**Supplementary Table S1.** Coverage Estimates of Indoor Residual Spraying (IRS) by district during the study period (January 2013-May 2017).

|  |  |  |
| --- | --- | --- |
| **District** |  | **Rounds of IRS** |
|  | **1st Round** | **2nd Round** | **3rd Round** | **4th Round** | **5th Round** |
| **Bugiri** | **Spray months** | May 2015 to Jun 2015 | Nov 2015 to Dec 2015 | Apr 2016 to May 2016 | Apr 2017 to May 2017 | -- |
| **Insecticide\*** | Bendiocarb | Bendiocarb | Actellic | Actellic  | -- |
| **Coverage** | 94% | 95% | 95% | 96% | -- |
| **Kaberamaido** | **Spray months** | Dec 2014 to Feb 2015 | May 2015 to June 2015 | Nov 2015 to Dec 2015 | Apr 2016 toMay 2016 | July 2017 toAug 2017 |
| **Insecticide\*** | Bendiocarb | Bendiocarb | Bendiocarb | Actellic | Actellic |
| **Coverage** | 71% | 93% | 92% | 92% | 92% |
| **Namutumba** | **Spray months** | May 2015 to June 2015 | Nov 2015 to Dec 2015 | May-Jun 2016 | May-Jun 2017 | -- |
| **Insecticide\*** | Bendiocarb | Bendiocarb | Actellic | Actellic | -- |
| **Coverage** | 92% | 96% | 99% | 100% | -- |
| **Serere** | **Spray months** | April 2015 to May 2015 | Oct 2015 to Nov 2015 | Jun 2016 to Jul 2016 | Jul 2017 to Aug 2017 | -- |
| **Insecticide\*** | Bendiocarb | Bendiocarb | Bendiocarb | Actellic | -- |
| **Coverage** | 98% | 100% | 96% | 96% | -- |
| **Tororo** | **Spray months** | Dec 2014 to Feb 2015 | June 2015 to July 2015 | Nov 2015 to Dec 2015 | June 2016 to July 2016 | July 2017 to Aug 2017 |
| **Insecticide\*** | Bendiocarb | Bendiocarb | Bendiocarb | Actellic  | Actellic |
| **Coverage** | 85% | 95% | 96% | 93% | 95% |

**Supplementary Methods: Description of the Matrix Completion with Nuclear Norm Minimization (MC-NNM) Estimator**

Before discussing the methodology behind MC-NNM, we first need to provide an intuition of the data structure MC-NNM uses to impute counterfactuals.

**MC-NNM Data Structure.** Suppose we observe outcomes from N units (health facilities) at T time points (months). These observations are grouped as a matrix Y where each row is a unit, and each column is a time point such that the element Yit represents the outcome for health facility *i* at month *t*. A second matrix W represents the observed treatment value for each unit and time point. In our study, Wit=1 if IRS was implemented in the district where health facility *i* is located at month *t* and Wit=0 otherwise.

 and

Given that our goal is to estimate the potential outcomes for health facilities in IRS districts had those districts not received IRS, we can consider the above matrix Y as representing the observed values of two matrices of potential outcomes, one for the outcomes had the campaign occurred in districts where health facilities were located [matrix Y(1)] and one for the outcomes had the campaign never occurred in the districts where health facilities were located [matrix Y(0)]. In matrix Y, all unobserved values in these matrices are considered missing (denoted as ).

 and

Note that in the above Y(0) matrix, only the post-IRS campaign outcome values of the IRS group are missing, whereas in the Y(1) matrix, pre-IRS campaign periods for both IRS and control groups are missing.

The goal of MC-NNM (or any counterfactual estimator, including DiD) is to estimate the missing values of Y(0) (i.e., the potential outcome at each health facility had the IRS campaign never been implemented).

**Comparison with Difference-in-Differences (DiD).** The DiD method is the standard method of estimating causal effects with panel data. DiD estimates the missing potential outcomes of Y(0) using a two-way fixed-effects regression model. The following equation describes the standard DiD model, where and represent unit- and time-fixed effects, respectively, and represents the treatment effect.

|  |  |
| --- | --- |
|  | and  |

The standard DiD approach assumes that non-treated potential outcomes can be approximated by a linear combination of unit () and time-level () fixed effects, whereby adjusts for unobserved group-varying, but time-invariant confounders, while adjusts for unobserved time-varying, but group-invariant confounders. The validity of DiD models hinges on the parallel trends assumption, which would be violated had there been time-varying covariates that were associated with the outcome that also varied across units. If these exist, the DiD model will not accurately estimate Y(0) potential outcomes, resulting in biased treatment effect estimates. Thus, a different approach must be taken to model these heterogeneities more flexibly.

**MC-NNM Approach To Modeling Time- and Group-Varying Heterogeneity.** To relax theassumption of parallel trends, MC-NNM draws upon the economic literature on interactive fixed effects (IFE) models1-3 and the computer science and statistics literature on matrix completion4-6 to flexibly and efficiently incorporate these heterogeneous trends into estimating Y(0) potential outcomes.

**Comparison to Interactive Fixed Effects Model (IFE).** The IFE model assumes that the true data generating process of Y(0) values comprises of interacted unit and time effects. To incorporate these interactions, IFE extends the DiD model by including an additional term in the Y(0) model ():

|  |  |
| --- | --- |
|  | and  |

In the Y(0) equation above, represents a vector of unobserved latent time factors and represents a vector of unit-specific factor loadings, where = the number of unobserved latent factors.7 Intuitively, can be thought of as time-varying trends (or common time shocks) that affects all units at time and captures the unit-specific reactions to these common shocks.2, 8 Given these ‘common shocks’ are unmeasured, the challenge is how to best estimate .

**Comparison with the Synthetic Control Method.** By identifying patterns observed between health facilities during the pre-IRS period and applying these to estimate Y(0) potential outcomes during the post-IRS period, MC-NNM is in many ways similar to the synthetic control method (SCM).9 The difference is that SCM constructs synthetic controls based on a weighted average of control units.9, 10 In SCM, weights for control units are generated using pre-specified time periods during the pre-IRS period so that the root mean square prediction error is minimized between the synthetic control and the corresponding treated unit. Unlike SCM, where the analyst must pre-specify selected pre-intervention time points to construct weights, MC-NNM uses a data-driven approach to identify key time periods that have heterogeneous effects across units. Another advantage of MC-NNM is that it can estimate the average treatment effects of the treated (ATT) even in the presence of incomplete data (i.e. missing Y(0) values for control group) and for multiple treated units, which the standard SCM cannot do as efficiently.

**MC-NNM Method to Estimating Y(0) Potential Outcomes.** To estimate the potential outcomes of the Y(0) matrix, MC-NNM utilizes a latent factor modeling approach, known as singular value decomposition (SVD). Mathematically, SVD, decomposes a matrix into a unique product of three matrices [Y(0)=UΣVT] (**see Figure below**).



In this figure, matrix U represents unit-latent factor relationships, matrix VT representing time-latent factor relationships, and a diagonal matrix Σ containing the singular values of matrix Y(0). Singular values represent the ‘strength’ of each latent factor (i.e., how much of the variance in the data each latent factor explains). The goal of conducting SVD is to identify the singular values that explain the greatest proportion of the variance in the data and discard the ones associated with small singular values. Upon discarding latent factors associated with small singular values, a new matrix is constructed (matrix L) that approximates the desired Y(0) matrix, but is of lower rank (i.e., lower complexity than the original Y(0) matrix).

MC-NNM chooses optimal number of singular values (defined as the rank of the matrix) using nuclear norm regularization,11 an optimization procedure which seeks to minimize the root mean squared prediction error with as few latent factors as possible by penalizing poorly determined singular values (much like how LASSO penalizes poorly determined regression information). This is done by solving the following the minimization procedure:

where , is the chosen matrix norm of L, and is a tuning parameter used to choose the number of latent factors. The choice in using the nuclear norm as the regularizer is done to retain as much of the complex relationships between units and time periods, while making the overall computation feasible. Details of the optimization procedure are described in the original paper.11

**MC-NNM Outcome Model.** Once matrix is estimated, the outcome model for MC-NNM is as follows:

 and

where is a matrix approximated by nuclear norm regularization, and and are vectors of unit- and time-fixed effects, respectively. Note that the equation above does not include any pre-specified time-varying covariates, however, they can be added as linear terms (similar to the method DiD incorporates observed time-varying covariates into the model).

**Estimation of ATT.** Once values of the are estimated, the average treatment effect of the treated (ATT) is calculated by subtracting Y(0) values from Y(1) for treated units and averaged across all treated units and time periods during the post-IRS period. 95% confidence intervals aroundATT estimates can be generated using block bootstrapped replications.

**MC-NNM Limitations.** Athey et al11 note two limitations of the MC-NNM approach. First, MC-NNM does not take into account that the errors ( can be autocorrelated over time. Second, MC-NNM puts equal weight on the observed elements of Y(0)-L differences in attempting to minimize the root mean squared error to find the optimal matrix L, even though missingness increases with time *t*.

**Supplementary Figure S1.** Graphical representation of missing outcomes across health facility-months. White boxes represent months where no birth records were found for the health facility. Figure created using the panelView package in R.12 Of the 1,325 health facility-months included in our analysis, outcome data was missing for 78 facility months (5.9%).

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**Supplementary Figure S2.** Results estimating the overall, first, and second year impact of the Uganda IRS Project on low birthweight and stillbirth incidence usingalternative specifications of the outcome for MC-NNM analyses. For MC-NNM analyses using the log-transformed outcomes, a constant value of 1 was added to account for health facility-months when zero outcomes were observed. All analyses adjusted for number of deliveries per health facility months and covariates included in DiD analyses.

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**Supplementary Figure S3.** Results from sensitivity analysesestimating the overall, first-, and second-year impact of the Uganda IRS Project on low birthweight and stillbirth risk. Analyses were conducted using individual-level covariate and outcome data using DiD estimators.

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**Supplementary Table S2.** Results of placebo tests. Placebo tests were conducted by falsely introducing the campaign three and six months prior to the true start date of the campaign. MC-NNM analyses were conducted to determine whether a treatment effect would be detected during the ‘placebo’ period, which would invalidate the identifying assumption that the potential outcomes estimated by MC-NNM are independent of the observed treatment value, conditional on observed covariates and model specification.

|  |  |  |
| --- | --- | --- |
| **Outcome** | **Placebo Period (months)** | **IRR [95% CI]** |
| Low birthweight | -6 to 0 | 1.00 [0.94, 1.05] |
| -3 to 0 | 1.00 [0.94, 1.06] |
| Stillbirth | -6 to 0 | 1.08 [1.03, 1.14] |
| -3 to 0 | 1.14 [1.09, 1.18] |

**Supplementary Figure S4.** Trends in low birthweight and stillbirth incidence of the treated group estimated by MC-NNM generated synthetic controls. Black lines indicate the observed trend and blue lines indicate the synthetic control estimated by matrix completion method (MC-NNM). In the Figure below, the observed LBW trend in treated groups and the MC-NNM generated synthetic control appear perfectly overlayed due to small differences during the pre-campaign period.

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**Supplementary Figure S5.** Average monthly trend in low birthweight and stillbirth incidence between IRS and non-IRS control groups during study period. Separate graphs were produced based on the timing of the campaign initiation and outcome. The green and black solid lines indicate trend in the outcome averaged across IRS and control units, respectively. The grey shaded region highlights the time point when the IRS campaign was initiated in IRS units.



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