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Supplementary appendix

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Supplementary Appendix

S1- List of countries in the WHO Africa Region by income classifications

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S1- List of countries in the WHO Africa Region by income classifications

Table S1: Classification of the WHO AFRO countries according to income levels

High / Upper Middle Income	Lower-middle Income	Low Income
Seychelles (High Income)	Angola	Benin
Algeria	Cameroon	Burkina Faso
Botswana	Cabo Verde	Burundi
Equatorial Guinea	Comoros	Central African Republic
Gabon	Congo, Rep.	Chad
Mauritius	Cote d'Ivoire	Congo, Dem. Rep.
Namibia	Eswatini	Eritrea
South Africa	Ghana	Ethiopia
	Kenya	Gambia, The
	Lesotho	Guinea
	Mauritania	Guinea-Bissau
	Nigeria	Liberia
	Sao Tome and Principe	Madagascar
	Senegal	Malawi
	Zambia	Mali
	Zimbabwe	Mozambique
	United Republic of Tanzania	Niger
		Rwanda
		Sierra Leone
		South Sudan
		Togo
		Uganda

SUPPLEMENTARY APPENDIX 2: Parameter description and initialization

We utilized the parameters in the table below to fit into the model for the different states

Table S2. Parameter description and initialization

State	Description	Notation	Data description	Data	Source
Susceptible	Total population split between the immunised and not-immunised	N	Total population	As per country totals	Country census[13]
		ν	Birthrates	As per country	Estimated from Country census data[13]
		μ	Death rates	As per country	Estimated from Country census data[13]
		φ	Immunized population	As per country	From equation 1 (in the paper)
Exposed	Those who have gotten the virus but cannot transmit it to others yet. Consider different variants. The true identities of the variants to be given (alpha, beta, delta, omicron)	σ_{ij}	Incubation periods for each of the variants	Wuhan Reference Strain: 5 days Alpha: 3.5 days Beta: 5 days Delta: 4 days Omicron: 3[1] days	Cheng et al., 2021; Homma et al., 2021; Snell et al., 2021[1–3];
Infected	Those who have the virus and are contagious	$\lambda_{ij}(t)$	The force of infection (dynamic series, fourier) = infection rate (contact rate * transmission probability. Infection rates for the different variants for both immunised and not-immunised. Differences in the severities based on the variant in question and immunization status. The periodicity of the waves.	Immunization reduces severe infections by 80 – 87.5% No significant level of severity among the variants Proportion of the cases that are from immunied persons is 21% Reduction of risk of infection due to immunization is 68.97% Reduction of mortality due to immunization is 86.50% Reduction of re-infection due to immunization 90.40% Transmissibility of strains: Alpha strain is ~50% increase in comparison with the Wuhan reference (original) strain Beta strain is 25% increase in transmissibility compared with the Wuhan reference (original) strain Delta strain is 97% increase in transmissibility compared with the Wuhan reference (original) strain Omicron has a transmission advantage of 189% (162-217%) over Delta	Akkiz, 2021; Jara et al., 2021; Levine-Tiefenbrun et al., 2021; Mahase, 2021; Marfe et al., 2021; Thompson et al., 2021; Tregoning et al., 2021; Vasireddy et al., 2021[4–10] Kojima et al 2021[11] Campel et al, 2021 [14] WHO update #6: 2022 [15]
Recovered	Recoveries as function of the duration of illness	γ_{ij}	Recovery rate = 1/infectious period. The infectious period to be considered under each of the identified variants for both immunised and not-immunised. The recovery period with respect to the severities.	Recovery period: (Mild/ asymptomatic; Moderate, Severe, Critical)	Cabore et al. (2020)
		ε_{ij}	Movement from the recovered to the susceptible.	Immunized vs unimmunized: Immunized persons have 2.8 days shorter recovery period if hospitalized	Baltas et al., 2021
Dead	Number of COVID-19 related deaths	ω_{ij}	COVID-19 related death with respect to disease severities and immunization status	Immunization reduces deaths by 81-86.5% in real-world experiences Death by disease severity: Mild/asymptomatic: Moderate Severe Critical	Jara et al., 2021 Marfe et al., 2021; Tregoning et al., 2021[5,8,9] Cabore et al (2020)

SUPPLEMENTARY APPENDIX 3: Model development for the SEIRD Partially Observed Markov Process

The evolutionary process of Covid-19 cases data is modeled as a Partially Observed Markov Process (POMP) also called Hidden Markov Model.[12] A POMP is a statistical Markov Model in which the hidden states are assumed to have the Markov property and emit symbols or observations. For the compartment model (SEIRD), the hidden states are the number of individuals in the compartments.

From Figure 1 in the text, let S(t), E(t), I(t), R(t) and D(t) be the numbers of individuals within the respective compartment at time *t*. Let also n_{ij} be a stochastic counting process with the value at time *t* being the number of individuals transiting from compartment *i* to *j* during the interval $[t_0, t)$, where t_0 is the starting point. Further, let $n_{.i}$ and $n_{i.}$ be the births and deaths, respectively, in compartment *i*. The infinitesimal increment probabilities specify the continuous-time Markov process. Writing $\Delta n(t) = n(t+h) - n(t)$, we therefore have:

$$\Pr\left[\Delta n_{.S_1}(t) = 1 \middle| F_t\right] = \nu N(t) h + o(h) \quad (1)$$

For i = 1, 2 for the not – immunized and immunized sub-models,

$\Pr\left[\Delta n_{S_1 S_2}(t) = 1 \middle| F_t\right] = \varphi(t) N(t) h + o(h)$, transiting from the not-immunized to the immunized at time t (2)

$\Pr\left[\Delta n_{S_{i.}}(t) = 1 \middle| F_t\right] = \mu S_i(t) h + o(h)$, general population mortality among the susceptible at time *t* (3)

$\Pr\left[\Delta n_{S_{ij}E_{ij}}(t) = 1 \middle| F_t\right] = \sigma_{ij} S_i(t) h + o(h)$, with $j \in \{1,2,3,4\}$ for exposure to the variants (4)

$\Pr\left[\Delta n_{E_{ij}I_{ij}}(t) = 1 \middle| F_t\right] = \lambda_{ij}(t) E_{ij}(t) h + o(h)$, with $j \in \{1,2,3,4\}$ for different infection severity levels (5)

$\Pr\left[\Delta n_{I_{ij}R_{ij}}(t) = 1 \middle| F_t\right] = \gamma_{ij} I_{ij}(t) h + o(h)$, with $j \in \{1,2\}$ for recovery differentials between the immunized and not immunized (6)

$\Pr\left[\Delta n_{I_{ij}D_{ij}}(t) = 1 \middle| F_t\right] = \omega_{ij} I_{ij}(t) h + o(h)$, with $j \in \{1,2\}$ for COVID-19 mortality differentials between the immunized and not immunized (7)

$\Pr\left[\Delta n_{R_{ij}S_2}(t) = 1 \middle| F_t\right] = \varepsilon_{ij} R_{ij}(t) h + o(h)$, with $j \in \{1,2\}$ for the different rates of moving from the recovered to susceptible among the immunized and not immunized groups (8)

Allowing for non-zero probability general population mortality in the compartments, we have:

$$\Pr\left[\Delta n_{E_{ij.}}(t)=1\middle|F_t\right]=\mu E_{ij}(t)h+o(h) \tag{9}$$

$$\Pr\left[\Delta n_{I_{ij.}}(t)=1\middle|F_t\right]=\mu I_{ij}(t)h+o(h) \tag{10}$$

$$\Pr\left[\Delta n_{R_{ij.}}(t)=1\middle|F_t\right]=\mu R_{ij}(t)h+o(h) \tag{11}$$

With the filtration $F_t=\left\{S_i(u),E_{ij}(u),I_{ij}(u),R_{ij}(u),\text{for all } 0\le u\le t\right\}$ represents the history of the process up to time *t*. The counting processes governing Figure 1 are represented by the following identities:

$$\begin{aligned}
\Delta S_1(t)&=\Delta n_{.S_1}-\Delta n_{S_1S_2}-\Delta n_{S_1E_{1j}}-\Delta n_{S_1.}\\
\Delta S_2(t)&=\Delta n_{S_1S_2}+\Delta n_{R_{1j}S_2}+\Delta n_{R_{2j}S_2}-\Delta n_{S_2E_{2j}}-\Delta n_{S_2.}\\
\Delta E_{1j}(t)&=\Delta n_{S_1E_{1j}}-\Delta n_{E_{1j}I_{1j}}-\Delta n_{E_{1j.}}\\
\Delta E_{2j}(t)&=\Delta n_{S_2E_{2j}}-\Delta n_{E_{2j}I_{2j}}-\Delta n_{E_{2j.}}\\
\Delta I_{1j}(t)&=\Delta n_{E_{1j}I_{1j}}-\Delta n_{I_{1j}D_{1j}}-\Delta n_{I_{1j.}}-\Delta n_{I_{1j}R_{1j}}\\
\Delta I_{2j}(t)&=\Delta n_{E_{2j}I_{2j}}-\Delta n_{I_{2j}D_{2j}}-\Delta n_{I_{2j.}}-\Delta n_{I_{2j}R_{2j}}\\
\Delta R_{1j}(t)&=\Delta n_{I_{1j}R_{1j}}-\Delta n_{R_{1j.}}-\Delta n_{R_{1j}S_2}\\
\Delta R_{2j}(t)&=\Delta n_{I_{2j}R_{2j}}-\Delta n_{R_{2j.}}-\Delta n_{R_{2j}S_2}\\
\Delta D_{1j}(t)&=\Delta n_{I_{1j}D_{1j}}\\
\Delta D_{2j}(t)&=\Delta n_{I_{2j}D_{2j}}
\end{aligned} \tag{12}$$

By taking expectations on both sides of the set of equations, dividing through by *h*, and taking the limit as $h\to 0+$, substituting the values in the set of probability equations we obtain:

$$\frac{dS_1(t)}{dt}=(\nu-\varphi)N(t)-\sigma_{1j}S_1(t)-\mu S_1(t)$$

$$\frac{dS_2(t)}{dt}=\varphi N(t)+\varepsilon_{1j}R_{1j}(t)+\varepsilon_{2j}R_{2j}(t)-\sigma_{2j}S_2(t)-\mu S_2(t)$$

$$\begin{aligned}
\frac{dE_1(t)}{dt}&=\sigma_{1j}S_1(t)-\lambda_{1j}(t)E_{1j}(t)-\mu E_{1j}(t)\\
\frac{dE_2(t)}{dt}&=\sigma_{2j}S_2(t)-\lambda_{2j}(t)E_{2j}(t)-\mu E_{2j}(t)\\
\frac{dI_1(t)}{dt}&=\lambda_{1j}(t)E_{1j}(t)-\omega_{1j}I_{1j}(t)-\mu I_{1j}(t)-\gamma_{1j}I_{1j}(t)\\
\frac{dI_2(t)}{dt}&=\lambda_{2j}(t)E_{2j}(t)-\omega_{2j}I_{2j}(t)-\mu I_{2j}(t)-\gamma_{2j}I_{2j}(t)
\end{aligned} \tag{13}$$

$$\frac{dR_1(t)}{dt} = \gamma_{1j} I_{1j}(t) - \mu R_{1j}(t) - \varepsilon_{1j} R_{1j}(t)$$
$$\frac{dR_2(t)}{dt} = \gamma_{2j} I_{2j}(t) - \mu R_{2j}(t) - \varepsilon_{2j} R_{2j}(t)$$
$$\frac{dD_1(t)}{dt} = \omega_{1j} I_{1j}(t)$$
$$\frac{dD_2(t)}{dt} = \omega_{2j} I_{1j}(t)$$

Stochasticity in the system was accounted for by factoring in gamma noise. The main challenge while monitoring the compartments *S, E, I, R* and *D,* is that the process is evaluated based on the number of cases recorded/observed. The observed cases represent the "top layer" of the Partially Observed Markov Processes and it is modelled using a count process. Aaron A. King Dao Nguyen, and Edward L. Ionides (2016) model the number of cases, $C(t_1, t_2)$, recorded within a given reporting interval $[t_1; t_2)$ using a negative binomial process,[12]

That is

$$C(t_1, t_2) \sim NegBin\left(\rho \Delta n_{SI}(t_1, t_2), \theta\right) \tag{14}$$

where $\Delta n_{SI}(t_1, t_2)$ *is the true incidence (the accumulated number of new infections that have occurred over the* $[t_1; t_2)$ *interval),* ρ *is the reporting rate, (the probability that an infection is observed and recorded),* θ *is the negative binomial "size" parameter.*

The historical data were applied in the Exposed to the Infected ($E \to I$) and the most appropriate count process for the data will be fitted. Similarly, the methodology was also applied to the number of deaths observed, given that some of the COVID-19 deaths may have been missed out in the records. This implies that we have two levels of output, the observed incidence “top layer” and the “Hidden layer”.

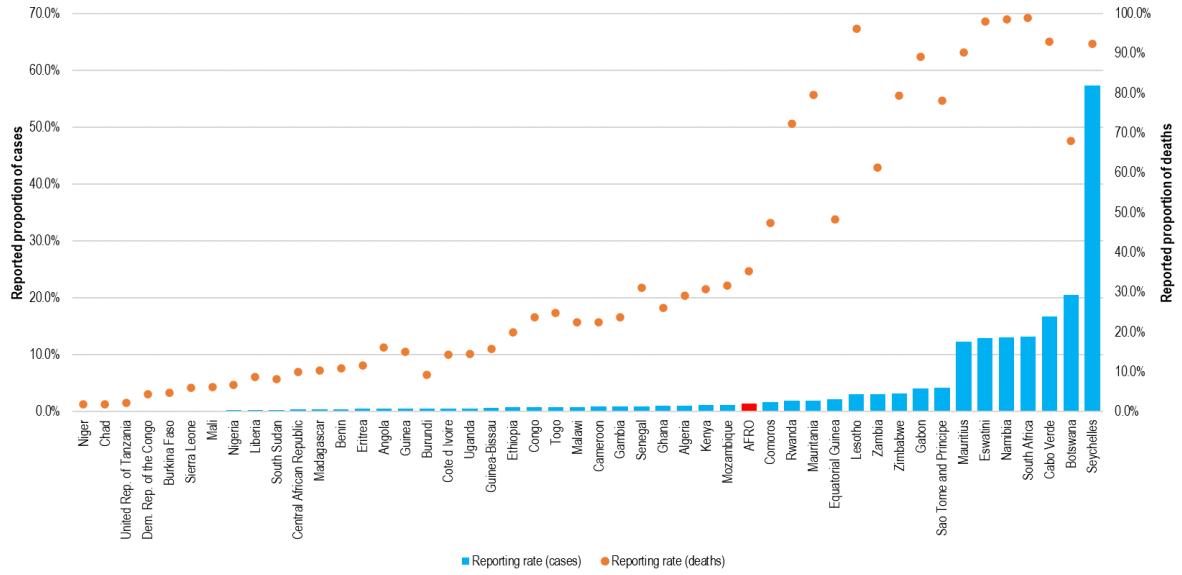

Figure S1: Reporting rates for the COVID-19 cases and deaths across the countries giving the proportions of the "top layer" to the "Hidden layer" (Source: Model output)

The model's measurement component "top layer" was estimated in relation to the observed data using gradient search methods, deriving a quantity *contact rate* for each of the country. The optimization involved minimizing the difference between the observed data and the top layer of the model estimates that is directly linked to the hidden layer. Country specific contact rates were later explored and found to be dependent on, but not limited to: Population ages 0-14 (% of total), Population ages 15-64 (% of total), Population ages 65 and above (% of total), Total proportion of the population in formal employment, in services, Population living in slums (% of urban population), Proportion of population living in urban areas, Connectivity per sq km, Population density, People using at least basic sanitation services (% of population) all of which accounted for 30.7% ($R^2 = 0.307$) of the variations across the countries.

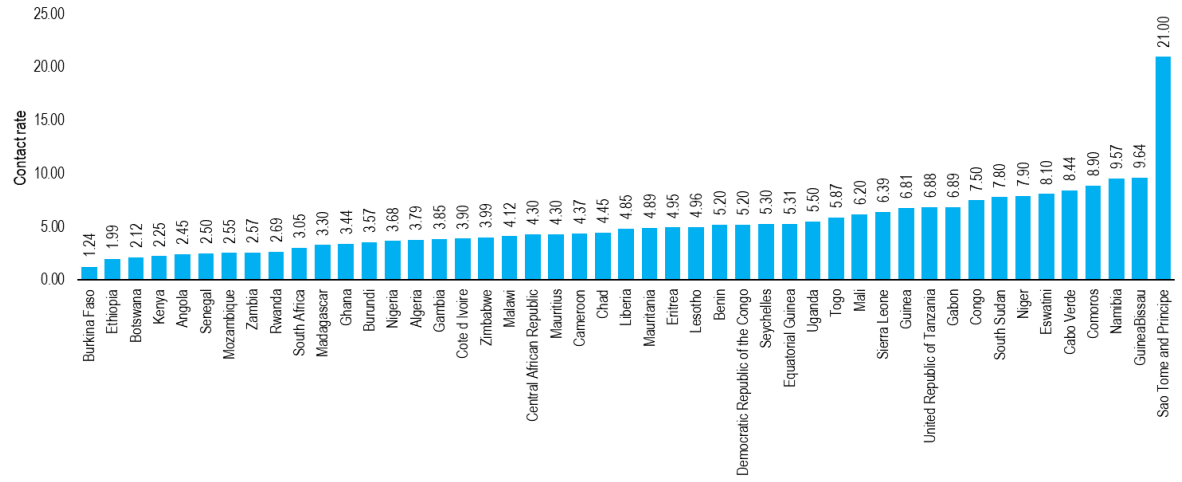

Figure S2: Contact rates across the 47 WHO AFRO countries

The model was sensitive to the number of COVID-19 specific deaths reported as a function of the population according to a power function

$$y = ax^b \quad (15)$$

where a = 48,064.9 and b = -0.992, with y being the weight and x, the population size. Vulnerability index[31] for each of the countries were also used to modulate the death rates according to the country specific experience. Immunized population was determined by factoring in the vaccinated among the true burden, which was obtained from the community infections. This was done using the following formula:

*Immunized population proportion = vaccinated proportion *(1 – True burden proportion) + True burden proportion* (16)

SUPPLEMENTARY APPENDIX 4

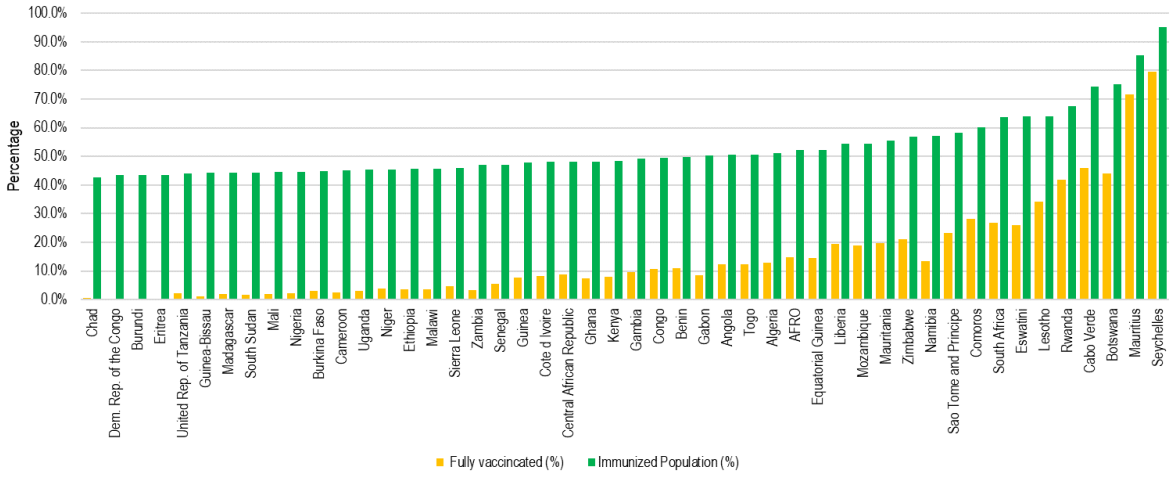

Figure S3: Proportions of fully vaccination vs immunized population as at Dec 31, 2021

Regional analysis Tables

Table S4: Estimated burden and deaths per 100,000 populations across the different income groups

	2020		2021		2020 and 2021	
	Estimated burden	Estimated deaths	Estimated burden	Estimated deaths	Estimated burden	Estimated deaths
Income group	per 100,000 (95% CI)	per 100,000 (95% CI)	per 100,000 (95% CI)	per 100,000 (95% CI)	per 100,000 (95% CI)	per 100,000 (95% CI)
High/Upper-Middle-Income Economies	675 (492 - 566)	0.5 (0.2 - 0.7)	449 (328 - 402)	1.5 (1.0 - 1.5)	553 (403 - 477)	1.0 (0.7 - 1.1)
Lower-Middle-Income Economies	561 (533 - 589)	0.2 (0.1 - 0.3)	390 (362 - 418)	0.6 (0.5 - 0.7)	468 (441 - 496)	0.4 (0.3 - 0.5)
Low-Income Economies	538 (513 - 563)	0.2 (0.1 - 0.3)	380 (355 - 405)	0.5 (0.4 - 0.6)	453 (428 - 478)	0.4 (0.3 - 0.5)
AFRO	568 (518 - 574)	0.2 (0.1 - 0.3)	394 (354 - 410)	0.7 (0.5 - 0.8)	474 (429 - 485)	0.5 (0.3 - 0.6)

Table S5: Estimated burden and deaths per 100,000 population across the different regional blocks

	2020		2021		2020 and 2021	
	Estimated burden	Estimated deaths	Estimated burden	Estimated deaths	Estimated burden	Estimated deaths
REC	per 100,000 (95% CI)	per 100,000 (95% CI)	per 100,000 (95% CI)	per 100,000 (95% CI)	per 100,000 (95% CI)	per 100,000 (95% CI)
CEN-SAD	546 (521 - 571)	0.2 (0.1 - 0.3)	385 (360 - 410)	0.5 (0.5 - 0.7)	459 (434 - 484)	0.4 (0.3 - 0.5)
COMESA	591 (498 - 547)	0.2 (0.1 - 0.3)	402 (338 - 387)	0.7 (0.5 - 0.7)	489 (411 - 461)	0.5 (0.3 - 0.5)
EAC	540 (513 - 568)	0.1 (0.1 - 0.2)	381 (353 - 409)	0.4 (0.3 - 0.5)	454 (426 - 482)	0.3 (0.2 - 0.4)
ECCAS	544 (517 - 570)	0.1 (0.1 - 0.2)	384 (358 - 411)	0.4 (0.4 - 0.5)	457 (431 - 484)	0.3 (0.2 - 0.4)
ECOWAS	548 (522 - 574)	0.2 (0.1 - 0.3)	384 (359 - 410)	0.6 (0.5 - 0.7)	459 (434 - 485)	0.4 (0.3 - 0.5)
IGAD	545 (522 - 568)	0.1 (0.1 - 0.2)	379 (356 - 402)	0.5 (0.4 - 0.6)	455 (432 - 478)	0.3 (0.3 - 0.4)
SADC	612 (510 - 579)	0.4 (0.2 - 0.5)	416 (343 - 411)	1.1 (0.8 - 1.2)	506 (420 - 488)	0.8 (0.5 - 0.9)
UMA	552 (526 - 578)	0.2 (0.1 - 0.3)	382 (356 - 408)	0.5 (0.4 - 0.6)	460 (434 - 486)	0.4 (0.3 - 0.5)
AFRO	568 (518 - 574)	0.2 (0.1 - 0.3)	394 (354 - 410)	0.7 (0.5 - 0.8)	474 (429 - 485)	0.5 (0.3 - 0.6)

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