# **Supplemental Online Content**

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This supplemental material has been provided by the authors to give readers additional information about their work.

### **eMethods 1.** Sample Size Calculation in Survey

This study applied the household-based cluster survey method recommended by the WHO.<sup>1</sup> The sample size of this survey was calculated based on the formula as follows:

$$
n = \frac{Z_{1-\alpha/2}^2 \cdot P \cdot (1-P)}{\delta^2}
$$

where  $\delta$  is the permissible error, a two-tailed  $\alpha$  error is 5%, confidence level 1- $\alpha$  is the degree of confidence, and *P* is the vaccination rate of 6-59 month-old children. In this study, the confidence level of 95% is taken, and the error does not exceed 5%. So  $Z^2_{(1-\alpha/2)}$  is equal to 1.96. According to the calculation formula, the closer the vaccination rate P is to 50%, the larger the required sample size (the most conservative estimated sample size). At this time, the minimum valid sample size is n=((1.96)^2⋅0.5⋅(1-0.5))/(0.05)^2 ≈384. The smallest sample size of each province is 384 children, and the smallest sample size of children surveyed would be 3840 for ten provinces totally. In practice, we collected a larger sample size than expected to increase the reliability of the results.

### **eReference:**

1. Cutts FT. The use of the WHO cluster survey method for evaluating the impact of the expanded programme on immunization on target disease incidence. The Journal of tropical medicine and hygiene. 1988;91:231-9.

**eMethods 2.** Details of Vaccine Economics Research for Sustainability and Equity Model

The composite vaccination equity assessment metric in the Vaccine Economics Research for Sustainability & Equity (VERSE) model is derived from literature on the measurement of socioeconomic equity by Wagstaff and Erreygers combined with measures of direct unfairness in healthcare access outlined in the works of Fleurbaey, Schokkaert, Cookson, and Barbosa  $1-8$ . The composite metric takes the form of a concentration index of vaccination coverage, where instead of ranking individuals by income, individuals are ranked by a multi-dimensional score of unfair disadvantage in access. Unfair disadvantage as parameterized in the VERSE metric is an adaptation of a direct unfairness measure. It computes the predicted vaccination coverage from a logistic model-based, for binary outcomes, or a generalized linear model, for continuous outcomes, upon multiple dimensions of fair and unfair sources of variation in vaccination coverage<sup>5</sup>.

Fair sources of variation in coverage include whether the child is underage to receive the vaccine according to Chinese national immunization schedule for NIP vaccines and expert consensus for non-NIP vaccines. We used the birth date and the survey date to calculate the age of a child and compared it with the appropriate vaccination schedule to determine whether the child was underage. Unfair sources of variation included in the standard model are the gender of the child, and respondents (caregivers)' education level, socioeconomic status (monthly family income per capita), medical insurance, place of residence (urban or rural), and provinces. These were chosen based on stakeholder engagement and near-universal data collection on these dimensions through national health information systems <sup>9</sup>. The direct unfairness ranking metric is then assessed as the predicted probability of vaccination, holding the fair determinants at reference levels and allowing the unfair determinants to vary. For continuous variables, the predicted value of the continuous output holds the fair determinants at reference levels and allows the unfair determinants to vary. This unfair disadvantage metric is then utilized as the ranking variable in a concentration index, alongside the cumulative share of the outcome, to compute the composite coverage equity metric.

For the binary case of vaccination coverage where the outcome takes a value of 1 if the child receives the vaccine and 0 otherwise, the direct unfairness metric for vaccination coverage indicator (*vcidu*) can be written as:

$$
v_{\text{C}idu} = v_{\text{C}ipredicted} \left( N_{\text{ref}}, P_{\text{ref}}, Z_i, X_{\text{ref}} \right) \left[ \begin{smallmatrix} 1 \\ 0 \\ 0 \end{smallmatrix} \right]
$$

where:

 $N =$  Vector of need variables (in the vaccine case, only the age of the child is used)

 $P =$  Vector of preference for healthcare variables

 $Z =$  Vector of unfair variables (e.g., socioeconomic status, urban/rural, sex of the child, caregiver's education)

 $X =$  Vector of neither fair nor unfair variables (e.g., variables that may confound the relationship between unfair predictors and coverage)

*vcipredicted* = Predicted probability of receiving vaccines holding need (*N*) & neutral (*X*) variables at reference levels

For the VERSE model, the basic assumption is that there are no neutral variables and that parental (or caregiver's) preferences for vaccination are either not observable or are a function of the *Z* vector variables (e.g., parental education) and therefore should be counted as unfair sources of variation and not true preferences. As such, the direct unfairness in vaccination coverage indicator (vcidu) can be simplified as:

$$
vci_{du} = vci_{predicted} (N_{ref}, Z_i) \underbrace{z_i}_{S_i}.
$$

Therefore, under the logistic framework letting vaccination status  $(v) = 1$  if vaccinated and 0 otherwise, the predicted *vcidu* can be written as:

Let  $p_i = Pr(v = 1 | N_{ref}, Z_i)$ Logit( $p_i$ ) = α+ βZ<sub>i</sub>+ γ $N_{ref}$  + ε<sub>i</sub>

Using this setup, the predicted values are defined by:  $\hat{p}_i = vci_{du}$ .

Once *vcidu* is obtained, it is then used as the ranking variable to compute a Wagstaff's concentration index, replacing the more traditional ranking variable of socioeconomic status <sup>6,8</sup>. As such, the predicted probability of vaccination conditional on unfair determinants (*vcidu*), or in the continuous case the predicted healthcare access level based on unfair determinants, functions in the same manner as a wealth index creating a scale where the relative rank of individuals over (*vcidu*) depicts their degree of relative unfair disadvantage in obtaining the outcome in question. This is utilized alongside the cumulative share of attainment of the health outcome to compute the final index, which, as a concentration-style index, exhibits the properties of a Gini-index: bounded between -1 and 1 and, therefore, standardized by construction.

The VERSE toolkit enables the production of a traditional Wagstaff concentration index  $(Cl_W)$ :

$$
CI_{W} = \frac{2 \, Cov(vci_{direct}, F(vci_{du}))}{\mu vc}
$$

Where:

 $vci_{direct}$  = Directly standardized individual level of healthcare (observed vaccination coverage)

 $F(vci_{du})$  = The cumulative distribution function of direct unfairness

 $\mu\nu c$  = Mean level of healthcare (vaccination coverage) across the entire population

Since the metric is based Wagstaff's concentration index, regression-based Kitagawa-Blinder-Oaxaca decomposition can be employed to generate the cumulative share of overall observed inequality relating to each of the fair and unfair predictor<sup>3,10—11</sup>.

Finally, it is possible to compute the Absolute Equity Gap derived from the concentration index above. This involves subtracting the outcome from the top 20% of the study sample (ranked by multidimensional unfairness) and the bottom 20% of the study sample.

 $AEG = hci_{observed}(top 20\% (F(hci_{du})) - hci_{observed}(Bottom 20\% (F(hci_{du})))$ 

A fundamental assumption of the VERSE model is that every child should be vaccinated by the recommended age in the national immunization schedule. As such, the only source of fair variation in vaccination status should be the *age of the child*. This means that children who are younger than the recommended age for a specific vaccination can fairly be expected not to have received a vaccination and should be netted out of the unfair disadvantage metric computation process. All other sources of variation in vaccination status (socioeconomic status, gender of the child, and respondents (caregivers)' education level, socioeconomic status (monthly family income per capita), medical insurance, place of residence (urban or rural), and province) should be considered as unfair sources of vaccination coverage. The reference levels for all determinants in the analysis are set at the subnational level, so negative indices will signal a protective relationship between unfair risk factors and outcomes. Such negative values will indicate a pro-disadvantaged distribution of vaccination within that sub-unit with respect to national-level drivers of disadvantage.

### **eReferences:**

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**eFigure 1.** Provinces and Municipalities Selected for Study



Note: The 1st layer includes the least developed provinces, and the 5th layer includes the most developed provinces in China. The ten provinces/municipalities (equivalent to provinces) selected in the mainland China were Chongqing, Gansu, and Yunnan (the 1st layer); Henan, Jiangxi, and Jilin (the 2nd layer); Shandong (the 3rd layer); Guangdong (the 4th layer); and Beijing and Shanghai (the 5th layer). There were more provinces/municipalities in the first and second layers, so three provinces/municipalities were selected for each layer.

**eFigure 2.** Flow Chart of Location Selection and Participant Recruitment



**eTable 1.** Demographic Characteristics of Children With vs Without Complete Vaccination Records







Note: a, The education level and medical insurance type refer to those of the adult respondents;

b, CNY 1= USD 0.145 in 2019.



## **eTable 2.** Standard Schedules of National Immunization Program Vaccines

## **eTable 3.** Standard Schedules of Non–National Immunization Program Vaccines



Note: The immunization schedules of non-National Immunization Program vaccines are different by province in China, so the present study follows childhood immunization program in Shanghai as the standard schedule.









Abbreviations: AEG = Absolute Equity Gap.





















1 = Beijing<br>2 = Chongqing 3 = Gansu<br>4 = Guangdong 5 = Henan<br>6 = Jiangxi 7 = Jilin<br>8 = Shandong 9 = Shanghai<br>10 = Yunnan Province





1 = Beijing<br>2 = Chongqing 3 = Gansu<br>4 = Guangdong 5 = Henan<br>6 = Jiangxi 7 = Jilin<br>8 = Shandong Province





## **eFigure 4.** Decomposition of Vaccine Inequity



#### Decomposition of DTP3 Coverage Equity



Decomposition of EV711 Coverage Equity



#### Decomposition of EV712 Coverage Equity



Decomposition of Equity in Fully NIP Immunized for Age Status



#### Decomposition of HEPA1 Coverage Equity



**Decomposition of HEPB1 Coverage Equity** 



#### Decomposition of HEPB3 Coverage Equity



Decomposition of HIB1 Coverage Equity



#### Decomposition of HIB3 Coverage Equity



Decomposition of JE1 Coverage Equity



#### Decomposition of JE2 Coverage Equity



Decomposition of MCV1 Coverage Equity



#### Decomposition of MPSV\_A1 Coverage Equity



Decomposition of MPSV\_A2 Coverage Equity



#### Decomposition of MPSV\_AC1 Coverage Equity



Decomposition of PCV1 Coverage Equity



#### Decomposition of PCV3 Coverage Equity



Decomposition of PV1 Coverage Equity



#### Decomposition of PV2 Coverage Equity



Decomposition of PV3 Coverage Equity



#### Decomposition of ROTA1 Coverage Equity



Decomposition of ROTA3 Coverage Equity



#### Decomposition of VAR1 Coverage Equity



Decomposition of Zero-Dose Inequity

