# Stormborn: Evaluating the Impact of Facility-Based Delivery on Health and Economic Outcomes Using a Machine Learning Approach

Zoë McLaren*

School of Public Policy and Department of Economics

University of Maryland Baltimore County

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*School of Public Policy and Department of Economics, University of Maryland, Baltimore County, 1000 Hilltop Circle, Baltimore, MD 21250, zmclaren@umbc.edu. The author thanks Mohana Mahfuz Prema, Melody Pinamang, Felipe Munoz Castillo, Jeffrey Fitch and Alexandra Nguyen for research assistance and Claus Pörtner, Yevgeniy Davydov and conference attendees at the Population Association of America, American Society of Health Economists, American Public Health Association, European Society for Popu-

**Abstract**

There is wide consensus among social scientists about the importance of early life investments in determining outcomes later in life. Therefore, encouraging women to give birth in health facilities rather than at home remains a key policy objective in low- and middle-income countries. Despite this focus, there is little unconfounded evidence on whether facility-based delivery leads to improved child health and economic outcomes relative to delivering at home. This paper uses a rigorous instrumental variables approach with a machine learning component to examine the impact of facility-based delivery on child, maternal and household outcomes in Africa, including spillovers between siblings.

My identification strategy uses exogenous weather shocks such as rain and high temperatures in the days leading up to birth as instruments for facility-based delivery since weather shocks may hinder travel and therefore induce at least some women who considered delivering in a health facility to instead deliver at home. I use rich data from the 2012-2019 Demographic and Health Surveys that includes women's detailed birth histories as well as family, household and geographic data. I link births with high-resolution and high-frequency weather data from the ERA5-Land database. I exclude births occurring in the days following extreme weather shocks like flooding since they may influence birth and maternal outcomes in ways other than

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via the likelihood of facility-based delivery and are therefore likely to violate the exclusion restriction. I use machine learning methods (lasso, ridge regression and elastic net) to select the strongest instruments from a large set of 400 potential instruments for facility-based delivery.

Results from the elastic net instrumental variables estimation show that facility-based delivery is statistically significantly associated with a 7.8 percentage point increase in under-five survival, an 26.5 point increase in the height-for-age percentile, an 19.4 point increase in the weight-for-age percentile, and a 4.5 month shorter subsequent birth interval relative to children who were delivered at home. These children are 5.5 percentage points more likely to be vaccinated, however this is not statistically significant. I found a large positive spillover effect of having an elder sibling deliver in a health facility on the likelihood of receiving at least one vaccination but no effect on survival or anthropometrics. There were no spillover effects on any outcomes from having a younger sibling delivered in a health facility. There are no differences in the likelihood of being breastfed.

The local average treatment effect estimate from this novel instrumental variables approach identifies large overall benefits of facility-based delivery that accrue to children of women who are dissuaded from traveling to a health facility by relatively small, potentially surmountable barriers. There is therefore a need for better interventions to encourage, incentivize and enable facility-based delivery for this key

target group: women who may be undecided about delivering in a facility or for whom small barriers are constraining. Policy interventions targeting this marginal population are therefore likely to yield a large return on investment.

# 1 Introduction

There is wide consensus among social scientists of the importance of early life investments in determining health and wealth outcomes later in life (Currie 2009, Almond and Currie 2011). Improving maternal and child outcomes has therefore been a key policy objective in both high-income and low-income countries. As part of this agenda, encouraging women to give birth in a health facility rather than at home was a key strategy for achieving Millennium Development Goals and continues to be a high priority (United Nations 2023).

However, in low- and middle-income countries it remains an open question whether delivering in a health facility leads to improved outcomes relative to delivering at home. On one hand, facility-based delivery provides women with access to skilled birth attendants, emergency obstetrics, health information and other medical resources at the time of delivery (Gage et al. 2019). It may also increase long-term engagement with formal health services (Moyer et al. 2014). On the other hand, the quality of care received in health facilities in low- and middle-income countries varies widely and may not meet

minimal standards. Attending a low quality health facility may therefore not provide the full range of benefits (Fink et al. 2015). Moreover, travel to health facilities incurs both out-of-pocket and opportunity costs which can be a burden to women and families (Richard et al. 2009).

Despite the focus on encouraging facility-based delivery in low- and middle-income countries, there is little unconfounded causal evidence demonstrating that facility-based delivery leads to better child and maternal outcomes relative to home delivery. Because women who deliver at a facility are likely to differ from women who deliver at home in many ways (e.g. education, wealth), a rigorous research design is needed to disentangle correlation from causation. However, even among studies with robust econometric approaches, the evidence is mixed. Given the importance accorded to birth outcomes in development economics and the lack of consensus in the literature, this paper fills a key gap in the literature. More evidence is needed to guide policy.

This study examines the causal impact of facility-based delivery on child health and economic outcomes using a large, multi-country sample of births from the Demographic and Health Survey (DHS) that is powered to detect small effects (ICF 2023). I implement a rigorous instrumental variables (IV) strategy that uses weather shocks as an instrument for facility-based delivery and employs machine learning methods (i.e. lasso, ridge regression and elas-

tic net) to select optimal instrumental variable specifications from a large set of potential instruments. I use high-resolution and high-frequency weather data that allows me to link birth outcomes with local weather in the days preceding birth, which reduces measurement error and increases statistical power. Weather shocks such as rain or high daytime temperatures may hinder travel and therefore induce at least some women who considered delivering in a health facility to instead deliver at home. These weather shocks affect the ability or willingness of laboring women to travel to a health facility but do not otherwise directly affect child, maternal or household outcomes.

I find substantial benefits associated with facility-based delivery. Children born to women who are induced to deliver at health facilities due to weather shocks are a statistically significant 5.4 percentage points more likely to survive to age five, have a statistically significant 8.4 point higher height-for-age percentile, have a statistically significant 8.4 point higher weight-for-age percentile, are an 11 percentage point greater likelihood of being vaccinated, and have a 2.5 month shorter subsequent birth interval. I find a positive spillover effect of having an elder sibling deliver in a health facility on the likelihood of receiving at least one vaccination for both urban and rural populations but no spillover effect on any outcomes for having a younger sibling delivered in a health facility.

The instrumental variables approach identifies the local average treat-

ment effect for a group that is a key target for policy intervention: women who are dissuaded from traveling to a health facility by relatively small, potentially surmountable barriers. The large magnitude of the overall benefits of facility-based delivery for this marginal group suggests that investing in targeted policy will reap a large return.

The contribution of this paper is three fold: First, this study contributes to an area of the literature where there is a lack of consensus on the benefits of facility-based delivery and that uses robust causal inference methods to identify the impact in low- and middle- income countries. In particular, this paper's identification strategy – using weather shocks as instrumental variables – estimates the impact for women who may be undecided about delivering in a facility or for whom small barriers are constraining. This marginal group can serve as a key target for policy intervention.

Second, this paper demonstrates that small barriers nevertheless prevent people from accessing high-return health care (see Thirumurthy et al. 2023 for a discussion). It provides evidence that women may forgo facility based delivery due to relatively minor weather shocks, which highlights the importance of barriers such as liquidity constraints, lack of transportation, or information asymmetries about the relative benefits of facility-based delivery. It also suggests an additional pathway through which climate change negatively affects vulnerable populations.

Third, this paper makes a methodological contribution to the economics literature more broadly in the use of machine learning methods within a causal inference framework. To my knowledge, this paper is the first to use machine learning to specify the rainfall instrument, which is widely used in development economics. Machine learning methods present a solution to the weak instrument problem by systematically selecting instruments with the greatest predictive power in order to reduce bias and improve inference.

The rest of this paper is organized as follows: Section 2 evaluates related studies, Section 3 describes the data used for the analysis, Section 4 presents the methods, Section 5 reports the results and Section 6 discusses the implications of the findings and concludes.

# 2 Literature Review

A broad literature has examined the drivers of and barriers to facility-based delivery in low- and middle-income countries (see Moyer and Mustafa 2013 for a systematic review). Many studies have examined the impact of facility-based delivery on wide range of health and well-being outcomes (see for example Neal and Matthews (2013), Hanson et al. (2015) and Altman et al. (2017)). However, the majority of these studies are cross-sectional and cap-

ture potentially confounded estimates. A meta-analysis by Chinkhumba et al. (2014) found only 9 population-based cohort studies assessing the impact of facility-based delivery on perinatal and maternal mortality, and notes that these studies are likely biased due to selection bias and confoundedness.

Only a few studies used a rigorous research design and econometric methods to identify plausibly causal estimates of the impact of facility-based delivery on child, mother and household outcomes. The conclusions are mixed, however. Four studies found no impact of facility-based delivery on newborn mortality or maternal mortality (Chari and Okeke (2015), Okeke et al. (2015), Godlonton and Okeke (2016), Gitobu et al. (2018)), while two others found a statistically significant improvement in newborn mortality (McKinnon et al. (2015), Okeke and Chari (2018)). One recent study found that although eliminating user fees for facility-based delivery in Ghana had no impact on neonatal mortality, it led to improvements in child health in the longer run (Friedman and Keats 2020). This suggests that an understanding of longer-run and spillover impacts of facility-based delivery is essential to determine its true impact and properly inform policy.

# 3 Data

I use a large data set of Demographic and Health Survey (DHS) data that includes women's detailed birth histories that are linked to DHS family, household and geographic data. The analysis sample includes all children under age 5 who were born between 2012-2019 in 18 African DHS countries in surveys that included day of birth, geographic coordinates and information about facility-based delivery. Figure 1 shows a map of the countries included in the sample.

I use GPS data to link children in the DHS data with local weather data for the days preceding birth from the Copernicus Climate Data Store ERA5-Land Hourly database produced by the European Centre for Medium-Range Weather Forecasts (ECMWF) (Muñoz-Sabater et al. 2021). ERA5-Land provides weather data for points on a grid of 0.1 degrees of latitude and longitude, which corresponds to approximately 6.8 miles or 11 kilometers. I extracted data on hourly surface (2 meter) temperature and accumulated precipitation measures and linked it to DHS clusters based on the nearest grid point. The DHS cluster GPS coordinates are randomly displaced (jittered) to preserve respondent confidentiality: urban clusters are displaced up to 2 kilometers and rural clusters are displaced up to 5 kilometers, with 1 percent of the rural clusters displaced up to 10 kilometers (Demographic and Health Surveys 2023).

The ERA data is a *re-analysis* data set, meaning that it inputs high-frequency observations from multiple sources into a large-scale atmospheric model, which is used to estimate past weather measures. Estimations are benchmarked against actual weather observations. Re-analysis methods are a vast improvement over simple distance-weighted interpolation, often over sparse data points (like that used in Willmott and Matsuura (Matsuura et al. 2022), for example) because it models the entire weather system based on measured benchmarks. See Auffhammer et al. (2011) for a discussion of re-analysis data sets.

The DHS contains 186,952 births occurring between 2012-2019 in 18 African countries that have day of birth, GPS coordinates and facility-based delivery data (see map in Figure 1). After excluding 19,173 births occurring in the week following extreme weather, the analysis sample consists of 167,779 observations. Table 1 presents descriptive statistics for the analysis sample. The column totals show that about two-thirds of the sample are born in a health facility which the DHS defines as including any type of health facility including clinics and hospitals, whereas home-based is defined as being at the respondent's home or another home. Of the health facility births, 31 percent are in a hospital and 69 percent are in a smaller health clinic. Fourteen percent of facility-based births are (primarily) attended by a doctor and 76 percent are attended by another highly-skilled health pro-

fessional like a nurse or midwife. By contrast, 42 percent of home births are attended by a trained birth attendant or traditional birth attendant and 36 percent are either attended by a friend or family member or in rare cases not attended at all.

As expected, children born in health facilities have more favorable characteristics overall. Children who have a facility-based delivery are more likely to survive to age 5, have higher height-for-age and weight-for-age percentiles, are more likely to receive vaccination and are slightly more likely to be breast-fed. Their mothers are slightly younger, have more than twice as many years of education, are more likely to be urban residents, are wealthier and are less likely to report that travel distance is a barrier for obtaining health care. Firstborn children constitute 26 percent of the facility-based births (compared to only 15 percent of the home births) and this declines as birth order increases through birth order six. The fact that children delivered in health facilities have both better home characteristics and better access to health care demonstrates the need for a methodological approach to addressing sample selection and motivates the use of an instrumental variable methodology.

# 4 Methods

This paper evaluates the impact of facility-based delivery on child health and economic outcomes using the following equation:

$$y_{ijt} = \mu + \gamma FacilityBasedDelivery_{ijt} + \delta X_{ijt} + \eta_{jt} + \epsilon_{ijt} \quad (1)$$

where $y_{ijt}$ represents an outcome for child i in region j for period t, $X_{ijt}$ a vector of control variables including sex of child, whether the child is a twin, birth order dummies, mother's age categories, mother's years of education attainment, urban resident and wealth index. I examine the following outcomes: survival to age five, height-for-age percentile, weight-for-age percentile, receiving any vaccination, birth interval spacing until subsequent sibling. I also included birth year dummies, birth month dummies and sub-national-region controls ($\eta_{jt}$). Some specifications add year by sub-national-region controls.

Because facility-based delivery is not assigned randomly, I implement a two-stage least squares approach where I predict facility-based delivery using the following first-stage equation:

$$FacilityBasedDelivery_{ijt} = \theta + \pi\ X_{ijt} + \phi Z_{ijt} + \xi_{jt} + \nu_{ijt} \quad (2)$$

where $X_{ijt}$ is the same vector of control variables as above, and $Z_{ijt}$ is a set of weather shock instruments based on air temperature and amount of

precipitation in the week prior to the day of birth.

The identification assumption for this approach is that conditional on the vector of covariates, the weather in the week prior to birth doesn't affect the child health and economic outcomes other than through the impact on facility-based delivery. The sample therefore excludes births that occurred in the week following extreme weather shocks such as heavy rains that are likely to lead to flooding or very high temperatures that could cause serious medical issues for pregnant women. These extreme shocks are likely to violate the exclusion restriction since they may influence birth and maternal outcomes in ways other than via influencing the likelihood of facility-based delivery.

I also investigate the spillover impact of having a sibling delivered in a health facility, conditional on one's own delivery location. The specification uses weather on the day of the child's birth and that on the day of their older sibling's birth to predict whether the child, their older sibling or both (i.e. the interaction term) were delivered in a health facility:

$$y_{ijt} = \mu + \gamma FBD_{ijt} + \tau SiblingFBD_{ijt} + \zeta FBD_{ijt} * SiblingFBD_{ijt} + \delta X_{ijt} + \eta_{jt} + \epsilon_{ijt} \quad (3)$$

A similar approach is used for a separate analysis of the impact of a

younger sibling's delivery in a health facility. For these analyses, siblings are defined as having the same mother. The sample includes all children whose mother reports an older sibling or younger sibling, however, this is limited to siblings who are both under 5 years old since the DHS survey only asks mothers about children born in the previous 5 years.

For some specifications I include controls for the type of birth attendant. I group attendants as follows: whether the mother reported having a high-skilled birth attendant (doctor, nurse or midwife), or a lower-skilled birth attendant (trained birth attendant or traditional birth attendant) relative to a combined category of either a birth attendant with no training (i.e. friend or family member) or having no attendant at all. I use weather variations to instrument for the type of birth attendant in a similar approach as I use to instrument for facility-based delivery. For these specifications, the second stage equation is as follows:

$$y_{ijt} = \mu + \alpha HighSkillAtt_{ijt} + \beta LowSkillAtt_{ijt} + \delta X_{ijt} + \eta_{jt} + \epsilon_{ijt} \qquad (4)$$

To satisfy the exclusion restriction I exclude births occurring in the week following any extreme weather event that is likely to be extreme enough to impact the outcomes of interest directly rather than solely via the decision to deliver in a health facility. I define extreme weather days as any of the

following: having a maximum temperature below 5 degrees Celsius (41 degrees Fahrenheit), total daily precipitation standard deviation in the top 1 percent for that grid square (geographic location) during the prior week, or having a maximum temperature standard deviation in the top 1 percent for that grid square (geographic location) during the prior week which is *also* over 35 degrees Celsius (95 degrees Fahrenheit). I perform sensitivity analyses to these cutoffs using thresholds of below 10 degrees Celsius (50 degrees Fahrenheit), the top 0.5 or 2 percent of standard deviations in precipitation, and a maximum temperature over 32 degrees Celsius (90 degrees Fahrenheit).

## 4.1 Instrument selection using machine learning

I leverage machine learning methods within a causal inference framework to select instrumental variables specifications. This is an improvement over theory-driven or ad hoc instrument selection alone because with machine learning methods, instruments are selected via an efficient, systematic, data-driven process that is designed to identify the instruments that are most predictive out of the set of all potential variables. Additionally, it minimizes the influence of potentially weak instruments.

I estimate the first-stage (Equation 2) not only using standard two-stage-least-squares (2SLS), but also using three machine learning methods: (1) the lasso (least absolute shrinkage and selection operator) that selects a subset of

the strongest instruments from a large set of potential weather instruments, (2) ridge regression that systematically weights regression coefficients to produce the best prediction, and (3) the elastic net which is a linear combination of the two approaches (Hastie et al. 2008).

I input an initial large set of approximately 400 potential instruments including: daily maximum daytime (2 meter) temperature and total (cumulative daily) precipitation. For these two variables, I include daily values for 1, 3, 5 and 7 days prior, averages for the 1, 3, 5 and 7 day period prior, and cumulative precipitation for the 1, 3, 5 and 7 day period prior. It also includes within-time-period (first-order) interactions between temperature and precipitation variables. The high-dimensional set includes linear, quadratics and cubics in all continuous variables as well as discretized versions of each measure. All variables are normalized to be expressed as deviations from the mean for each month-of-year by grid quadrant (11 kms square).

### 4.1.1 Covariate selection using the lasso

Shrinkage methods such as the lasso reduce the number of instruments included in a model by imposing an adaptively estimated, constant, continuous

penalty truncated at zero:

$$\hat{\beta}^{lasso} = \text{argmin}\beta \left\{ \sum_{i=1}^{n} \left( y_i - \sum_j x_{ij}\beta_j \right)^2 + \lambda \sum_{j=1}^{p} |\beta_j| \right\} \tag{5}$$

where variables with a zero-valued penalty are effectively dropped from the estimation model (Hastie et al. 2008). The first term is simply OLS and the second term is a penalty equal to the absolute value of each coefficient. Intuitively, the lasso performs variable selection by applying a penalty in a regression specification that drives coefficients to zero unless they have adequate predictive power in the regression.

The lasso relies on the assumption of approximate sparsity: that linear combinations of relatively few regressors can provide an approximation to the true specification with small approximation errors. This is weaker than the assumption of perfect model selection that implicitly underlies most mainstream analytical approaches. The lasso therefore allows for the imperfect selection of controls.

In all instances I use the post-lasso, which first selects instruments using regressions with the penalty in Equation 5 and then performs standard (unpenalized) regressions with the instruments selected in the first step. First, the lasso selects a set of instrumental variables ($Z_{it}$) from the high-dimensional input set that are strong predictors of the endogenous regressor. Then I es-

timate the first-stage regression of interest (Equation 2) without penalties, using the selected set of instruments. This provides valid confidence intervals for causal inference (Chernozhukov, Hansen, Spindler 2015).

### 4.1.2 Instrument selection using the ridge regression

I also implemented the ridge regression because the lasso results may have high variance and when regressors are highly correlated (Hastie et al. 2008). The ridge regression is more stable because it is a shrinkage rather than a selection estimator. It penalizes coefficients with a squared term so it retains all covariates in the regression but shrinks the magnitude of the coefficients towards zero:

$$\hat{\beta}^{ridge} = \text{argmin}\beta \left\{ \sum_{i=1}^{n} \left( y_i - \sum_{j} x_{ij}\beta_j \right)^2 + \lambda \sum_{j=1}^{p} \beta_j^2 \right\} \tag{6}$$

Just as with the lasso, the first term is OLS and the second term is the penalty. The squared penalty term in the ridge regression shrinks strong predictors relatively more than the absolute value penalty term in the lasso, which brings more stability to the estimates by limiting the impact any single regressor has on the prediction. In the case of highly correlated regressors, the ridge regression would therefore shrink their coefficients whereas the lasso would drop one of the highly correlated regressors from the specification.

### 4.1.3 Instrument selection using the elastic net

The elastic net method is considered the most robust because the regression penalty is the weighted average of the lasso penalty and the ridge regression penalty.

$$\hat{\beta}^{elasticnet} = \text{argmin}\beta \left\{ \sum_{i=1}^{n} \left( y_i - \sum_{j} x_{ij}\beta_j \right)^2 + \alpha(\lambda \sum_{j=1}^{p} |\beta_j|) + (1-\alpha)(\lambda \sum_{j=1}^{p} \beta_j^2) \right\} \tag{7}$$

The elastic net leverages the strengths of the lasso and the ridge regression to select variables and shrink coefficients towards zero. I use the selected regressors and the set of penalized coefficients to estimate the first stage (Equation 2) and then estimate the second stage (Equation 1) with unpenalized coefficients.

I run the machine learning first-stage using the *elasticnet* command in Stata version 18 (Ahrens et al. (2018)) and then run second stage estimations. I adjust standard errors in the second stage regression to account for the generated regressor(s) (Baum 2023). I report results for several values of $\alpha$ which notes the relevant weight on the lasso penalty relative to the ridge regression penalty.

In contrast to the lasso results which report *unpenalized* coefficients, the ridge regression and elastic net report *penalized* coefficients. Note that the regression-specific selection of regressors and shrinkage of coefficients in the first stage leads to slightly different specifications for each outcome-sample pair with the lasso and elastic net.

# 5 Results

Table 2 shows the first-stage results for the two-stage least squares estimation my three endogenous variables that measure peri-natal health care – (1) whether the delivery was in a health facility, (2) whether it was attended by either a doctor, nurse or midwife and (3) whether it was attended by a nurse or midwife. The table shows only a *subset* of the approximately 400 weather instruments included in the regression. The first row of Column 1 shows that each standard deviation of total precipitation on the day of birth is associated with a 0.8 percentage point reduction in the likelihood of delivering at a health facility, but it is not statistically significant. This is as expected since most women will make the final decision to travel to a health facility or not in the day prior to giving birth. All of the coefficients in the first row are small and none are statistically significant. Row 2 shows the impact of precipitation in the day prior to birth. By contrast to row 1, coefficients in row 2 range between 2.6 and 4.9 percentage points and all by

one are statistically significant or marginally statistically significant.

The preferred specification in Columns 7 through 9 of Table 2 shows that one standard deviation increase in precipitation on the day prior to birth is associated with a 3.2 percentage point reduction in the likelihood that the delivery was in a health facility, a 3.5 percentage point reduction in the likelihood that the delivery was attended by a doctor, nurse or midwife, and a 3 percentage point reduction in the likelihood that the delivery was attended by a nurse or midwife. There is no statistically significant relationship between any of the temperature variables and outcomes in Columns 7 through 9, but other temperature coefficients not shown are statistically significant. Note the large F-statistics for these specifications.

Table 3 shows estimates of the impact of facility-based delivery on under-5 child survival for the full sample of sub-Saharan African countries. Column 1 shows the results from the two-stage least squares estimation when I instrument for facility-based delivery using the full high-dimensional set of weather instruments.

Facility-based delivery is associated with a statistically significant 6.8 percentage point higher likelihood of child survival compared to home delivery for women whose travel to a facility was impeded due to weather shocks. This corresponds to a 7.2 percent reduction from an average of 94 percent

rate of child survival in the sample. Column 2 adds the full set of country-by-year which increases the coefficient to 7.3 percentage points. Column 2 also shows that girls are 1.2 percentage points more likely to survive until age five, but there is no survival benefit from mother's education, urban residence or household wealth.

Columns 3 through 5 report estimates using machine learning methods for instrument selection and/or penalization. The elastic net method in Column 4, which is the preferred machine learning method because it is a weighted average of the ridge regression and the lasso, shows an estimate of a 7.8 percentage point increase in the likelihood of under-five survival. Though all three machine learning estimates are positive, only the elastic net is statistically significant at the 90-percent level. Column 4 shows that the lasso component of the elastic net selected 102 instruments for facility-based delivery out of the high-dimensional set of a possible 405 instruments. The alpha value notes the relevant weight on the lasso penalty relative to the ridge regression penalty: the elastic net specification with an alpha of 0.75 implies a 75 percent weight on the lasso and a 25 percent weight on the ridge regression.

Column 6 shows the time path of the effect by age of the child. The overall benefit of facility-based delivery is concentrated in the first year of life – a 5.7 percentage point increase in survival before age 1, which is not statistically significant however. There is also suggestive evidence of a 1.9

percentage point benefit for 4-year-old children.

Columns 7 and 8 of Table 3 report 2SLS estimates for the impact of sibling facility-based delivery on under-5 survival. The first coefficient in each column represents the impact of a child's own facility-based delivery, the second represents the impact of their sibling's facility-based delivery and the third coefficient represents the interaction of these two (i.e. the premium or penalty for having both siblings delivered in a health facility). Note that both own and sibling facility-based delivery are instrumented using weather shocks on their day of birth. Column 7 shows that children whose next-older sibling was induced to be delivered in a health facility by weather shocks were 4.8 percentage points more likely to survive until age 5, all else equal, however it is not statistically significant. The interaction term of negative 3.8 percentage points implies that the benefit from having both children born in a health facility is 5.8 percentage points, including a small 1 percentage point premium. I find no statistically significant impact of having the next-younger sibling delivered in a health facility on under-5 survival. Note that the sample sizes in Columns 7 and 8 are less than 20 percent of the full sample since it's conditional on having two children under 5 in the household at the time of the survey.

Table 4 presents child survival results from several subgroups of the data. Column 2 of Table 6 repeats Column 1 of Table 5. In addition, Column 1

presents results for the late years of the sample only (2016-2019), Column 3 is urban residents, Column 4 is rural residents, Column 5 is respondents who reported that the distance to the nearest facility represents a barrier, and Column is respondents who reported that the distance to the nearest facility is a not a barrier. The coefficients are all positive for all subgroups. Note that the positive 2.8 percentage point coefficient for urban residents is not statistically significant, and the 5.1 percentage point coefficient for rural residents is only marginally statistically significant. Children of respondents who reported that the distance to the nearest facility is a not a barrier are 8.5 percentage points more likely to survive until age 5 if they are born in a health facility.

Table 5 presents results for the relationship between facility-based delivery and child's height-for-age percentile. The 2SLS preferred specification in Column 2 and the preferred elastic net specification (Column 4) show a benefit associated with facility-based delivery of an 9.3 point increase and a 26.5 point increase, respectively, in the child's height-for-age percentile, both of which are statistically significant. By contrast to the results for child survival (Tables 3 and 4), there are statistically significant increases in height-for-age percentile for children of mothers with more education, who are urban residents and who have a higher score on the wealth index (Table 5, Column 2).

The time path effect in Column 6 shows that the benefits are concen-

trated in children ages 2 to 4 years old. Column 7 shows that children with a next-older sibling induced to be delivered in a health facility have a 3.5 percentage point higher height-for-age percentile, however this is not statistically significant. Younger siblings have no statistically significant impact on height-for-age percentile of this group (Column 8).

Table 6 shows remarkable homogeneity across sub groups which all show the impact of facility-based delivery on the height-for-age percentile between 5.8 and 7.9 percentage points. The impact is statistically significant for children of respondents who reported that the distance to the nearest facility represents a barrier (Column 5) and children of respondents who reported that the distance to the nearest facility was not a barrier (Column 6), and marginally statistically significant for rural children (Column 4).

Table 7 presents results for the relationship between facility-based delivery and child's weight-for-age percentile. The 2SLS specification (Column 2) and the preferred machine learning specification (Column 5) show statistically significant increase in the child's weight-for-age percentile of 8.9 and 19.4 points, respectively. There are no statistically significant impacts of sibling's facility-based delivery. In fact both the coefficients for elder and younger siblings are negative which suggests that there may be a slight disadvantage in weight-for-age percentile of having a sibling delivered in a health facility.

Table 8 shows results for weight-for-age percentile that are similar those of height-for-age percentile. All coefficients are positive and range between 3.8 and 7.5, with only the 7.5 percentage point coefficient for children of respondents who reported that the distance to the nearest facility was not a barrier being statistically significant (Column 6).

Table 9 presents results for the relationship between facility-based delivery and whether a child is reported to have received any vaccinations. The two-stage least squares estimates show a positive and statistically significant association of 11.3 percentage points (Column 2). The machine learning elastic net estimates in Column 5 show a smaller, but still substantial positive estimate of 5.5 percentage points, though it is not statistically significant. Column 6 shows suggestive evidence that the observed benefits are larger above age 2 than before.

Column 7 of Table 9 shows that children whose next-older sibling was induced to be delivered in a health facility by weather shocks were a statistically significant and substantial 20.4 percentage points more likely to receive at least one vaccination, all else equal. This coefficient is about two-thirds the size of the own-facility-based-birth effect in the top row of 29.7 percentage points indicating a substantial spillover effect. Having the next-younger sibling delivered in a health facility is associated with a 10.3 percentage point

increase in the likelihood of receiving at least one vaccination, however, it is not statistically significant.

Table 10 shows that, across all subgroups, being born in a health facility is associated with between 11.8 and 18.4 percentage point increase in the likelihood of receiving any vaccinations. Coefficients are statistically significant for all groups.

Children born in a health facility are only slightly more likely to be breastfed, on average, but none of the two-stage least squares or machine learning specifications is statistically significant. Column 7 shows that having an elder sibling delivered at a health facility increases the likelihood of being breastfed by 6.1 percentage points, which is statistically significant at the 90 percent level. As expected, there is no impact of having a younger sibling delivered in a facility since the younger sibling would arrive long after the breastfeeding decision had been made.

Table 12 shows that there is no statistically significant relationship between being born in a health facility and being breastfed, with the exception of urban residents who are 7.8 percentage points more likely to be breastfed if they are delivered in a health facility.

Facility-based delivery leads to a shorter subsequent birth spacing for

women induced to deliver in health facilities due to weather shocks (Table 13). The two-stage least squares estimates in Columns 1 and 2 show a small and not-significant reduction in birth spacing of 2-4 weeks. However, the elastic net estimate in Column 4 shows a reduction in birth spacing of about 4.5 months (136 days) which is significant at the 90 percent level and corresponds to a 17 percent reduction off an average birth spacing interval of 2.2 years.

Table 14 shows no statistically significant relationship between being delivered in a health facility and the subsequent birth spacing before the next sibling, with the exception of the statistically significant negative 3 month (92 day) coefficient for the sample of respondents who reported that the distance to the nearest facility represented a barrier to accessing health care.

Note that because the lasso and elastic net are designed to select an *approximation* to the true model that prioritizes low variance over unbiasedness, the specific coefficients are not generally reported or discussed since variables may be excluded if they had high predictive power, but a good proxy was selected, or if they had little predictive power. For example, to adhere to the principle of sparsity, the lasso will not generally select two variables that are highly correlated with each other, so relevant variables may be omitted because the selected specification contains proxies. Additionally, coefficients on first stage regressions for the elastic net are penalized to improve predic-

tion but biases them towards zero.

Table 15 shows two-stage least squares estimates for all six outcomes using binary variables for the type of birth attendant rather than a binary variable for facility based delivery. Note that 96 percent of facility-based deliveries are attended by either a doctor, nurse or midwife, so the first row of coefficients in the table are similar to the magnitude of previous results. Row 2 shows the relationship between having a traditional birth attendant or trained birth attendant relative to being attended by friends or family or having no attendant. Though none of these coefficients are statistically significant, the magnitude shows us that having a traditional birth attendant or trained birth attendant increases survival, increases height-for-age percentile, increases weight-for-age percentile, reduces the likelihood of receiving any vaccinations, reduces the likelihood of breastfeeding and very slightly increases the birth interval until the subsequent sibling.

# 6 Discussion

This study examines the impact of facility-based delivery on child health and economic outcomes. I implemented an instrumental variables approach that linked a multi-country African sample of rich Demographic and Health Survey data to measure outcomes with high-resolution, high-frequency weather

data to measure weather shocks used as instruments. I used machine learning methods – lasso, ridge regression and elastic net – to perform the first-stage estimation of the two-stage least squares method.

Results from the instrumental variable approach using the elastic net to estimate the first stage show that children born to women who are induced to deliver at health facilities due to weather shocks are a statistically significant 7.8 percentage points more likely to survive to age five, have a statistically significant 26.5 point higher height-for-age percentile, have a statistically significant 19.4 point higher weight-for-age percentile and have a 4.5 month shorter subsequent birth interval. These children are 5.5 percentage points more likely to be vaccinated, however this is not statistically significant. There are no differences in the likelihood of being breastfed. The results are quite similar by urban or rural residents and by whether travel distance is reported as a barrier to accessing health care. I find a positive spillover effect of having an elder sibling deliver in a health facility on the likelihood of receiving at least one vaccination for both urban and rural populations but no spillover effect on any outcomes for having a younger sibling delivered in a health facility. These estimates indicate substantial benefits to the child and their younger siblings from being delivered in a health facility relative to being delivered at home, which is in line with the findings of Friedman et al. (2022).

Facility-based delivery is associated with a higher likelihood of child survival to age 5, which appears to be driven by mechanisms that operate in the first year of life. Health facilities not only provide care at the time of birth and can reduce the risk of peri-natal and post-natal mortality, but also may provide home care guidance and resources for the following months. Facility-based delivery may also strengthen the relationship that mothers have with the health care system, leading them to increase care seeking particularly in the first year of their child's life. Somewhat surprisingly, there is a substantial, though not statistically significant, increase in survival for four-year-old children, which suggests that the mechanisms through which facility-based delivery improves child survival may be more complex. Given the evidence of increased vaccination rates among children delivered in a health facility, it could be that vaccinated children fare better at age four when they face a higher risk of infectious disease due to being more independent of their parents more likely to interact with other children in their community.

I found improved anthropometric outcomes for children who were delivered in a health facility. The relatively constant benefit throughout the child's life through age five for both the height-for-age percentile, which captures cumulative long-term access to nutrition and good health and the weight-for-age percentile, which measures shorter-term access, suggests that there are several mechanisms at play. Being delivered in a health facility may provide mothers with more information on infant care, including about feeding

and the importance of vaccination, which would children's health and enable them to thrive. Peri-natal health care at the facility is likely to lead to fewer birth and post-birth complications for mothers delivering in facilities which would help women recover from birth more quickly and thereby improve the economic well-being of the household going forward.

The positive association between health facility delivery and receiving vaccinations is likely due to exposure to health care during a facility-based delivery strengthens the connection mothers have with the health care system (Moyer et al. 2014). It is somewhat surprising that this holds despite the fact that mothers dissuaded from a facility delivery by relatively minor weather shocks may have very low connection with the health system to begin with. This also holds despite the fact that traditional and non-traditional birth attendants may also have greater persuasive power among this population compared to health facility clinicians, perhaps due to more frequent follow-up visits compared to the health system. The facility-based delivery may therefore be enough to encourage vaccination in the post-natal period or to build long-standing connection. Estimates from the time path analysis show that the increase in vaccination due to facility-based delivery is not limited to the first year of life and in fact persists at least through age 5, which suggests there may be longer-term mechanisms at play.

The estimated impact on vaccination of having one's next-older sibling

delivered in a health facility is approximately two-thirds the magnitude of the direct effect of one's own facility-based delivery. This implies large spillover effects of facility-based delivery on younger siblings that may be unlikely to be taken into account when women make decisions about delivering in a health facility. Moreover, government and non-profit programs aiming to encourage women to deliver in health facilities also potentially underestimate the true household benefits of interventions in this realm because they do not fully take spillovers into account.

There is little impact of facility-based delivery on the proportion of children who have ever been breastfed. It may be that this margin is inelastic because the decision to breastfeed is determined ahead of birth and there are few barriers to at least attempting breastfeeding in the early days. Additionally, the rate of breastfeeding in this sample is already very high (96 percent). Further work will examine whether facility-based delivery affects the duration of breastfeeding.

I find that children who are induced to be delivered in a health facility by weather shocks have shorter subsequent birth intervals until the following sibling. One might expect that delivering in a health facility would provide mothers with greater access to birth control and education about increasing the time before subsequent births. However, that effect appears to be outweighed by factors reducing birth spacing. Mothers may receive higher-

quality peri-natal health care that reduces post-birth complications leading to a quicker recovery. This, along with guidance about infant care, may improve the experience of motherhood for new mothers who would be more willing to have another child sooner. Note that I control for mother's age so this effect is not being driven by younger mothers delivering in facilities.

The decision to travel to a health facility to give birth is influenced by a complex interaction between road conditions, personal safety and comfort, all of which are affected by weather conditions in the days before birth. The amount of precipitation matters, but so does the temperature since it influences the degree of evaporation and subsequent road condition. However, we don't have a robust understanding of the true relationship between weather patterns and the choice to travel to deliver in a health facility. The use of machine learning methods in this paper therefore represents a valuable methodological contribution because it can estimate and leverage this relationship despite little being known about it a priori. Machine learning methods provide an efficient, systematic, data-driven process of identifying instruments that are most predictive in the first stage, which not only improves prediction but also directly addresses the weak instrument problem. These approaches also require weaker assumptions than are implicitly made with ad hoc specification choices. Multiple machine learning methods are presented for comparison with the preferred method being the elastic net because it combines the advantages of the lasso (parsimony) with the advan-

tages of ridge regression (stability of the estimates). The machine learning methods are preferred over the two-stage least squares estimates with the large set of instruments because the potential inclusion of weak instruments in the large set is likely to lead to bias.

My estimates identify substantial benefits to facility-based delivery that accrue to women who were dissuaded from traveling to a health facility by relatively small, seemingly surmountable barriers. In this case, the instrumental variables method estimates the effect of facility-based delivery on outcomes for children whose mothers were induced to deliver at home rather than a facility due to weather shocks (i.e. the local average treatment effect (LATE)). The weather shocks used in the estimation are relatively minor – rain showers and higher-than-normal heat – rather than floods or heatwaves. I am therefore likely to be estimating the impact for women who had a weaker preference for delivering in health facilities, were more undecided about whether to deliver in a health facility, live farther from health facilities, have poor or no access to transport, and/or have low wealth levels. For example, women who were undecided about delivering in a facility would be more likely to let minor weather shocks influence their decision than those who had predetermined preference regarding delivering in a facility or not.

This study estimates the local average treatment effect for a marginal group that can serve as a key target for policy intervention, even though

the IV results cannot be generalized to the broader population. My results suggest that this remains an avenue of high-return-on-investment for policy intervention: encouraging women to deliver at health facilities and eliminating small barriers standing in the way.

Moreover, my estimates are likely to be a lower bound to the benefits of facility-based delivery for two reasons. First, because the data come from interviews with mothers, my estimates do not take into account potential differences in maternal mortality for facility-based delivery compared to home-based births. The risk of maternal mortality is likely to be higher during home-based births, ceteris paribus, because emergency health interventions may not be accessible. Second, negative outcomes for home-based births such as neonatal deaths, are likely to be under-reported in the data. Further work using the Demographic and Health Survey sisterhood mortality data and sub-group analyses will be performed to quantify the potential implications for my results.

When comparing these results to those from similar studies examining the impact of facility-based delivery on child outcomes, it is important to differentiate between studies estimating a *local* average treatment effect, such as this one, and those estimating an average treatment effect. This local average treatment effect corresponds more to the effect of a policy intervention that is more akin to removing user fees or providing travel subsidies which affect

women on the margin compared to health-worker strikes (see Friedman et al. 2022) or bans on traditional birth attendants (see Godlonton and Okeke 2016) that affect the full population.

The primary limitation in this approach is that using weather shocks as instrumental variables may introduce bias since women who are induced to deliver at home at the last minute are more likely to have an unplanned and unattended birth compared to those who planned ahead for a home-based birth. Further work will examine subgroup effects by whether there was a trained birth attendant at the home-based births or not.

My estimates suggest that while the current broad policy focus on encouraging facility-based delivery is an efficient use of funds, it would be improved by adding a more targeted approach for women on the margin. These women are dissuaded by seemingly small barriers and face large unrealized benefits of facility-based delivery as a result. These findings take on increased importance in the COVID-19 era, when women who are dissuaded from facility-based delivery due to the additional risk of COVID-19 transmission may forgo a large net benefit to their children. Global public health policy should therefore focus on encouraging and incentivizing facility-based delivery among targeted groups likely to benefit.

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Figure 1: Shaded countries included in the analysis sample



Table 1: Descriptive Statistics

| | (1) | (2) | (3) | | | |
|---|---|---|---|---|---|---|
| | Facil-based | Home-based | Difference | | | |
| | deliv mean | deliv mean | b | se | t | p |
| Home | 0.00 | 1.00 | 1.000 | (0.000) | 19867.49 | 0.00*** |
| Hospital | 0.31 | 0.00 | -0.301 | (0.001) | -220.14 | 0.00*** |
| Clinic | 0.69 | 0.00 | -0.698 | (0.001) | -510.26 | 0.00*** |
| Doctor | 0.14 | 0.01 | -0.125 | (0.001) | -117.54 | 0.00*** |
| Nurse/Midwife | 0.76 | 0.07 | -0.691 | (0.002) | -416.95 | 0.00*** |
| TBA - low skill | 0.07 | 0.42 | 0.350 | (0.002) | 156.58 | 0.00*** |
| No skill/no one | 0.03 | 0.36 | 0.332 | (0.002) | 156.22 | 0.00*** |
| Alive | 0.94 | 0.91 | -0.027 | (0.001) | -20.20 | 0.00*** |
| Height-for-age pctile | 24.87 | 19.89 | -4.560 | (0.195) | -23.41 | 0.00*** |
| Height-for-age pctile | 25.86 | 19.98 | -5.617 | (0.187) | -30.09 | 0.00*** |
| Any vaccination | 0.86 | 0.56 | -0.308 | (0.005) | -67.03 | 0.00*** |
| Ever breastfed | 0.97 | 0.96 | -0.008 | (0.001) | -7.70 | 0.00*** |
| Mother's age | 28.73 | 29.13 | 0.374 | (0.037) | 10.16 | 0.00*** |
| Years of ed | 5.29 | 2.51 | -2.736 | (0.021) | -130.63 | 0.00*** |
| Urban | 0.37 | 0.18 | -0.190 | (0.002) | -88.28 | 0.00*** |
| Wealth Index | 7.08 | -63.92 | -70.362 | (0.695) | -101.31 | 0.00*** |
| Dist. barrier to facil. | 0.33 | 0.47 | 0.161 | (0.003) | 63.14 | 0.00*** |
| Female | 0.49 | 0.50 | 0.013 | (0.003) | 5.10 | 0.00*** |
| Twin | 0.04 | 0.03 | -0.012 | (0.001) | -13.18 | 0.00*** |
| Birth ord 1 | 0.26 | 0.15 | -0.101 | (0.002) | -50.30 | 0.00*** |
| Birth ord 2 | 0.20 | 0.17 | -0.029 | (0.002) | -14.31 | 0.00*** |
| Birth ord 3 | 0.16 | 0.15 | -0.009 | (0.002) | -4.76 | 0.00*** |
| Birth ord 4 | 0.12 | 0.13 | 0.010 | (0.002) | 5.85 | 0.00*** |
| Birth ord 5 | 0.09 | 0.11 | 0.021 | (0.002) | 12.92 | 0.00*** |
| Birth ord 6 | 0.06 | 0.09 | 0.025 | (0.001) | 17.47 | 0.00*** |
| Birth ord 7+ | 0.10 | 0.19 | 0.083 | (0.002) | 44.54 | 0.00*** |
| $N$ | 112,404 | 55,375 | 167,779 | | | |

Table shows difference in means of child and mother characteristics by facility-based or home-based delivery. Standard errors clustered by DHS cluster are in parentheses. Samples include all births occurring to mothers during the 5 years prior to the survey year. *** - Significant at the 1% level, ** - 5% level, * - 10% level.

Table 2: Likelihood of facility-based delivery (first-stage regression)

| Variable | FBD (1) | Doc/nurse/ midwife (2) | Nurse/ midwife (3) | FBD (4) | Doc/nurse/ midwife (1) | Nurse/ midwife (2) | FBD (3) | Doc/nurse/ midwife (8) | Nurse/ midwife (9) |
|---|---|---|---|---|---|---|---|---|---|
| Tot precip 0d | -0.008 | -0.022 | -0.018 | 0.003 | -0.011 | -0.012 | 0.003 | -0.006 | -0.008 |
| | (0.016) | (0.014) | (0.014) | (0.015) | (0.013) | (0.014) | (0.015) | (0.012) | (0.014) |
| Tot precip 1d | -0.049*** | -0.046*** | -0.033** | -0.032* | -0.033** | -0.026 | -0.032* | -0.035** | -0.030* |
| | (0.019) | (0.016) | (0.017) | (0.017) | (0.015) | (0.017) | (0.017) | (0.014) | (0.016) |
| Tot precip 3d | -0.029* | -0.005 | -0.015 | -0.014 | 0.007 | -0.007 | -0.015 | -0.002 | -0.014 |
| | (0.016) | (0.015) | (0.015) | (0.015) | (0.013) | (0.015) | (0.015) | (0.012) | (0.014) |
| Tot precip 7d | -0.020* | -0.023** | -0.023** | -0.002 | -0.011 | -0.016 | -0.003 | -0.008 | -0.014 |
| | (0.012) | (0.011) | (0.011) | (0.011) | (0.010) | (0.011) | (0.011) | (0.009) | (0.011) |
| Max temp 0d | -0.001 | 0.005 | 0.015* | -0.005 | -0.001 | 0.012 | -0.005 | -0.006 | 0.006 |
| | (0.009) | (0.008) | (0.009) | (0.009) | (0.008) | (0.009) | (0.009) | (0.007) | (0.008) |
| Max temp 1d | 0.002 | 0.005 | 0.006 | 0.010 | 0.010 | 0.008 | 0.010 | 0.006 | 0.004 |
| | (0.010) | (0.009) | (0.009) | (0.010) | (0.008) | (0.009) | (0.010) | (0.008) | (0.009) |
| Max temp 3d | 0.001 | 0.007 | -0.003 | -0.004 | 0.001 | -0.006 | -0.004 | 0.003 | -0.003 |
| | (0.014) | (0.012) | (0.013) | (0.013) | (0.012) | (0.013) | (0.013) | (0.011) | (0.012) |
| Max temp 7d | -0.002 | 0.027** | 0.029** | -0.001 | 0.023** | 0.027** | 0.000 | 0.006 | 0.011 |
| | (0.013) | (0.012) | (0.012) | (0.012) | (0.011) | (0.012) | (0.012) | (0.011) | (0.012) |
| Tot precip 0d x Max temp 0d | 0.001 | -0.001 | -0.002 | 0.000 | -0.002 | -0.002 | 0.000 | -0.000 | -0.001 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Tot precip 1d x Max temp 1d | 0.001 | -0.001 | -0.001 | 0.001 | -0.001 | -0.001 | 0.001 | 0.000 | -0.000 |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| Urban | | | | 0.114*** | 0.112*** | 0.079*** | 0.114*** | 0.111*** | 0.078*** |
| | | | | (0.007) | (0.006) | (0.006) | (0.007) | (0.006) | (0.006) |
| Birth order FE | N | N | N | Y | Y | Y | Y | Y | Y |
| Birth month FE | N | N | N | Y | Y | Y | Y | Y | Y |
| Country FE | N | N | N | Y | Y | Y | Y | Y | Y |
| Country*birth year FE | N | N | N | N | N | N | Y | Y | Y |
| Sample size | 167,780 | 167,780 | 167,780 | 167,780 | 167,780 | 167,780 | 167,780 | 167,780 | 167,780 |
| Clusters | 10,038 | 10,038 | 10,038 | 10,038 | 10,038 | 10,038 | 10,038 | 10,038 | 10,038 |
| F-statistic | 22.67 | 136.48 | 80.09 | 55.67 | 179.89 | 89.59 | 46.51 | 259.15 | 135.29 |

Notes: Table shows point estimates $\pi$ and $\phi$ from Equation 2. Standard errors clustered by DHS cluster are in parentheses. Each coefficient shows the difference in the likelihood of a facility-based delivery. Sub-national-region fixed effects are included. Standard controls include set of demographic and geographic covariates as noted in the text. Samples include all births occurring to mothers during the 5 years prior to the survey year. *** - Significant at the 1% level, ** - 5% level, * - 10% level.

Table 3: Likelihood of child survival under age five

| Variable | 2SLS (1) | 2SLS (2) | Ridge (3) | Elastic net (4) | IV Lasso (5) | Time path (6) | Elder sib (7) | Younger sib (8) |
|---|---|---|---|---|---|---|---|---|
| Fac. deliv | 0.068*** | 0.073*** | 0.033 | 0.078* | 0.042 | | 0.048 | -0.054 |
| | (0.025) | (0.025) | (0.024) | (0.042) | (0.027) | | (0.051) | (0.065) |
| Fac. x age 0 | | | | | | 0.057 | | |
| | | | | | | (0.039) | | |
| Fac. x age 1 | | | | | | -0.020 | | |
| | | | | | | (0.048) | | |
| Fac. x age 2 | | | | | | -0.061 | | |
| | | | | | | (0.048) | | |
| Fac. x age 3 | | | | | | -0.010 | | |
| | | | | | | (0.040) | | |
| Fac. x age 4 | | | | | | 0.019 | | |
| | | | | | | (0.047) | | |
| Elder facil. | | | | | | | 0.048 | |
| | | | | | | | (0.040) | |
| Elder+ facil. | | | | | | | -0.038 | |
| | | | | | | | (0.063) | |
| Younger facil. | | | | | | | | -0.023 |
| | | | | | | | | (0.063) |
| Younger+ facil. | | | | | | | | 0.119 |
| | | | | | | | | (0.087) |
| Sample size | 167,779 | 167,779 | 167,779 | 167,779 | 167,779 | 167,779 | 30,343 | 32,970 |
| Clusters | 10,038 | 10,038 | 10,038 | 10,038 | 10,038 | 10,038 | 7,963 | 8,117 |
| Selected IVs | | | 405 | 102 | 102 | | | |
| Full IV set | | | 405 | 405 | 405 | | | |

Notes: Table shows point estimates ($\gamma$) from Equation 1. Standard errors clustered by DHS cluster are in parentheses. Each coefficient shows the difference in outcomes. All specifications include sub-national-region fixed effects. Standard controls include set of demographic and geographic covariates as noted in the text. Samples include all births occurring to mothers during the 5 years prior to the survey year. *** - Significant at the 1% level, ** - 5% level, * - 10% level.

Table 4: Likelihood of child survival under age five - sub-samples

| Variable | 2016-19 (1) | Full (2) | Urban (3) | Rural (4) | Dist barrier (5) | Dist not barrier (6) |
|---|---|---|---|---|---|---|
| Fac. deliv | 0.030 | 0.068*** | 0.028 | 0.051* | 0.043 | 0.085*** |
| | (0.028) | (0.025) | (0.037) | (0.029) | (0.033) | (0.028) |
| Female | 0.010*** | 0.012*** | 0.011*** | 0.012*** | 0.012*** | 0.012*** |
| | (0.002) | (0.002) | (0.003) | (0.002) | (0.002) | (0.002) |
| Years of ed | 0.001 | 0.000 | 0.001 | 0.001 | -0.000 | 0.001 |
| | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) | (0.001) |
| Urban | -0.000 | -0.001 | | | 0.005 | -0.003 |
| | (0.003) | (0.004) | | | (0.006) | (0.003) |
| Wealth Index | 0.000 | 0.000 | 0.000** | 0.000 | -0.000 | 0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Constant | 0.976*** | 0.870*** | 0.890*** | 0.881*** | 0.877*** | 0.863*** |
| | (0.021) | (0.009) | (0.022) | (0.009) | (0.011) | (0.012) |
| Sample size | 78,904 | 167,779 | 50,023 | 117,756 | 64,644 | 103,135 |
| Clusters | 7,334 | 10,038 | 3,622 | 6,416 | 7,840 | 9,577 |

Notes: Table shows point estimates ($\gamma$) from Equation 1. Standard errors clustered by DHS cluster are in parentheses. Each coefficient shows the difference in outcomes. All specifications include sub-national-region fixed effects. Standard controls include set of demographic and geographic covariates as noted in the text. Samples include all births occurring to mothers during the 5 years prior to the survey year. *** - Significant at the 1% level, ** - 5% level, * - 10% level.

Table 5: Height-for-age percentile

| Variable | 2SLS (1) | 2SLS (2) | Ridge (3) | Elastic net (4) | IV Lasso (5) | Time path (6) | Elder sib (7) | Younger sib (8) |
|---|---|---|---|---|---|---|---|---|
| Fac. deliv | 7.914** | 9.307*** | 5.689* | 26.553*** | 12.112*** | | 0.222 | 9.054* |
| | (3.215) | (3.140) | (2.914) | (8.024) | (3.925) | | (5.150) | (4.625) |
| Fac. x age 0 | | | | | | 8.569 | | |
| | | | | | | (6.719) | | |
| Fac. x age 1 | | | | | | -3.578 | | |
| | | | | | | (7.526) | | |
| Fac. x age 2 | | | | | | 17.506*** | | |
| | | | | | | (6.709) | | |
| Fac. x age 3 | | | | | | 13.422** | | |
| | | | | | | (6.540) | | |
| Fac. x age 4 | | | | | | 12.694* | | |
| | | | | | | (7.456) | | |
| Elder facil. | | | | | | | 3.574 | |
| | | | | | | | (4.955) | |
| Elder+ facil. | | | | | | | 1.656 | |
| | | | | | | | (6.327) | |
| Younger facil. | | | | | | | | -3.670 |
| | | | | | | | | (5.036) |
| Younger+ facil. | | | | | | | | -3.260 |
| | | | | | | | | (6.374) |
| Sample size | 90,700 | 90,700 | 90,700 | 90,700 | 90,700 | 90,700 | 17,015 | 16,519 |
| Clusters | 9,652 | 9,652 | 9,652 | 9,652 | 9,652 | 9,652 | 6,402 | 6,290 |
| Selected IVs | | | 405 | 68 | 68 | | | |
| Full IV set | | | 405 | 405 | 405 | | | |

Notes: Table shows point estimates ($\gamma$) from Equation 1. Standard errors clustered by DHS cluster are in parentheses. Each coefficient shows the difference in outcomes. All specifications include sub-national-region fixed effects. Standard controls include set of demographic and geographic covariates as noted in the text. Samples include all births occurring to mothers during the 5 years prior to the survey year. *** - Significant at the 1% level, ** - 5% level, * - 10% level.

Table 6: Height-for-age percentile - subsamples

| Variable | 2016-19 (1) | Full (2) | Urban (3) | Rural (4) | Dist barrier (5) | Dist not barrier (6) |
|---|---|---|---|---|---|---|
| Fac. deliv | 7.086** | 7.914** | 7.618 | 5.820* | 6.875** | 7.665** |
| | (3.508) | (3.215) | (4.943) | (3.121) | (3.367) | (3.800) |
| Female | 2.683*** | 2.353*** | 2.453*** | 2.253*** | 2.498*** | 2.274*** |
| | (0.297) | (0.207) | (0.417) | (0.232) | (0.314) | (0.268) |
| Years of ed | 0.204*** | 0.477*** | 0.494*** | 0.301*** | 0.288*** | 0.555*** |
| | (0.073) | (0.076) | (0.093) | (0.078) | (0.102) | (0.080) |
| Urban | 0.569 | 2.710*** | | | 2.311*** | 2.738*** |
| | (0.500) | (0.532) | | | (0.809) | (0.541) |
| Wealth Index | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Constant | 54.969*** | 3.114** | 3.737 | 6.095*** | 5.422*** | 2.091 |
| | (6.107) | (1.329) | (3.297) | (1.168) | (1.458) | (2.031) |
| Sample size | 45,122 | 90,700 | 27,584 | 63,116 | 33,834 | 56,866 |
| Clusters | 6,669 | 9,652 | 3,388 | 6,264 | 6,787 | 8,656 |

Notes: Table shows point estimates ($\gamma$) from Equation 1. Standard errors clustered by DHS cluster are in parentheses. Each coefficient shows the difference in outcomes. All specifications include sub-national-region fixed effects. Standard controls include set of demographic and geographic covariates as noted in the text. Samples include all births occurring to mothers during the 5 years prior to the survey year. *** - Significant at the 1% level, ** - 5% level, * - 10% level.

Table 7: Weight-for-age percentile

| Variable | 2SLS (1) | 2SLS (2) | Ridge (3) | Elastic net (4) | IV Lasso (5) | Time path (6) | Elder sib (7) | Younger sib (8) |
|---|---|---|---|---|---|---|---|---|
| Fac. deliv | 6.918** | 8.904*** | 6.525** | 19.359** | 13.322*** | | 1.943 | 10.294** |
| | (3.299) | (3.162) | (2.988) | (8.200) | (4.126) | | (5.411) | (4.344) |
| Fac. x age 0 | | | | | | -1.019 | | |
| | | | | | | (6.709) | | |
| Fac. x age 1 | | | | | | 1.354 | | |
| | | | | | | (7.523) | | |
| Fac. x age 2 | | | | | | 24.086*** | | |
| | | | | | | (6.489) | | |
| Fac. x age 3 | | | | | | 17.747*** | | |
| | | | | | | (6.453) | | |
| Fac. x age 4 | | | | | | 3.743 | | |
| | | | | | | (7.282) | | |
| Elder facil. | | | | | | | -2.763 | |
| | | | | | | | (5.029) | |
| Elder+ facil. | | | | | | | 9.484 | |
| | | | | | | | (6.694) | |
| Younger facil. | | | | | | | | -3.683 |
| | | | | | | | | (4.831) |
| Younger+ facil. | | | | | | | | -3.474 |
| | | | | | | | | (6.112) |
| Sample size | 90,700 | 90,700 | 90,700 | 90,700 | 90,700 | 90,700 | 17,015 | 16,519 |
| Clusters | 9,652 | 9,652 | 9,652 | 9,652 | 9,652 | 9,652 | 6,402 | 6,290 |
| Selected IVs | | | 405 | 68 | 68 | | | |
| Full IV set | | | 405 | 405 | 405 | | | |

Notes: Table shows point estimates ($\gamma$) from Equation 1. Standard errors clustered by DHS cluster are in parentheses. Each coefficient shows the difference in outcomes. All specifications include sub-national-region fixed effects. Standard controls include set of demographic and geographic covariates as noted in the text. Samples include all births occurring to mothers during the 5 years prior to the survey year. *** - Significant at the 1% level, ** - 5% level, * - 10% level.

Table 8: Weight-for-age percentile - subsamples

| Variable | 2016-19 (1) | Full (2) | Urban (3) | Rural (4) | Dist barrier (5) | Dist not barrier (6) |
|---|---|---|---|---|---|---|
| Fac. deliv | 6.327* | 6.918** | 6.468 | 3.818 | 5.371 | 7.572** |
| | (3.499) | (3.299) | (5.007) | (3.064) | (3.329) | (3.862) |
| Female | 1.982*** | 1.750*** | 1.900*** | 1.631*** | 1.912*** | 1.662*** |
| | (0.285) | (0.203) | (0.405) | (0.229) | (0.326) | (0.256) |
| Years of ed | 0.346*** | 0.508*** | 0.507*** | 0.444*** | 0.452*** | 0.526*** |
| | (0.074) | (0.077) | (0.095) | (0.077) | (0.101) | (0.082) |
| Urban | -0.524 | 1.269** | | | 1.699** | 0.968* |
| | (0.491) | (0.523) | | | (0.731) | (0.515) |
| Wealth Index | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Constant | 89.118*** | 7.863*** | 9.603*** | 8.118*** | 9.101*** | 7.041*** |
| | (5.127) | (1.365) | (3.341) | (1.160) | (1.512) | (2.047) |
| Sample size | 45,122 | 90,700 | 27,584 | 63,116 | 33,834 | 56,866 |
| Clusters | 6,669 | 9,652 | 3,388 | 6,264 | 6,787 | 8,656 |

Notes: Table shows point estimates ($\gamma$) from Equation 1. Standard errors clustered by DHS cluster are in parentheses. Each coefficient shows the difference in outcomes. All specifications include sub-national-region fixed effects. Standard controls include set of demographic and geographic covariates as noted in the text. Samples include all births occurring to mothers during the 5 years prior to the survey year. *** - Significant at the 1% level, ** - 5% level, * - 10% level.

Table 9: Received any vaccinations - Full sample

| Variable | 2SLS (1) | 2SLS (2) | Ridge (3) | Elastic net (4) | IV Lasso (5) | Time path (6) | Elder sib (7) | Younger sib (8) |
|---|---|---|---|---|---|---|---|---|
| Fac. deliv | 0.118** | 0.113** | 0.056 | 0.055 | 0.035 | | 0.297*** | 0.219*** |
| | (0.051) | (0.050) | (0.046) | (0.166) | (0.070) | | (0.083) | (0.069) |
| Fac. x age 0 | | | | | | 0.133 | | |
| | | | | | | (0.094) | | |
| Fac. x age 1 | | | | | | 0.115 | | |
| | | | | | | (0.086) | | |
| Fac. x age 2 | | | | | | 0.096 | | |
| | | | | | | (0.071) | | |
| Fac. x age 3 | | | | | | 0.505 | | |
| | | | | | | (0.389) | | |
| Fac. x age 4 | | | | | | | | |
| Elder facil. | | | | | | | 0.204*** | |
| | | | | | | | (0.076) | |
| Elder+ facil. | | | | | | | -0.244** | |
| | | | | | | | (0.109) | |
| Younger facil. | | | | | | | | 0.103 |
| | | | | | | | | (0.071) |
| Younger+ facil. | | | | | | | | -0.092 |
| | | | | | | | | (0.091) |
| Sample size | 35,800 | 35,800 | 35,800 | 35,800 | 35,800 | 35,800 | 9,239 | 3,371 |
| Clusters | 8,241 | 8,241 | 8,241 | 8,241 | 8,241 | 8,241 | 4,352 | 2,494 |
| Selected IVs | | | 405 | 55 | 55 | | | |
| Full IV set | | | 405 | 405 | 405 | | | |

Notes: Table shows point estimates ($\gamma$) from Equation 1. Standard errors clustered by DHS cluster are in parentheses. Each coefficient shows the difference in outcomes. All specifications include sub-national-region fixed effects. Standard controls include set of demographic and geographic covariates as noted in the text. Samples include all births occurring to mothers during the 5 years prior to the survey year. *** - Significant at the 1% level, ** - 5% level, * - 10% level.

Table 10: Received any vaccinations - Subsamples

| Variable | 2016-19 (1) | Full (2) | Urban (3) | Rural (4) | Dist barrier (5) | Dist not barrier (6) |
|---|---|---|---|---|---|---|
| Fac. deliv | 0.184*** | 0.118** | 0.167*** | 0.121** | 0.155*** | 0.143*** |
| | (0.053) | (0.051) | (0.054) | (0.058) | (0.060) | (0.051) |
| Female | 0.010 | 0.004 | 0.004 | 0.004 | 0.002 | 0.005 |
| | (0.006) | (0.005) | (0.008) | (0.006) | (0.008) | (0.006) |
| Years of ed | 0.008*** | 0.011*** | 0.009*** | 0.010*** | 0.012*** | 0.009*** |
| | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) | (0.002) |
| Urban | 0.002 | 0.038*** | | | 0.032* | 0.023* |
| | (0.013) | (0.011) | | | (0.019) | (0.012) |
| Wealth Index | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000*** | 0.000** |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Constant | -0.328*** | 0.682*** | 0.710*** | 0.635*** | 0.579*** | 0.756*** |
| | (0.051) | (0.045) | (0.066) | (0.057) | (0.069) | (0.053) |
| Sample size | 24,005 | 35,800 | 10,646 | 25,154 | 14,721 | 21,079 |
| Clusters | 5,440 | 8,241 | 2,886 | 5,355 | 4,870 | 6,794 |

Notes: Table shows point estimates ($\gamma$) from Equation 1. Standard errors clustered by DHS cluster are in parentheses. Each coefficient shows the difference in outcomes. All specifications include sub-national-region fixed effects. Standard controls include set of demographic and geographic covariates as noted in the text. Samples include all births occurring to mothers during the 5 years prior to the survey year. *** - Significant at the 1% level, ** - 5% level, * - 10% level.

Table 11: Ever breastfed

| Variable | 2SLS (1) | 2SLS (2) | Ridge (3) | Elastic net (4) | IV Lasso (5) | Time path (6) | Elder sib (7) | Younger sib (8) |
|---|---|---|---|---|---|---|---|---|
| Fac. deliv | 0.019 | 0.015 | 0.021 | 0.010 | 0.016 | | 0.009 | 0.064* |
| | (0.020) | (0.020) | (0.019) | (0.032) | (0.022) | | (0.039) | (0.033) |
| Fac. x age 0 | | | | | | 0.033 | | |
| | | | | | | (0.038) | | |
| Fac. x age 1 | | | | | | 0.039 | | |
| | | | | | | (0.047) | | |
| Fac. x age 2 | | | | | | -0.040 | | |
| | | | | | | (0.047) | | |
| Fac. x age 3 | | | | | | -0.030 | | |
| | | | | | | (0.040) | | |
| Fac. x age 4 | | | | | | 0.041 | | |
| | | | | | | (0.047) | | |
| Elder facil. | | | | | | | 0.061* | |
| | | | | | | | (0.032) | |
| Elder+ facil. | | | | | | | -0.059 | |
| | | | | | | | (0.049) | |
| Younger facil. | | | | | | | | -0.040 |
| | | | | | | | | (0.038) |
| Younger+ facil. | | | | | | | | -0.009 |
| | | | | | | | | (0.051) |
| Sample size | 167,779 | 167,779 | 167,779 | 167,779 | 167,779 | 167,779 | 30,343 | 32,970 |
| Clusters | 10,038 | 10,038 | 10,038 | 10,038 | 10,038 | 10,038 | 7,963 | 8,117 |
| Selected IVs | | | 405 | 102 | 102 | | | |
| Full IV set | | | 405 | 405 | 405 | | | |

Notes: Table shows point estimates ($\gamma$) from Equation 1. Standard errors clustered by DHS cluster are in parentheses. Each coefficient shows the difference in outcomes. All specifications include sub-national-region fixed effects. Standard controls include set of demographic and geographic covariates as noted in the text. Samples include all births occurring to mothers during the 5 years prior to the survey year. *** - Significant at the 1% level, ** - 5% level, * - 10% level.

Table 12: Ever breastfed - sub-samples

| Variable | 2016-19 (1) | Full (2) | Urban (3) | Rural (4) | Dist barrier (5) | Dist not barrier (6) |
|---|---|---|---|---|---|---|
| Fac. deliv | 0.002 | 0.019 | 0.078** | 0.006 | 0.026 | 0.022 |
| | (0.022) | (0.020) | (0.031) | (0.022) | (0.027) | (0.022) |
| Female | 0.003* | 0.003*** | 0.007*** | 0.002 | 0.002 | 0.003** |
| | (0.002) | (0.001) | (0.002) | (0.001) | (0.002) | (0.001) |
| Years of ed | -0.000 | -0.000 | -0.001** | -0.000 | -0.001 | -0.000 |
| | (0.000) | (0.000) | (0.001) | (0.001) | (0.001) | (0.001) |
| Urban | -0.002 | -0.004 | | | -0.003 | -0.005* |
| | (0.003) | (0.003) | | | (0.005) | (0.003) |
| Wealth Index | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 | -0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Constant | 0.927*** | 0.932*** | 0.898*** | 0.926*** | 0.933*** | 0.931*** |
| | (0.029) | (0.008) | (0.019) | (0.010) | (0.010) | (0.011) |
| Sample size | 78,904 | 167,779 | 50,023 | 117,756 | 64,644 | 103,135 |
| Clusters | 7,334 | 10,038 | 3,622 | 6,416 | 7,840 | 9,577 |

Notes: Table shows point estimates ($\gamma$) from Equation 1. Standard errors clustered by DHS cluster are in parentheses. Each coefficient shows the difference in outcomes. All specifications include sub-national-region fixed effects. Standard controls include set of demographic and geographic covariates as noted in the text. Samples include all births occurring to mothers during the 5 years prior to the survey year. *** - Significant at the 1% level, ** - 5% level, * - 10% level.

Table 13: Birth spacing interval until subsequent child (months)

| Variable | 2SLS (1) | 2SLS (2) | Ridge (3) | Elastic net (4) | IV Lasso (5) | Time path (6) |
|---|---|---|---|---|---|---|
| Fac. deliv | -29.656 | -13.355 | -32.148 | -136.099* | -67.471* | |
| | (31.714) | (31.523) | (27.350) | (78.789) | (37.622) | |
| Fac. x age 0 | | | | | | 111.793 |
| | | | | | | (96.370) |
| Fac. x age 1 | | | | | | 25.833 |
| | | | | | | (161.318) |
| Fac. x age 2 | | | | | | 20.413 |
| | | | | | | (74.080) |
| Fac. x age 3 | | | | | | -94.046* |
| | | | | | | (51.176) |
| Fac. x age 4 | | | | | | -2.855 |
| | | | | | | (58.436) |
| Sample size | 41,515 | 41,515 | 41,515 | 41,515 | 41,515 | 41,515 |
| Clusters | 8,487 | 8,487 | 8,487 | 8,487 | 8,487 | 8,487 |
| Selected IVs | | | 403 | 64 | 64 | |
| Full IV set | | | 403 | 403 | 403 | |

Notes: Table shows point estimates ($\gamma$) from Equation 1. Standard errors clustered by DHS cluster are in parentheses. Each coefficient shows the difference in outcomes. All specifications include sub-national-region fixed effects. Standard controls include set of demographic and geographic covariates as noted in the text. Samples include all births occurring to mothers during the 5 years prior to the survey year. *** - Significant at the 1% level, ** - 5% level, * - 10% level.

Table 14: Birth spacing interval until subsequent child (months) - Sub-samples

| Variable | 2016-19 (1) | Full (2) | Urban (3) | Rural (4) | Dist barrier (5) | Dist not barrier (6) |
|---|---|---|---|---|---|---|
| Fac. deliv | -34.013 | -29.656 | 19.633 | -21.774 | -92.491*** | 0.075 |
| | (31.202) | (31.714) | (40.510) | (34.257) | (34.488) | (35.107) |
| Female | 8.687 | 0.562 | 0.825 | 0.725 | -6.784 | 5.257 |
| | (5.718) | (3.055) | (6.232) | (3.416) | (4.762) | (3.963) |
| Years of ed | 0.720 | 0.678 | -1.276 | 1.115 | 2.204* | 0.179 |
| | (1.082) | (0.917) | (1.181) | (0.987) | (1.190) | (0.990) |
| Urban | -2.151 | 2.530 | | | 15.858* | -2.481 |
| | (8.444) | (5.793) | | | (8.840) | (6.272) |
| Wealth Index | 0.000 | -0.000 | -0.000 | -0.000 | 0.000 | -0.000 |
| | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) | (0.000) |
| Constant | 63.014 | 913.101*** | 898.300*** | 895.233*** | 946.419*** | 887.275*** |
| | (44.977) | (14.006) | (28.566) | (14.524) | (17.905) | (19.534) |
| Sample size | 7,583 | 41,515 | 11,520 | 29,995 | 16,468 | 25,047 |
| Clusters | 3,596 | 8,487 | 2,860 | 5,627 | 5,345 | 7,112 |

Notes: Table shows point estimates ($\gamma$) from Equation 1. Standard errors clustered by DHS cluster are in parentheses. Each coefficient shows the difference in outcomes. All specifications include sub-national-region fixed effects. Standard controls include set of demographic and geographic covariates as noted in the text. Samples include all births occurring to mothers during the 5 years prior to the survey year. *** - Significant at the 1% level, ** - 5% level, * - 10% level.

Table 15: Birth attendant - all outcomes

| Variable | Survival (1) | H-f-a (2) | W-f-a (3) | Vacc. (4) | Breastfed (5) | Birth spacing (6) |
|---|---|---|---|---|---|---|
| High skill | 0.076*** | 13.586*** | 10.331*** | 0.031 | -0.008 | -20.938 |
| | (0.027) | (3.557) | (3.546) | (0.060) | (0.021) | (34.357) |
| TBA - low skill | 0.029 | 6.161 | 4.333 | -0.099 | -0.046 | 19.018 |
| | (0.042) | (4.981) | (5.031) | (0.069) | (0.034) | (49.614) |
| Female | 0.012*** | 2.395*** | 1.793*** | 0.002 | 0.003** | 1.230 |
| | (0.002) | (0.204) | (0.195) | (0.005) | (0.001) | (2.983) |
| Years of ed | 0.000 | 0.405*** | 0.467*** | 0.013*** | -0.000 | 0.681 |
| | (0.001) | (0.069) | (0.067) | (0.002) | (0.000) | (0.856) |
| Urban | -0.002 | 2.166*** | 0.960* | 0.039*** | -0.005 | 4.258 |
| | (0.004) | (0.581) | (0.560) | (0.012) | (0.004) | (5.889) |
| Wealth Index | 0.000 | 0.004*** | 0.006*** | 0.000*** | -0.000 | -0.000 |
| | (0.000) | (0.001) | (0.001) | (0.000) | (0.000) | (0.021) |
| Constant | 0.849*** | -2.628 | 2.313 | 0.762*** | 0.969*** | 912.740*** |
| | (0.027) | (3.494) | (3.477) | (0.111) | (0.022) | (35.135) |
| Sample size | 167,779 | 90,700 | 90,700 | 35,800 | 167,779 | 41,515 |
| Clusters | 10,038 | 9,652 | 9,652 | 8,241 | 10,038 | 8,487 |

Notes: Table shows point estimates ($\gamma$) from Equation 1. Standard errors clustered by DHS cluster are in parentheses. Each coefficient shows the difference in outcomes. All specifications include sub-national-region fixed effects. Standard controls include set of demographic and geographic covariates as noted in the text. Samples include all births occurring to mothers during the 5 years prior to the survey year. *** - Significant at the 1% level, ** - 5% level, * - 10% level.