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

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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.

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. 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 exclude births occurring in the days following extreme weather shocks like flooding since they may influence birth and maternal outcomes in ways other than 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 5.4 percentage point increase in under-five survival, an 8.4 point increase in the height-for-age percentile, an 8.4 point increase in the weight-for-age

percentile, an 11 percentage point increase in the likelihood of the child receiving any vaccinations and a 2.5 month shorter subsequent birth interval relative to children who were delivered at home. 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.

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 elastic 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 treatment 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 sur-

mountable 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 the 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 capture 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.

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 analysis sample contains 186,952 births occurring between 2012-2019 in 18 Sub-Saharan Countries that have day of birth, GPS coordinates and facility-based delivery data. Table 1 presents descriptive statistics for the analysis sample. 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. Children who have a facility-based delivery are more likely to survive to age 5, have a higher height-for-age percentile and receive vaccination. This demonstrates the need for a methodological approach to addressing sample selection. The rate of facility-based delivery is approximately 65 percent for first-born children and declines as birth order increases.

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 (η_{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 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 a pregnant woman. 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.

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 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), as noted in the results.

I input an initial large set of 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:

$$\hat{\beta}^{lasso} = \text{argmin}\beta \left\{ \sum_{i=1}^{n} \left(y_i - \sum_j x_{ij}\beta_j \right)^2 + \lambda \sum_{j=1}^{p} |\beta_j| \right\} \tag{3}$$

where variables with a zero-valued penalty are effectively dropped from the estimation model (Hastie et al. 2008). The term on the left is simply OLS and the term on the right 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 3 and then performs standard (unpenalized) regressions with the instruments selected in the first step. This provides valid confidence intervals for causal inference (Chernozhukov, Hansen, Spindler 2015).

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 estimate the first-stage regression of interest (Equation 2) without penalties, using the selected set of instruments.

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:

$$\hat{\beta}^{ridge} = \text{argmin}\beta \left\{ \sum_{i=1}^{n} \left(y_i - \sum_j x_{ij}\beta_j \right)^2 + \lambda \sum_{j=1}^{p} \beta_j^2 \right\} \tag{4}$$

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 regres-

sor 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.

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

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 17 (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 α 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 with a subset of the 400 weather instruments in the regression. The first row of Column 1 shows that each standard deviation of total precipitation in the day prior to birth is associated with a statistically significant 8.4 percentage point increase in the likelihood of delivering at a health facility. The machine learning methods will help address potential concerns about weak weather instruments.

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 OLS estimate that women who deliver in health facilities have a 1.4 percentage point higher likelihood of child survival than those who deliver at home. This corresponds to a 1.5 percent reduction from an average of 94 percent rate of child survival in the sample. Column 2 shows that when I instrument for facility-based delivery using the full high-dimensional set of weather instruments in two-stage least squares, facility-based delivery is associated with a statistically significant 5.4 percentage point higher likelihood of child survival compared to home delivery for women whose travel to a facility was impeded due to weather shocks.

Comparing the OLS specification in Column 1 with the preferred 2SLS specification in Column 2 shows that once I instrument for facility-based delivery, the small survival benefit from mother's education, urban residence and household wealth are no longer statistically significant.

Column 3 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 6.8 percentage point increase in survival before age 1, which is statistically significant at the 90-percent level. There is also suggestive evidence of a benefit for 4-year-old children.

Columns 4 through 6 report estimates using machine learning methods for instrument selection and/or penalization. The elastic net in Column 5, 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 7.4 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 5 shows that the lasso component selected 100 instruments for facility-based delivery out of the high-dimensional set of a possible 400 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.

Columns 7 and 8 of Table 3 report 2SLS estimates for the impact of sibling facility-based delivery on under-5 survival. Column 7 shows that children whose next-older sibling was induced to be delivered in a health facility by weather shocks were 4 percentage points more likely to survive until age 5, all else equal. Note that both child and sibling facility-based delivery are instrumented using weather shocks on their day of birth. However, I find no statistically significant impact of having the next-younger sibling delivered in a health facility on

under-5 survival.

Table 4 presents estimates for the sub-sample of rural births, who are 3.3 percentage points (2SLS) and 5.9 percentage points (elastic net) more likely to survive to age five if they are delivered in a health facility, however, these estimates are not statistically significant. Rural children whose elder sibling was born in a health facility are a statistically significant 12.5 percentage points more likely to survive to age 5 if they are also born in a health facility. In contrast to the results for the full sample, rural children are 13.3 percentage points more likely to survive to age 5 if their younger sibling was induced to be delivered in a health facility.

Table 5 presents results for the relationship between facility-based delivery and child's height-for-age percentile. The 2SLS specification (Column 2) and the preferred elastic net specification (Column 5) shows a benefit associated with facility-based delivery of an 8.4 point increase and a 22.8 point increase, respectively, in the child's height-for-age percentile, both of which are statistically significant. The time path effect in Column 3 shows that the benefits are concentrated 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 6.1 percentage point higher likelihood of survival to age 5, however this is not statistically significant. Younger siblings have no statistically significant impact on height-for-age percentile of this group (Column 8). The impact of facility-based delivery on height-for-age percentile of rural children is broadly similar to that of the full population (Table 6).

By contrast to the results for child survival (Tables 3 and 4), there are sta-

tistically 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).

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 8.4 and 21.7 points, respectively. There are no statistically significant impacts of sibling's facility-based delivery. The results for rural children are broadly similar for this outcome (Table 8).

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 percentage points that is relatively constant between birth and age 5 (Columns 2 and 3). The machine learning estimates show smaller, but still substantial positive estimates ranging from 5.1 to 9.1 percentage points, though none of the three specifications is statistically significant (Columns 4 through 6).

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 18.9 percentage points more likely to receive at least one vaccination, all else equal. Having the next-younger sibling delivered in a health facility is associated with a 10.4 percentage point increase in the likelihood of receiving at least one vaccination, however, it is not statistically significant. Again, the estimates are similar for the rural sub-sample (Table 10).

Facility-based delivery leads to a shorter subsequent birth spacing for women induced to deliver in health facilities due to weather shocks (Table 11). Birth spacing is estimated to decrease by between 2.5 months (75 days, Column 2) and just under six months (174 days, Column 5). That's a range of approximately 10 to 22 percent reduction off an average birth spacing interval of 2.2 years. Children with a next-older sibling who was delivered in a health facility experience an increase of just over one month in the subsequent birth interval until the following sibling (Column 7). The estimates are similar for the rural sub-sample (Table 12).

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 prediction but biases them towards zero.

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 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, 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 (Table 9) 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 (Table 9), 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. It could be not only improved health for children allowing them to thrive, but also fewer birth and post-birth complications for mothers, which would improve economic well-being in the household.

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 (Table 9, Column 3) 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 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 (Table 9, Column 7). 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.

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.

7 Literature Cited

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Table 1: Descriptive Statistics

	(1)	(2)		(3)		
	Facil-based deliv	Home-based deliv		Difference		
	Mean	Mean	Diff.	Std. Err	t-Stat	p-value
Under-five survival	0.94	0.91	-0.030	(0.001)	-21.64	0.000***
Height for age	24.91	19.79	-4.735	(0.202)	-23.39	0.000***
Any vaccinations	0.86	0.57	-0.293	(0.005)	-61.72	0.000***
Female	1.49	1.50	0.011	(0.003)	4.28	0.000***
Twin	0.04	0.03	-0.011	(0.001)	-12.18	0.000***
Birthorder 1	0.26	0.15	-0.104	(0.002)	-50.80	0.000***
Birthorder 2	0.21	0.17	-0.033	(0.002)	-16.01	0.000***
Birthorder 3	0.16	0.15	-0.010	(0.002)	-5.34	0.000***
Birthorder 4	0.12	0.13	0.011	(0.002)	6.33	0.000***
Birthorder 5	0.09	0.11	0.021	(0.002)	13.25	0.000***
Birthorder 6	0.06	0.09	0.026	(0.001)	18.24	0.000***
Birthorder 7+	0.10	0.19	0.088	(0.002)	46.56	0.000***
Mother's age	28.74	29.16	0.450	(0.037)	12.08	0.000***
Educ years	5.62	2.57	-3.028	(0.021)	-140.95	0.000***
Urban	0.37	0.18	-0.188	(0.002)	-86.35	0.000***
Wealth Index	7328.81	-65741.89	-72534.373	(816.981)	-88.78	0.000***
N	101661	53170	161827			

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	(1)	(2)	(3)	(4)
Tot. precip 1d	-0.084***	-0.068***	-0.031**	-0.032**
	(0.017)	(0.016)	(0.015)	(0.015)
Max temp. 1d	0.014	0.018*	0.009	0.009
	(0.010)	(0.009)	(0.009)	(0.009)
Tot. precip 1w	-0.002	0.005	0.003	0.002
	(0.011)	(0.010)	(0.010)	(0.010)
Max temp. 1w	0.010	0.007	0.003	0.004
	(0.013)	(0.012)	(0.011)	(0.011)
Urban		0.058***	0.117***	0.117***
		(0.009)	(0.006)	(0.006)
Age 20-24		0.027***	0.014***	0.015***
		(0.007)	(0.005)	(0.005)
Age 25-29		0.065***	0.045***	0.046***
		(0.007)	(0.006)	(0.006)
Age 30-34		0.121***	0.085***	0.085***
		(0.008)	(0.007)	(0.007)
Age 35-39		0.166***	0.121***	0.121***
		(0.009)	(0.008)	(0.008)
Age 40-44		0.170***	0.124***	0.124***
		(0.011)	(0.009)	(0.009)
Age 45-49		0.160***	0.120***	0.120***
		(0.013)	(0.012)	(0.012)
Years of ed		0.018***	0.024***	0.024***
		(0.001)	(0.001)	(0.001)
Female		-0.011***	-0.011***	-0.012***
		(0.002)	(0.002)	(0.002)
Twin		0.091***	0.073***	0.072***
		(0.008)	(0.008)	(0.008)
Wealth Index		0.000***	0.000***	0.000***
		(0.000)	(0.000)	(0.000)
Birth order FE	N	Y	Y	Y
Birth month FE	N	N	Y	Y
Country FE	N	N	Y	Y
Country*birth year FE	N	N	N	Y
Sample size	186,450	186,450	186,450	186,450
Clusters	10,063	10,063	10,063	10,063
Mean of outcome	0.67	0.67	0.67	0.67
R-squared	0.02	0.13	0.31	0.31
F-statistic	4.67	17.06	56.18	47.05

Notes: Table shows point estimates π and ϕ 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 - full sample

Variable	OLS (1)	2SLS (2)	2SLS (3)	Ridge (4)	Elastic net (5)	IV Lasso (6)	Elder sib (7)	Younger sib (8)
Fac. deliv	0.014***	0.054**		0.028	0.074*	0.045	0.032	-0.034
	(0.002)	(0.025)		(0.024)	(0.042)	(0.028)	(0.050)	(0.066)
Fac. x age 0			0.068*					
			(0.040)					
Fac. x age 1			-0.066					
			(0.048)					
Fac. x age 2			-0.043					
			(0.046)					
Fac. x age 3			-0.052					
			(0.040)					
Fac. x age 4			0.060					
			(0.046)					
Elder facil.							0.040	
							(0.041)	
Elder+ facil.							-0.013	
							(0.062)	
Young facil.								0.007
								(0.061)
Young+ facil.								0.070
								(0.084)
Female	0.012***	0.012***	0.006***	0.012***	0.012***	0.012***	0.009***	0.026***
	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.003)	(0.004)
Years of ed	0.002***	0.001	0.002***	0.001**	0.000	0.001	0.001	0.002*
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Urban	0.005**	0.000	0.010***	0.003	-0.002	0.001	0.001	0.003
	(0.002)	(0.004)	(0.003)	(0.003)	(0.005)	(0.004)	(0.006)	(0.007)
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)	(0.000)	(0.000)	(0.000)	(0.000)
Sample size	186,450	186,450	186,450	186,450	186,450	186,450	32,018	38,712
Clusters	10,063	10,063	10,063	10,063	10,063	10,063	8,093	8,339
Selected IVs				400	100	101		
Full IV set				400	400	400		
Alpha				0.00	0.75	1.00		

Notes: Table shows point estimates (γ) 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 - Rural sub-sample

Variable	OLS (1)	2SLS (2)	2SLS (3)	Ridge (4)	Elastic net (5)	IV Lasso (6)	Elder sib (7)	Younger sib (8)
Fac. deliv	0.013***	0.033		0.010	0.059	0.025	-0.042	-0.065
	(0.002)	(0.029)		(0.026)	(0.053)	(0.034)	(0.049)	(0.071)
Fac. x age 0			0.044					
			(0.044)					
Fac. x age 1			-0.100**					
			(0.046)					
Fac. x age 2			-0.052					
			(0.047)					
Fac. x age 3			-0.057					
			(0.044)					
Fac. x age 4			0.014					
			(0.048)					
Elder facil.							-0.025	
							(0.043)	
Elder+ facil.							0.125**	
							(0.062)	
Younger facil.								0.133**
								(0.058)
Younger+ facil.								-0.026
								(0.089)
Female	0.011***	0.012***	0.005***	0.011***	0.012***	0.012***	0.009**	0.025***
	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.004)	(0.005)
Years of ed	0.001***	0.001	0.003***	0.001**	0.000	0.001	0.001	0.002*
	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
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)	(0.000)	(0.000)	(0.000)	(0.000)
Sample size	130,652	130,652	130,652	130,652	130,652	130,652	22,200	27,226
Clusters	6,427	6,427	6,427	6,427	6,427	6,427	5,321	5,487
Selected IVs				399	65	65		
Full IV set				399	399	399		
Alpha				0.00	0.75	1.00		

Notes: Table shows point estimates (γ) 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 - Full sample

Variable	OLS (1)	2SLS (2)	2SLS (3)	Ridge (4)	Elastic net (5)	IV Lasso (6)	Elder sib (7)	Younger sib (8)
Fac. deliv	2.312***	8.430***		5.229*	22.818***	8.819**	0.821	10.745**
	(0.274)	(3.149)		(2.825)	(6.569)	(3.424)	(5.138)	(4.775)
Fac. x age 0			10.168					
			(6.834)					
Fac. x age 1			-4.024					
			(7.272)					
Fac. x age 2			16.013**					
			(6.458)					
Fac. x age 3			13.638**					
			(6.604)					
Fac. x age 4			12.511*					
			(6.788)					
Elder facil.							6.069	
							(4.908)	
Elder+ facil.							0.244	
							(6.215)	
Younger facil.								-2.756
								(4.935)
Younger+ facil.								-3.787
								(6.369)
Female	2.196***	2.267***	2.315***	2.227***	2.314***	2.267***	1.993***	2.876***
	(0.197)	(0.199)	(0.200)	(0.199)	(0.200)	(0.200)	(0.457)	(0.447)
Years of ed	0.629***	0.497***	0.475***	0.563***	0.153	0.483***	0.489***	0.582***
	(0.035)	(0.074)	(0.076)	(0.069)	(0.153)	(0.082)	(0.095)	(0.095)
Urban	3.196***	2.449***	2.204***	2.855***	0.768	2.417***	2.113***	3.002***
	(0.347)	(0.519)	(0.533)	(0.488)	(0.867)	(0.544)	(0.775)	(0.741)
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)	(0.000)	(0.000)	(0.000)	(0.000)
Sample size	100,470	100,470	100,470	100,470	100,470	100,470	17,914	19,459
Clusters	9,721	9,721	9,721	9,721	9,721	9,721	6,559	6,669
Selected IVs				400	90	90		
Full IV set				400	400	400		
Alpha				0.00	0.75	1.00		

Notes: Table shows point estimates (γ) 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 - Rural only

Variable	OLS (1)	2SLS (2)	2SLS (3)	Ridge (4)	Elastic net (5)	IV Lasso (6)	Elder sib (7)	Younger sib (8)
Fac. deliv	1.870***	6.229**		3.978	8.383	1.683	2.859	6.710
	(0.292)	(3.132)		(2.559)	(5.724)	(3.103)	(4.624)	(4.158)
Fac. x age 0			14.701**					
			(6.358)					
Fac. x age 1			-5.644					
			(6.525)					
Fac. x age 2			13.940**					
			(6.236)					
Fac. x age 3			4.075					
			(5.962)					
Fac. x age 4			6.437					
			(6.003)					
Elder facil.							8.600*	
							(4.580)	
Elder+ facil.							-4.238	
							(5.942)	
Younger facil.								0.990
								(4.264)
Younger+ facil.								-3.208
								(5.712)
Female	2.050***	2.107***	2.136***	2.073***	2.079***	2.046***	1.800***	2.796***
	(0.220)	(0.223)	(0.223)	(0.221)	(0.222)	(0.222)	(0.508)	(0.490)
Years of ed	0.407***	0.311***	0.305***	0.356***	0.241*	0.409***	0.254**	0.236**
	(0.040)	(0.079)	(0.080)	(0.070)	(0.146)	(0.083)	(0.108)	(0.103)
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)	(0.000)	(0.000)	(0.000)	(0.000)
Sample size	69,746	69,746	69,746	69,746	69,746	69,746	12,268	13,437
Clusters	6,292	6,292	6,292	6,292	6,292	6,292	4,353	4,430
Selected IVs				399	87	86		
Full IV set				399	399	399		
Alpha				0.00	0.75	1.00		

Notes: Table shows point estimates (γ) 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 - Full sample

Variable	OLS (1)	2SLS (2)	2SLS (3)	Ridge (4)	Elastic net (5)	IV Lasso (6)	Elder sib (7)	Younger sib (8)
Fac. deliv	2.849***	8.392***		7.022**	21.745***	11.275***	0.791	14.167***
	(0.268)	(3.216)		(2.906)	(6.870)	(3.535)	(5.330)	(4.439)
Fac. x age 0			1.694					
			(6.773)					
Fac. x age 1			4.967					
			(7.067)					
Fac. x age 2			18.568***					
			(6.118)					
Fac. x age 3			20.176***					
			(6.488)					
Fac. x age 4			5.882					
			(6.641)					
Elder facil.							-1.353	
							(4.972)	
Elder+ facil.							9.437	
							(6.499)	
Younger facil.								-0.777
								(4.461)
Younger+ facil.								-7.538
								(5.762)
Female	1.684***	1.748***	1.768***	1.729***	1.789***	1.776***	1.613***	1.811***
	(0.189)	(0.193)	(0.192)	(0.193)	(0.194)	(0.194)	(0.459)	(0.394)
Years of ed	0.607***	0.488***	0.445***	0.514***	0.168	0.419***	0.405***	0.484***
	(0.035)	(0.074)	(0.074)	(0.070)	(0.159)	(0.083)	(0.099)	(0.084)
Urban	1.621***	0.944*	0.592	1.131**	-0.615	0.611	-0.387	0.663
	(0.323)	(0.509)	(0.520)	(0.476)	(0.885)	(0.541)	(0.757)	(0.635)
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)	(0.000)	(0.000)	(0.000)	(0.000)
Sample size	100,470	100,470	100,470	100,470	100,470	100,470	17,914	19,459
Clusters	9,721	9,721	9,721	9,721	9,721	9,721	6,559	6,669
Selected IVs				400	90	90		
Full IV set				400	400	400		
Alpha				0.00	0.75	1.00		
1st-stage R2				0.30	0.29	0.29		

Notes: Table shows point estimates (γ) 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 - Rural only

Variable	OLS (1)	2SLS (2)	2SLS (3)	Ridge (4)	Elastic net (5)	IV Lasso (6)	Elder sib (7)	Younger sib (8)
Fac. deliv	2.310***	3.659		4.683*	10.524*	4.442	3.133	5.237
	(0.288)	(3.110)		(2.520)	(5.568)	(2.997)	(4.930)	(3.961)
Fac. x age 0			7.500					
			(6.226)					
Fac. x age 1			-3.571					
			(6.347)					
Fac. x age 2			12.357**					
			(5.836)					
Fac. x age 3			7.552					
			(5.841)					
Fac. x age 4			-0.348					
			(5.659)					
Elder facil.							2.780	
							(4.660)	
Elder+ facil.							2.019	
							(6.106)	
Younger facil.								2.812
								(3.872)
Younger+ facil.								-3.974
								(5.186)
Female	1.562***	1.580***	1.586***	1.588***	1.599***	1.587***	1.888***	1.659***
	(0.213)	(0.216)	(0.212)	(0.215)	(0.216)	(0.216)	(0.532)	(0.431)
Years of ed	0.484***	0.454***	0.435***	0.426***	0.274*	0.430***	0.319***	0.376***
	(0.042)	(0.077)	(0.076)	(0.070)	(0.141)	(0.080)	(0.109)	(0.092)
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)	(0.000)	(0.000)	(0.000)	(0.000)
Sample size	69,746	69,746	69,746	69,746	69,746	69,746	12,268	13,437
Clusters	6,292	6,292	6,292	6,292	6,292	6,292	4,353	4,430
Selected IVs				399	87	86		
Full IV set				399	399	399		
Alpha				0.00	0.75	1.00		

Notes: Table shows point estimates (γ) 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	OLS (1)	2SLS (2)	2SLS (3)	Ridge (4)	Elastic net (5)	IV Lasso (6)	Elder sib (7)	Younger sib (8)
Fac. deliv	0.194***	0.110**		0.051	0.091	0.058	0.295***	0.156**
	(0.007)	(0.052)		(0.048)	(0.166)	(0.068)	(0.084)	(0.068)
Fac. x age 0			0.127					
			(0.096)					
Fac. x age 1			0.078					
			(0.086)					
Fac. x age 2			0.109					
			(0.073)					
Fac. x age 3			0.182					
			(0.375)					
Fac. x age 4			(dropped)					
Elder facil.							0.189**	
							(0.076)	
Elder+ facil.							-0.212*	
							(0.110)	
Younger facil.								0.104
								(0.074)
Younger+ facil.								-0.063
								(0.093)
Female	0.006	0.004	0.004	0.002	0.002	0.002	-0.000	0.008
	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.005)	(0.010)	(0.013)
Years of ed	0.009***	0.011***	0.011***	0.013***	0.012***	0.013***	0.008***	0.010***
	(0.001)	(0.002)	(0.002)	(0.001)	(0.004)	(0.002)	(0.002)	(0.002)
Urban	0.029***	0.041***	0.041***	0.050***	0.046**	0.049***	0.007	0.028
	(0.009)	(0.011)	(0.011)	(0.011)	(0.022)	(0.013)	(0.016)	(0.020)
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)	(0.000)	(0.000)	(0.000)	(0.000)
Sample size	38,712	38,712	38,712	38,712	38,712	38,712	9,757	3,836
Clusters	8,424	8,424	8,424	8,424	8,424	8,424	4,519	2,728
Selected IVs				400	60	59		
Full IV set				400	400	400		
Alpha				0.00	0.75	1.00		

Notes: Table shows point estimates (γ) 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 - Rural only sample

Variable	OLS (1)	2SLS (2)	2SLS (3)	Ridge (4)	Elastic net (5)	IV Lasso (6)	Elder sib (7)	Younger sib (8)
Fac. deliv	0.194***	0.113*		0.044	0.228	0.052	0.350***	0.100
	(0.009)	(0.060)		(0.045)	(0.242)	(0.079)	(0.088)	(0.069)
Fac. x age 0			-0.010					
			(0.111)					
Fac. x age 1			0.147					
			(0.092)					
Fac. x age 2			0.163**					
			(0.076)					
Fac. x age 3			-0.162					
			(0.348)					
Fac. x age 4			(dropped)					
Elder facil.							0.156**	
							(0.079)	
Elder+ facil.							-0.272**	
							(0.117)	
Younger facil.								0.126*
								(0.072)
Younger+ facil.								-0.014
								(0.092)
Female	0.004	0.003	0.003	0.001	0.000	0.001	-0.001	0.013
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.012)	(0.016)
Years of ed	0.008***	0.010***	0.010***	0.012***	0.007	0.012***	0.008***	0.010***
	(0.001)	(0.002)	(0.002)	(0.002)	(0.007)	(0.002)	(0.003)	(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)	(0.000)	(0.000)	(0.000)	(0.000)
Sample size	27,060	27,060	27,060	27,060	27,060	27,060	6,963	2,527
Clusters	5,469	5,469	5,469	5,469	5,469	5,469	3,039	1,786
Selected IVs				399	40	40		
Full IV set				399	399	399		
Alpha				0.00	0.75	1.00		
1st-stage R2				0.25	0.27	0.27		

Notes: Table shows point estimates (γ) 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: Birth spacing interval until subsequent child (months) - Full sample

Variable	OLS (1)	2SLS (2)	2SLS (3)	Ridge (4)	Elastic net (5)	IV Lasso (6)	Elder sib (7)	Younger sib (8)
Fac. deliv	3.200	-75.724**		-52.770*	-174.097*	-96.008**	-22.888	47.955
	(3.740)	(35.202)		(31.220)	(96.680)	(46.161)	(61.020)	(48.557)
Fac. x age 0			-14.545					
			(108.557)					
Fac. x age 1			-16.309					
			(176.306)					
Fac. x age 2			-5.249					
			(91.032)					
Fac. x age 3			-135.188**					
			(59.227)					
Fac. x age 4			-60.611					
			(59.850)					
Elder facil.							42.704	
							(62.559)	
Elder+ facil.							-64.332	
							(87.443)	
Younger facil.								173.366***
								(52.731)
Younger+ facil.								-121.085*
								(67.476)
Female	0.378	-0.889	-3.369	-0.708	-1.711	-1.596	15.175	-0.989
	(3.068)	(3.132)	(3.141)	(3.101)	(3.221)	(3.160)	(10.374)	(3.214)
Years of ed	0.205	2.271**	2.153**	1.544*	4.515*	2.627**	2.316	-1.930**
	(0.468)	(1.035)	(1.042)	(0.877)	(2.441)	(1.246)	(1.719)	(0.878)
Urban	-2.806	6.419	6.737	4.123	18.221	9.691	-20.066	-13.209**
	(4.753)	(6.314)	(6.320)	(6.086)	(12.615)	(7.627)	(14.655)	(5.842)
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)	(0.000)	(0.000)	(0.000)	(0.000)
Sample size	48,714	48,714	48,714	48,714	48,714	48,714	3,702	38,712
Clusters	8,666	8,666	8,666	8,666	8,666	8,666	2,575	8,339
Selected IVs				399	59	58		
Full IV set				399	399	399		
Alpha				0.00	0.75	1.00		

Notes: Table shows point estimates (γ) 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: Birth spacing interval until subsequent child (months) - Rural sample

Variable	OLS (1)	2SLS (2)	2SLS (3)	Ridge (4)	Elastic net (5)	IV Lasso (6)	Elder sib (7)	Younger sib (8)
Fac. deliv	1.154	-61.302*		1.960	-119.559	-61.438	-26.651	3.990
	(4.167)	(36.933)		(29.915)	(92.858)	(48.822)	(64.208)	(49.264)
Fac. x age 0			28.389					
			(102.584)					
Fac. x age 1			-103.205					
			(182.850)					
Fac. x age 2			-123.662					
			(80.386)					
Fac. x age 3			-80.333					
			(58.466)					
Fac. x age 4			3.238					
			(59.972)					
Elder facil.							47.139	
							(61.956)	
Elder+ facil.							-7.072	
							(88.682)	
Younger facil.								223.536***
								(47.916)
Younger+ facil.								-130.196**
								(65.087)
Female	-0.857	-1.449	-3.757	-0.843	-1.267	-1.683	6.753	-0.808
	(3.481)	(3.524)	(3.553)	(3.504)	(3.488)	(3.527)	(12.236)	(3.622)
Years of ed	1.015*	2.557**	2.209**	0.997	4.104*	2.534*	1.204	-1.362
	(0.570)	(1.058)	(1.062)	(0.898)	(2.435)	(1.309)	(2.125)	(0.952)
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)	(0.000)	(0.000)	(0.000)	(0.000)
Sample size	35,082	35,082	35,082	35,082	35,082	35,082	2,604	27,226
Clusters	5,713	5,713	5,713	5,713	5,713	5,713	1,782	5,487
Selected IVs				398	55	55		
Full IV set				398	398	398		
Alpha				0.00	0.75	1.00		

Notes: Table shows point estimates (γ) 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.