18.38	18.38	18.38	13.60	13.60	13.60
	PMTCT			**HIV**		
Facility birth with *	-0.023**	-0.025***	-0.015	-0.025**	-0.028***	-0.016
	(0.010)	(0.010)	(0.016)	(0.010)	(0.011)	(0.017)
Facility birth without*	-0.014	-0.013	-0.004	-0.018*	-0.015	-0.004
	(0.010)	(0.014)	(0.022)	(0.011)	(0.014)	(0.023)
First stage F-stat with*	99.39	99.39	99.39	98.00	98.00	98.00
First stage F-stat without*	65.68	65.68	65.68	63.78	63.78	63.78
	Store medicine			**Minor Surgical Services**		
Facility birth with *	-0.130***	-0.120**	-0.074	-0.047**	-0.047**	-0.020
	(0.047)	(0.055)	(0.071)	(0.020)	(0.022)	(0.028)
Facility birth without*	0.108	0.058	0.216	-0.015	0.003	0.021
	(0.307)	(0.328)	(0.436)	(0.023)	(0.027)	(0.040)
First stage F-stat with*	34.95	34.95	34.95	60.20	60.20	60.20
First stage F-stat without*	2.701	2.701	2.701	41.06	41.06	41.06

Note: First stage F-statistics are calculated separately for each regression. First stage F-stat with* uses the regression where we identify "functioning" health facilities with certain types specified in the table. First stage F-stat without* uses the regression where we identify "not functioning" health facilities with certain types specified in the table.
*** p<0.01, ** p<0.05, * p<0.1

The main point in this analysis is that good quality of services in health facilities is a plausible link to explain the causal effect of health facility births on newborn mortality. Daysal, Trandafir, and Van Ewijk (2015) addressed only one mechanism by emphasizing that hospitals with a neonatal intensive care unit (NICU) are the driving force of the main effect. The authors argued that this evidence might suggest that improvement of medical technology is the key factor in reducing newborn mortality if mothers give birth in hospital. Our study approaches the issue from a different point of view. The site of this study is Malawi, one of the poorest countries in the world, where most pregnant women experience lower quality health services than women in developed countries in general.

Mothers in low-income countries at the margin who would benefit from health facility births are likely to be different from mothers in high-income countries. Mothers in high-income countries have more ready access to medical resources than do those in low-income countries (Leisinger, Garabedian, and Wagner 2012). Thus, the mechanism through which health facility births reduce newborn mortality works differently in high- versus low-income countries. Mothers in high-income countries who benefit from health facility births would not suffer for the same reason as would mothers in low-income countries who give birth at health facilities. Consequently, the return to health facility births in Malawi is likely to rely on the basic healthcare service provided at health facilities.

Results in Table 4 is consistent with previous findings that quality care at birth is one of the key factors in improving neonatal survival (Lavy et al. 1996; Liu et al. 2012). In particular, the magnitude of coefficients is larger in "store medicine" and "cure under five." This suggests that health facilities that can provide immediate care service at birth might be the reason for our main results. However, we remain cautious about making strong claims about the mechanisms because we are not able to identify whether individual mothers who give birth at health facilities benefited from this service.

Threats to Identification

A. Instrumental Variable Validity

Finally, we address the potential threats to the validity of our identification strategy. As discussed in Section II, our IVs should satisfy two conditions: relevance to our main regressor and exclusion restriction. The first-stage F-statistics are large enough and our IVs are not correlated with observable characteristics that might affect our dependent variables. In addition, discuss potential concern about labor-contraction timing IV in the Chimutu 2013 sample. If labor-contraction timing at night is correlated not only with bad accessibility to health facilities but also with availability of medical personnel, then our IV does not satisfy the IV exclusion restriction. If mothers perceive in advance that medical personnel at night are not available, then our IV-2SLS not only picks up the effect of health facility births but also estimates the effect of mothers' perceptions of health facilities. Unfortunately, we do not have data to examine this possibility from the Chimutu 2013 sample. However, the MDHS SPA data surveyed whether staff are present around the clock at the facility. In 737 out of the total 977 health facilities (75.4 percent), healthcare workers or medical personnel are at the facility at all times. Thus, it is still possible that our IV-2SLS estimates are overestimated. However, according to the qualitative study by Kumbani et al. (2013), onset of labor at night and in the rainy season were the most significant barriers for mothers who failed to give birth at health facilities. We conclude that our IV-2SLS estimates are not confounded severely by health workers' availability at night.

As addressed by Adhvaryu and Nyshadham (2015), using the interaction of distance to health facilities and rainfall at birth might not be excludable if distance to health facilities is correlated with distance to marketplace. In other words, if our IV picks up the effect of lack of access to resources owing to general remoteness to community amenities, then our IV-2SLS estimates are biased. Unlike Adhvaryu and Nyshadham (2015), we do not have information about distance to marketplace. In addition, it is difficult to disentangle these effects because of endogeneity of distance to marketplace itself. More importantly, since our IV is an interaction of distance to health facilities with rainfall at birth, there is no reason to believe that exogenous variation generated by rainfall at birth should be related to general remoteness.

Another concern for excludability of the interaction IV is that distance to health facilities and rainfall at birth might have a direct effect on newborn mortality. Distance to health facilities, which has been used as an IV for health facility use, is likely to be associated directly with newborn mortality. Furthermore, rainfall at birth has been proven an important factor determining health outcomes (Maccini and Yang 2009). Thus, rainfall at birth might affect newborn mortality through channels other than health facility use. Consequently, the interaction of two variables is likely not to satisfy an IV exclusion restriction. However, we control for the main effect of distance to health facilities and rainfall at birth, and only the interaction is excluded (Adhvaryu and Nyshadham 2015). This might not remove potential concerns about nonexcludability, but we improve the often-used IV of distance to health facilities, making it more exogenous by interacting it with rainfall at birth.

Supply Side – Availability of Health Facilities

Since this study examines the effects of health facility delivery mainly through the demand for health services, of concern is the impact from the supply side of health services, the availability of health facilities, and the quality of health facilities. Since the number and quality of health facilities are likely to vary across years, it is possible that our IVs have a heterogeneous effect depending on the supply-side condition. To address this problem, we include the mother's year of birth fixed effect, child's year of birth fixed effect, and child's month of birth fixed effect to absorb any year effects. Furthermore, this concern is minimized in the MDHS 2015 analysis because at least we have the exact information of the health facilities. However, we have to address our assumption that the number of health facilities is the same between 2010 and 2015, when our child cohorts were born. SPA data were collected from 2012 and completed in 2014. Thus, it is reasonable to assume that the number of health facilities is the same between 2012 and 2014. We extrapolate this assumption to 2010, 2011, and 2015. To check whether this assumption is acceptable, we perform tests using only cohorts born between 2013 and 2015. We find similar results to main results although there is weaker significance owing to smaller sample size.

Mechanism Validity

We address the concern that the quality of health facilities might not drive the link between health facility births and newborn mortality. If our findings stem from the presence of delivery assistants, our suggested mechanism might not be applicable. In other words, health facility births are more beneficial than home births because mothers who give birth at home might go through the delivery process alone or with unskilled assistants. However, this possibility is very low because the government of Malawi has made home births with traditional birth attendants illegal since 2007 (Sarelin 2014). This law is intended to promote modernization and a safe system for newborn births with the final purpose of incentivizing mother to travel to health facilities or to give birth with skilled attendants. Our sample cohorts of children in the MDHS 2015 sample were born between 2010 and 2015 and thus, these cohorts are less likely to be confounded by this possibility. As further evidence, only 1.5 percent of mothers in the MDHS 2015 sample were not assisted by skilled attendants (including the case of health facility births).

Conclusion

We study the causal effect of health facility births on newborn mortality. Since health facility birth is an endogenous choice, we instrument it with labor contraction time and interaction of distance to health facilities and rainfall at birth using the unique village survey of Chimutu 2013 and the MDHS 2015. Our IVs affect the cost of accessibility to health facilities, and thus, accessibility must be closely related to demand for health facility births. Finally, we find that health facility births have a strong and statistically significant effect on early (7-day) mortality and neonatal (28-day) in both data sets.

Previous literature has neglected the potential endogeneity of IVs for health facility births, defining the distance to health facility as exogenously given. The possible correlational test of distance to health facility with observable characteristics that we perform shows statistical significance among many observables. This confirms that in order to estimate the causal effect of health facility births, it is important to improve the IV or to consider a stronger specification. Our IVs in this study passed several tests satisfying the IV condition, and thus, the estimates are more reliable.

The results suggest that the relationship between health facility births and newborn mortality is robust across two survey data sets with different IVs. Given the fact that our IV-2SLS estimates are LATE, it is surprising that our estimates are similar in magnitude, lending support to our argument that there is a causal relationship between health facility births and newborn mortality. We also examine the potential mechanisms by using health facility quality data. We show that the reason health facility births reduce newborn mortality compared to home births is due to immediate care after birth by help from readily available medical resources. It is noteworthy that our IV-2SLS estimates mostly pick up the effect from mothers from poorer backgrounds. In other words, mothers from poorer environments might benefit more from health facility births.

Our results show the importance of incentivizing pregnant women to use health services at health facilities, because health facility births significantly reduce newborn mortality. This is considered an extensive marginal benefit from health facility births. In addition, the mechanism analysis suggests that the most benefit could depend on the quality of health facilities, and we conjecture that intensive marginal benefit can be maximized by accompanying the improvement of availability of medical resources or medical technology. Regardless whether the return to medical technology is diminishing or increasing, the introduction of new medical technology is conducive to decreasing the newborn mortality rate conditional on health facility births, because even in developed countries, like the Netherlands, the return to medical technology seems to be high in terms of newborn mortality (Daysal, Trandafir, and Van Ewijk 2015). Thus, to meet the Sustainable Development Goals, future policy should focus on how to improve accessibility to health facilities for pregnant mothers as well as on the improvement of the quality of health facilities in terms of, for example, the number of clinicians (Farahani, Subramanian, and Canning 2009; Liebert and Mäder n.d.).

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