

Correlates of Protection through multidimensional immune modelling across respiratory viruses

David Hodgson | Dec 2025 | SWIM 2025
Charité — Universitätsmedizin Berlin

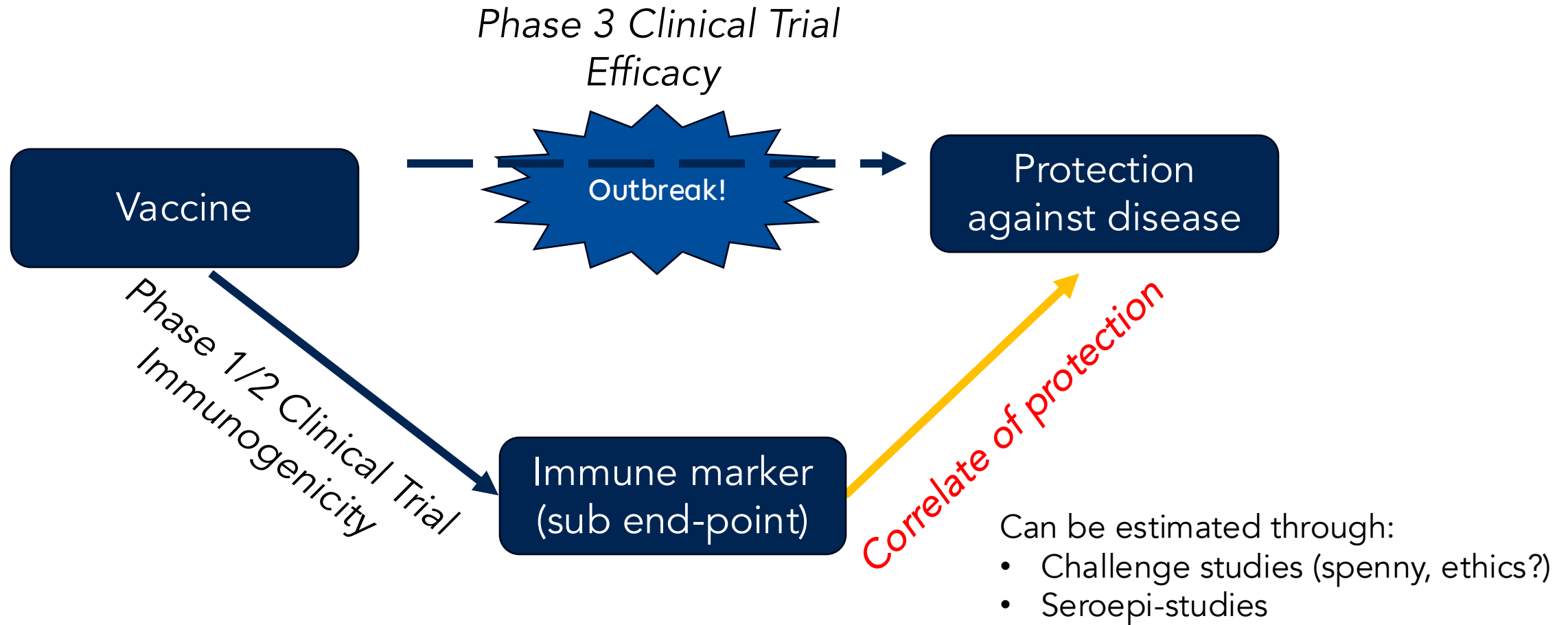
TALK AIM

“To systematically identify and compare correlates of protection across multiple biomarkers for respiratory viruses using rigorous statistical methods”

Specific objectives

1. Develop a framework for determining CoP in natural history cohort studies
 - Estimate CoR and CoP using serological and infection history data
 - Address key challenge: cannot directly measure exposure in real-world setting
2. Identify the “best” single biomarker CoP of biomarkers
 - Compare predictive capacity across multiple serum and mucosal biomarkers
 - Apply rigorous statistical criteria (AUC, out of sample prediction)
3. Assess value of combined biomarker CoP models
 - Test whether combining serum and mucosal markers improves predictive capacity
 - Quantify added benefit beyond single biomarkers

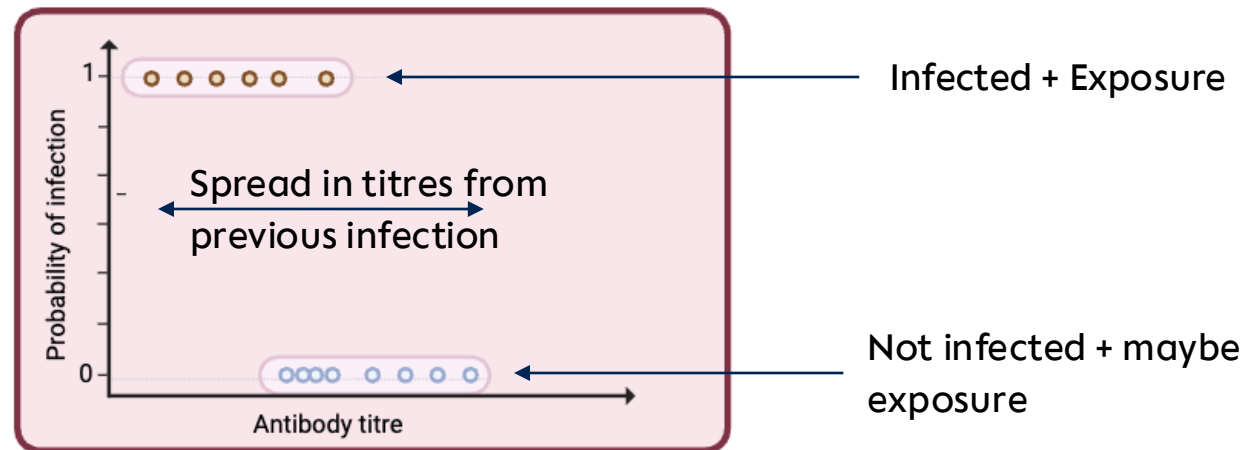
WHAT IS A CORRELATE OF PROTECTION?



NATURAL HISTORY STUDIES (NOT RCT)

Use of cohort studies

- In cohort studies, we can identify correlates by studying people who've been naturally infected previously



Limitation

- Don't know who's exposed
- No randomisation, hard to say anything truly causal as about these correlates of protection
- Thus, a correlate of risk and correlate of protection in this context has literal interpretation

STATISTICAL METHODS

Assume a continuous relationship between titre and infection

We fit a (bayesian) generalised logistic curve to the CoR/infection risk with:

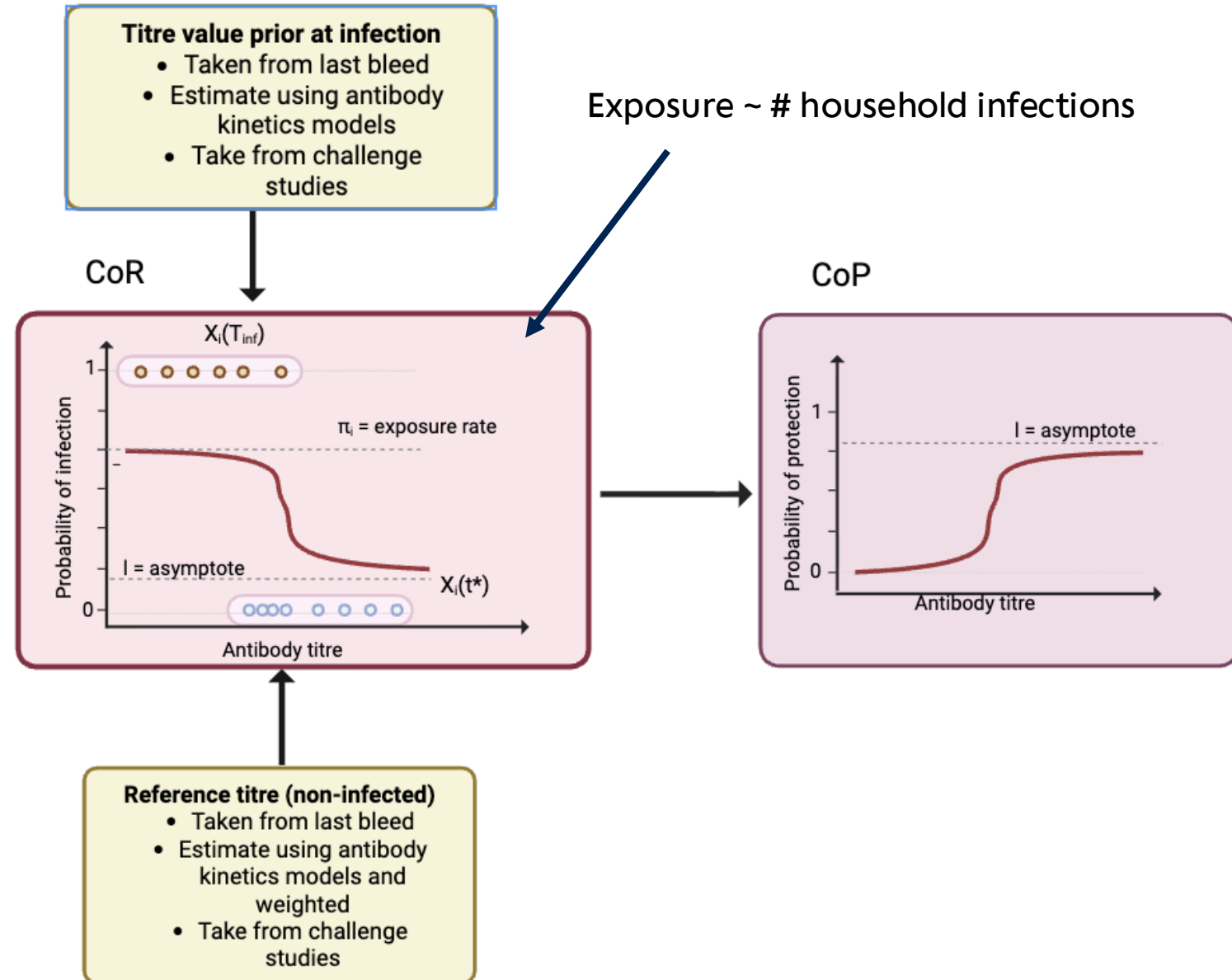
- Upper asymptote = exposure rate
- Lower asymptote = antibody doesn't provide full protection

To get CoP, marginalise out the exposure and find the inverse.

In maths:

$COR := \pi[1 - f(x, \beta)]$ <- we fit this

$COP := f(x, \beta)$



STATISTICAL METHODS

We fit a logistic curve to the CoR with

- Upper asymptote = exposure rate
- Lower asymptote = antibody doesn't provide full protection

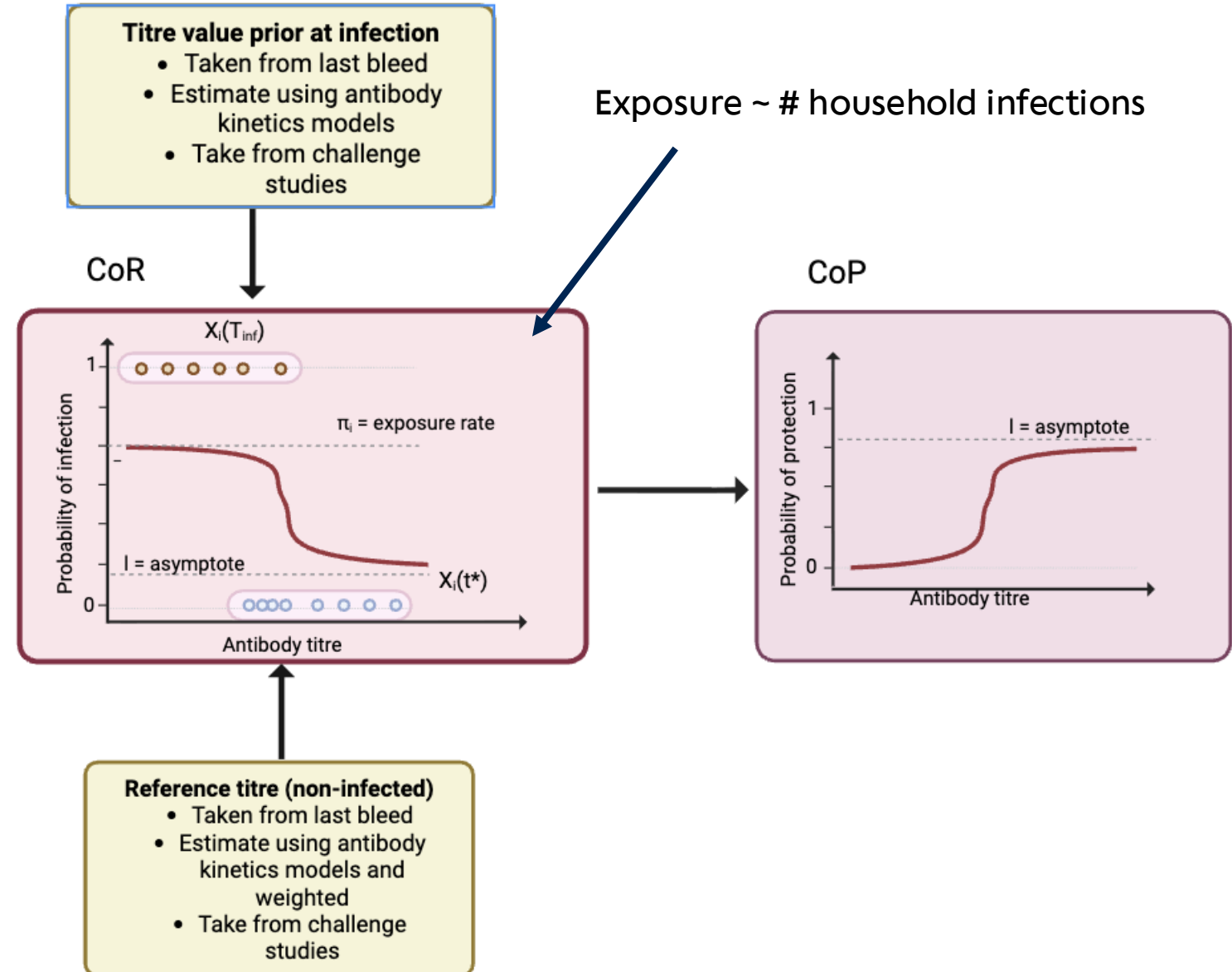
To get CoP, marginalise out the exposure and find the inverse.

In maths:

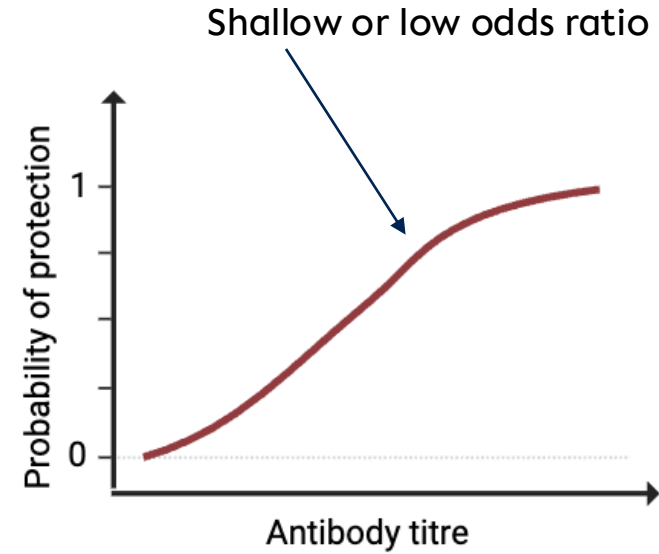
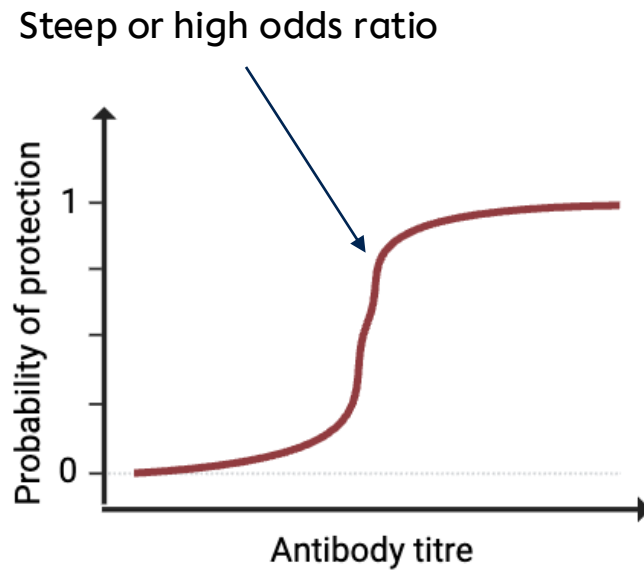
$COR := \pi[1 - f(x, \beta)]$ <- we fit this

$COP := f(x, \beta)$

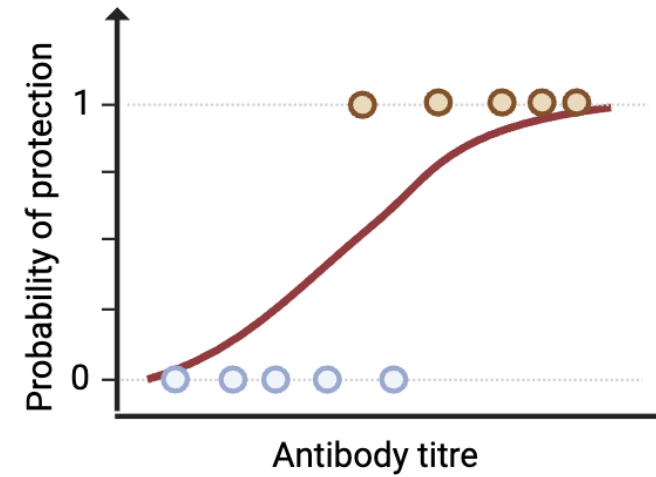
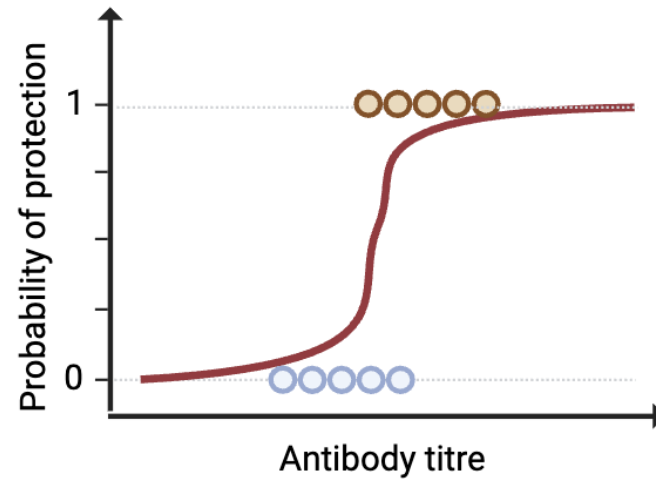
-> 2 biomarkers, multidimensional logistical regression



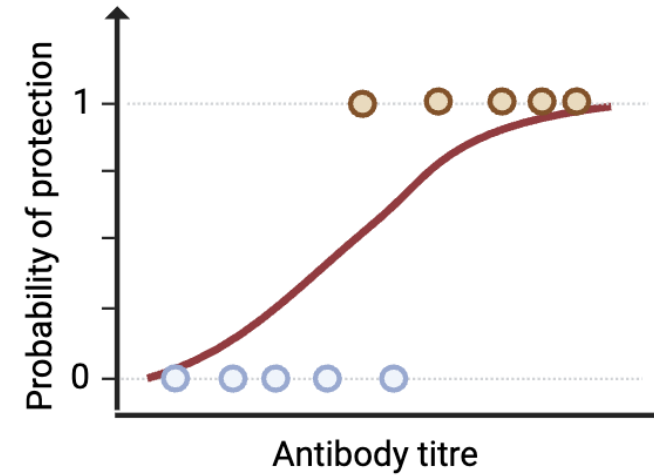
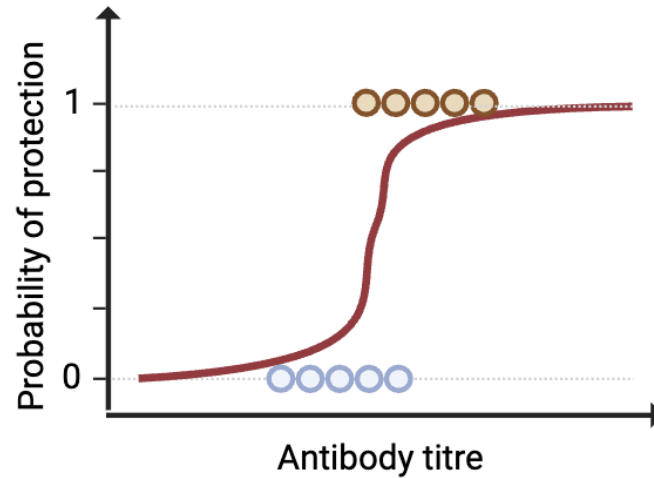
ASSESSMENT OF "GOODNESS" OF COP



ASSESSMENT OF "GOODNESS" OF COP



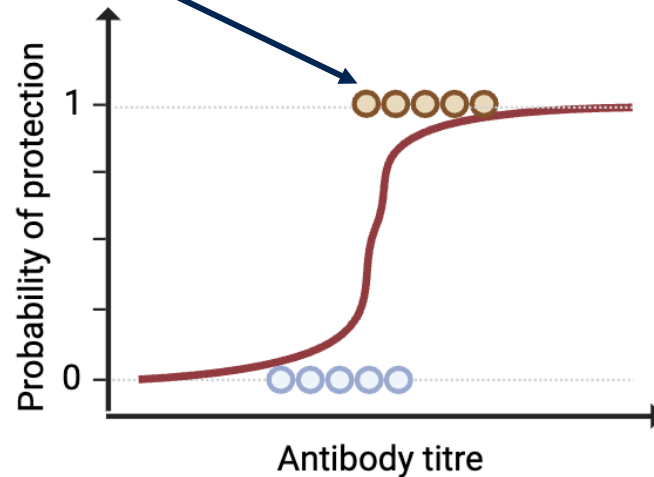
ASSESSMENT OF "GOODNESS" OF COP



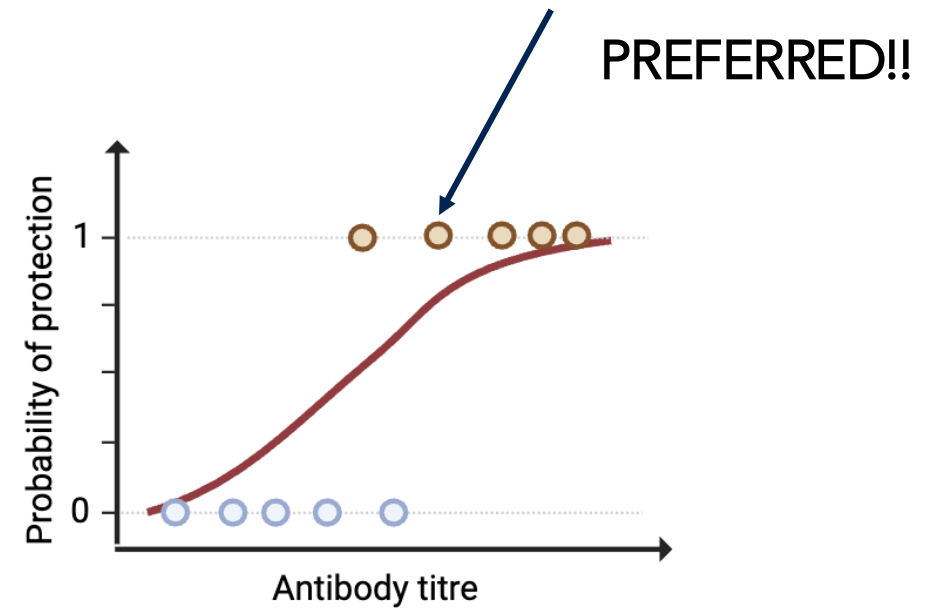
If you are making inferences using fitted model which isn't able to discriminate between those who are infection and those who are not, then it has limited practical use as a CoP => more of an association of protection

ASSESSMENT OF "GOODNESS" OF COP

Could have poor predictive performance



Could have better predictive performance



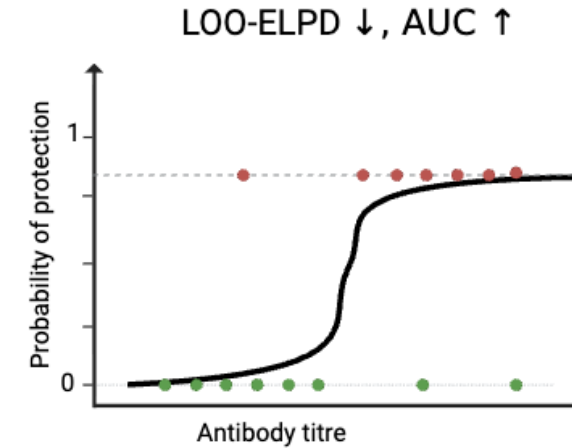
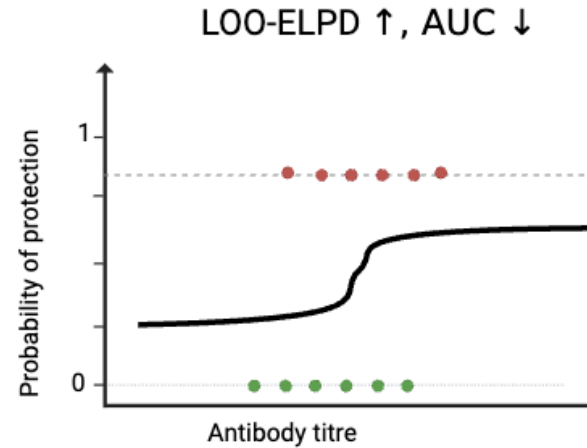
PLAN:

- Compare predictive performance of the fitted curve for each correlate
- Choose the biomarker with the best predictive performance -> better support for causality
- SIDE NOTE: generally in 1D [odds ratio + p-value] \approx performance, but not true in higher dimensions

METRICS USED

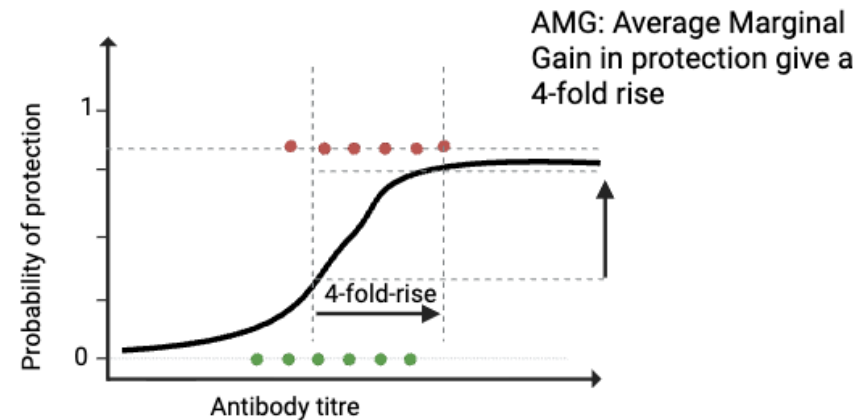
Predictive performance

- Discrimination: AUC
- Out-of-sample predictive fit: LOO-ELPD



Protection impact and applicability

- Impact: AMG, β
- Applicability: Coverage



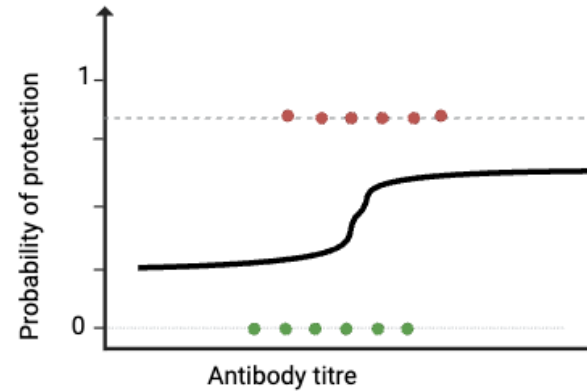
METRICS USED

Predictive performance

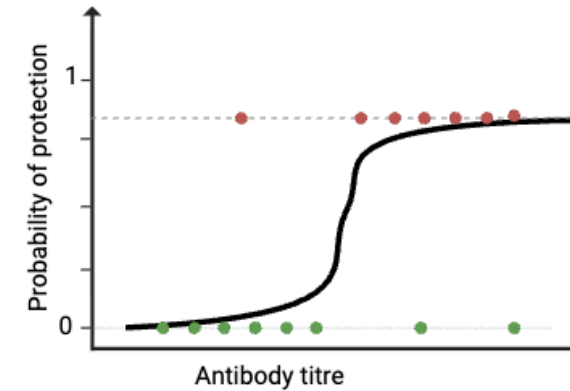
- Discrimination: AUC
- Out-of-sample predictive fit: LOO-ELPD

Trans-dimensionally comparable

LOO-ELPD \uparrow , AUC \downarrow

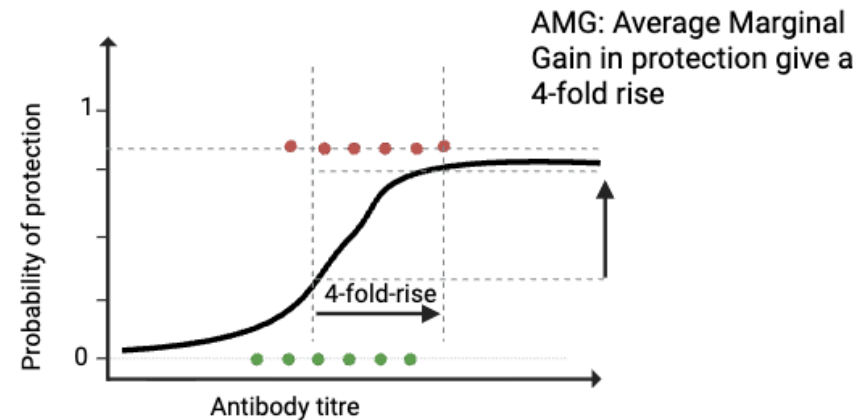


LOO-ELPD \downarrow , AUC \uparrow



Protection impact and applicability

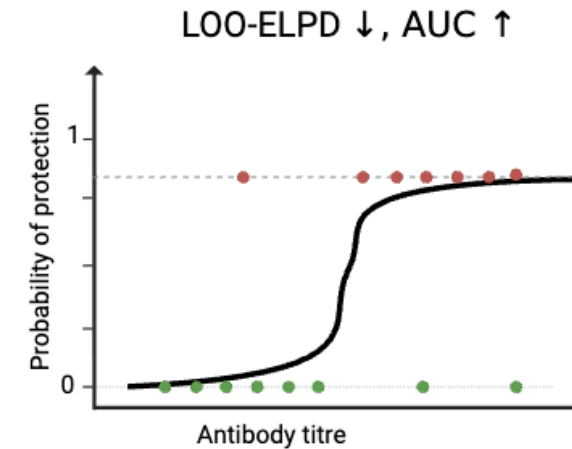
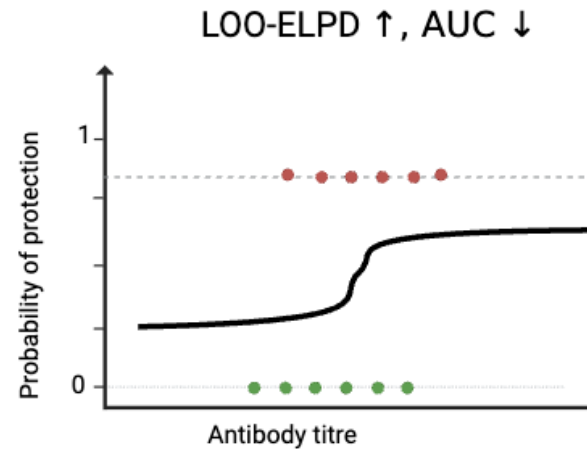
- Impact: AMG, β
- Applicability: Coverage



METRICS USED

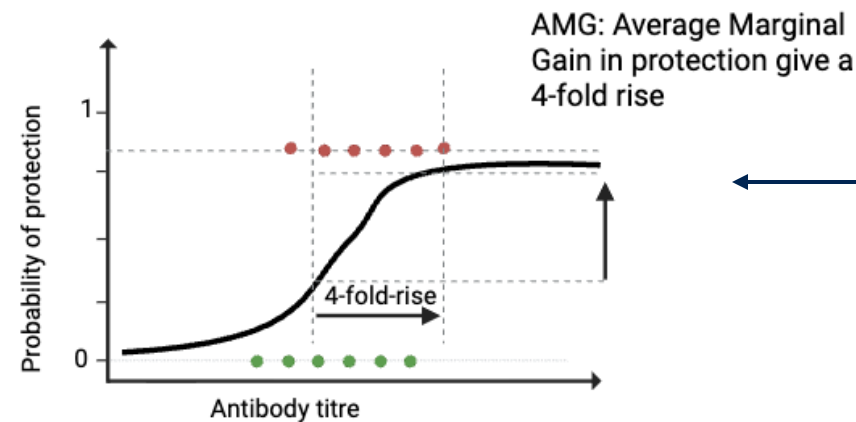
Predictive performance

- Discrimination: AUC
- Out-of-sample predictive fit: LOO-ELPD



Protection impact and applicability

- Impact: AMG, β
- Applicability: Coverage



If we boosted everyone's pre-exposure titre by 4-fold, how much more protected would the population be?

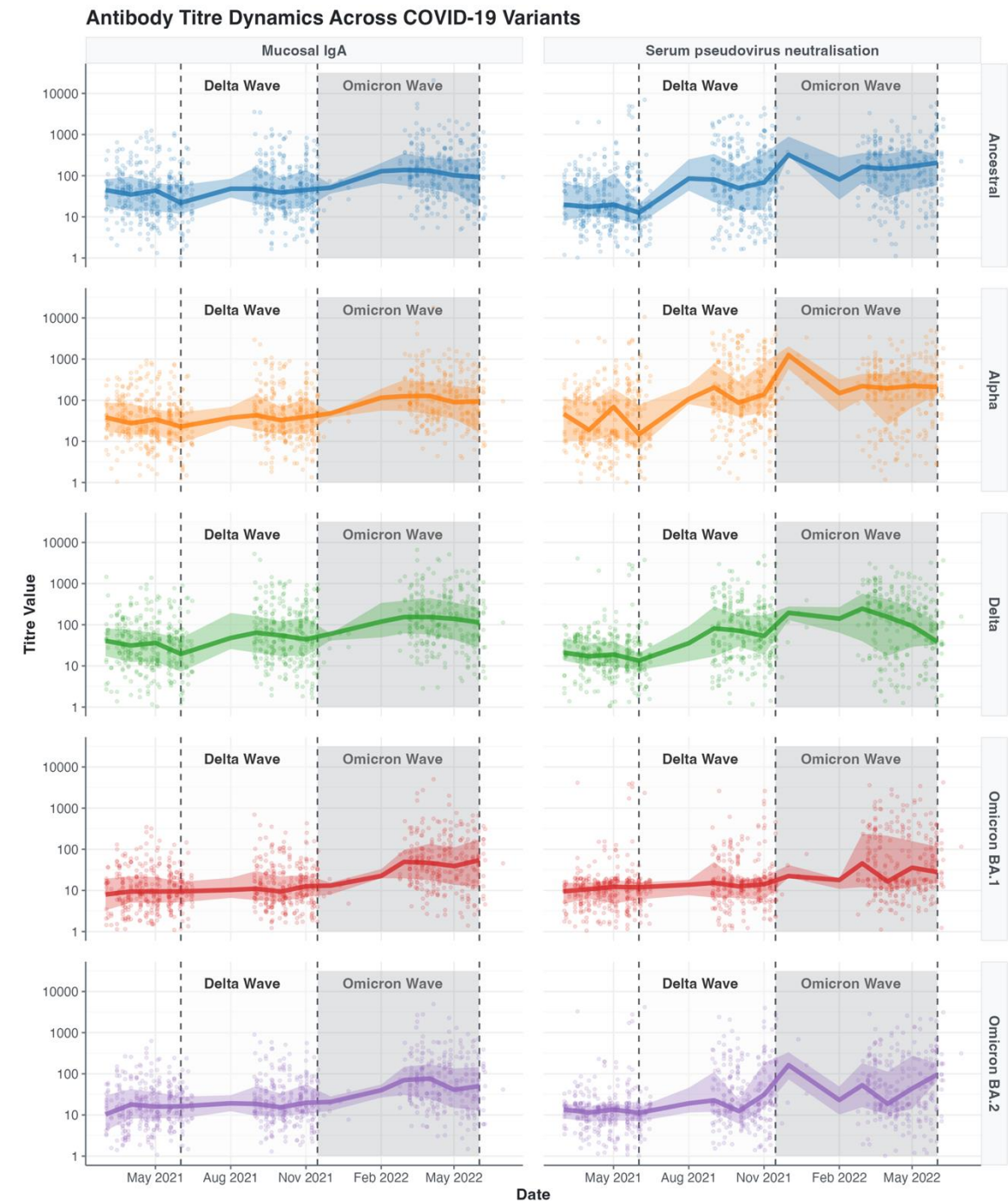
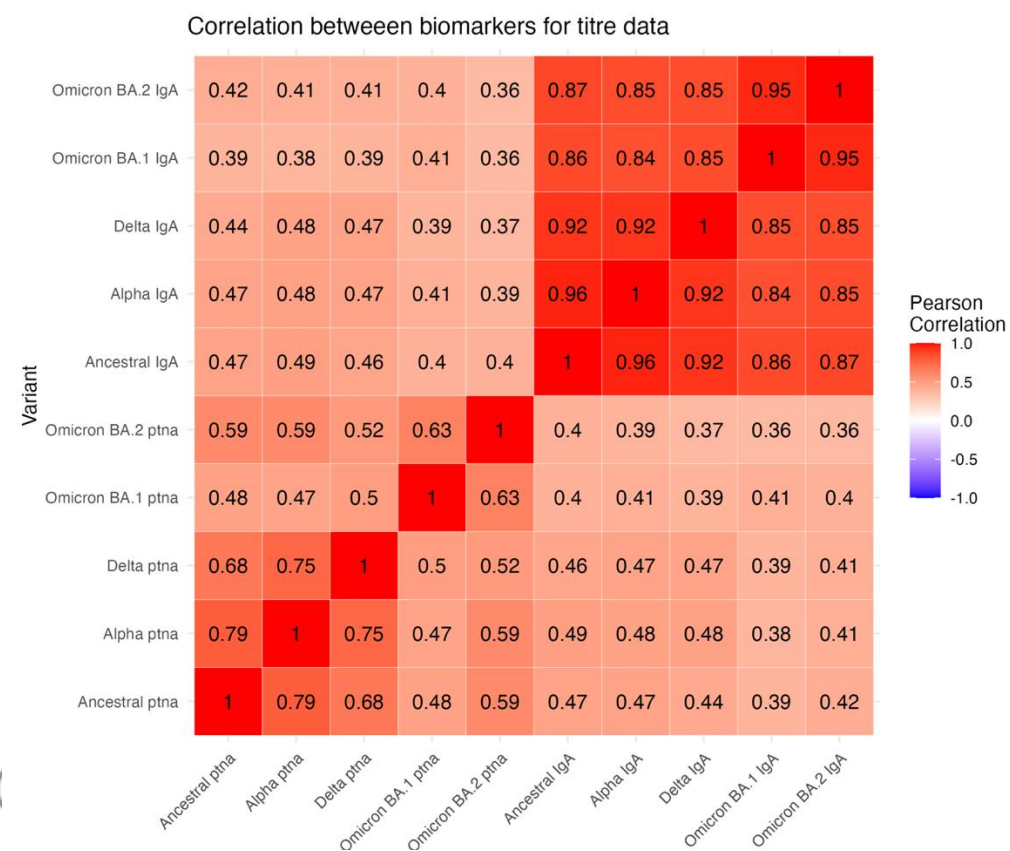
CASE 1: SARS-CoV-2 in The Gambia

TRANSVIR Study (vaccine naïve)

N = 256 people, 308 days, 2 bleeds person,

Two wave; Delta wave and Omicron BA.1 wave

PCR swabbing weekly, CoP against infection (~70% asymptomatic)



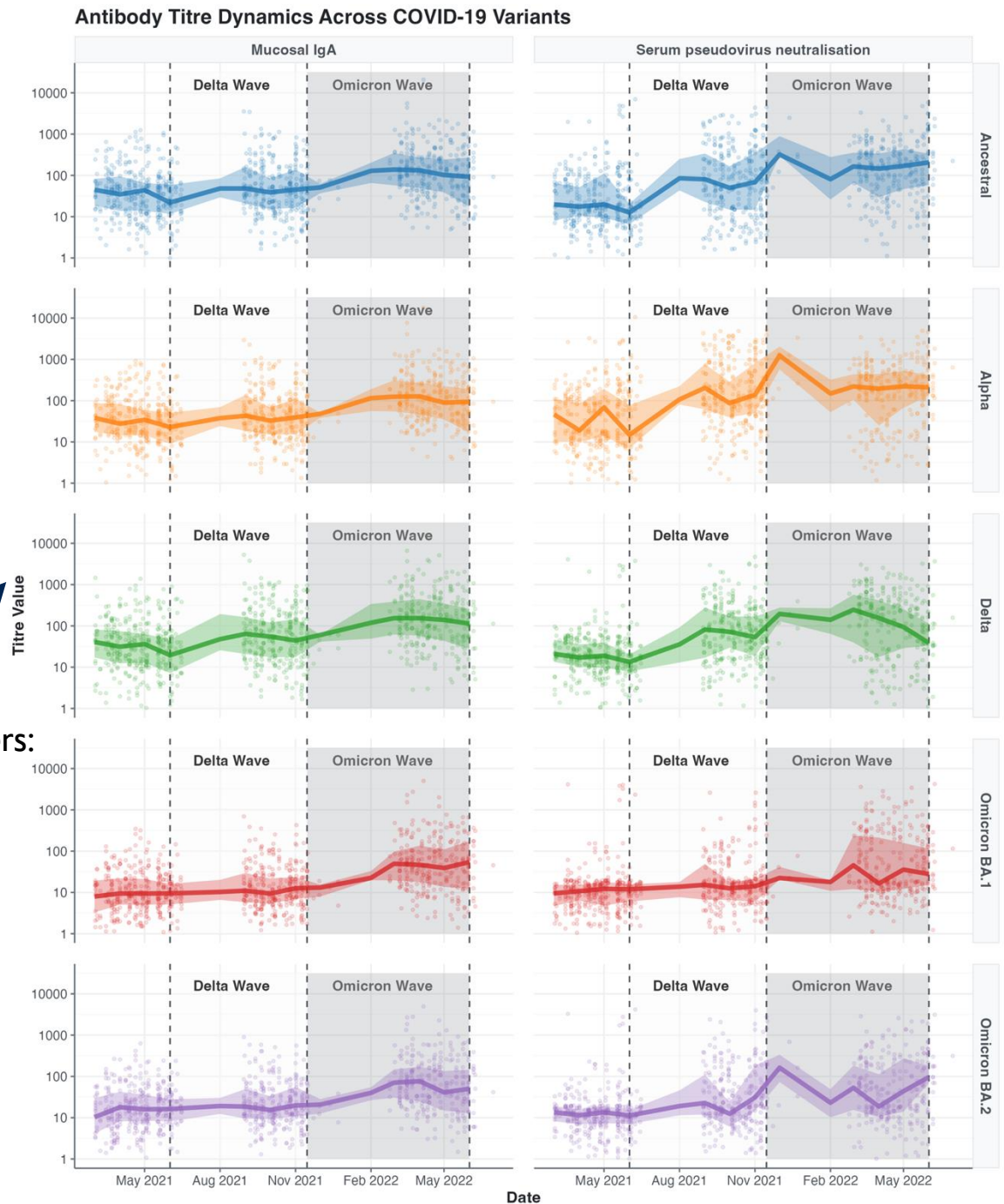
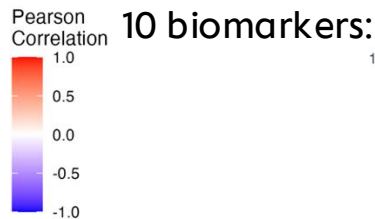
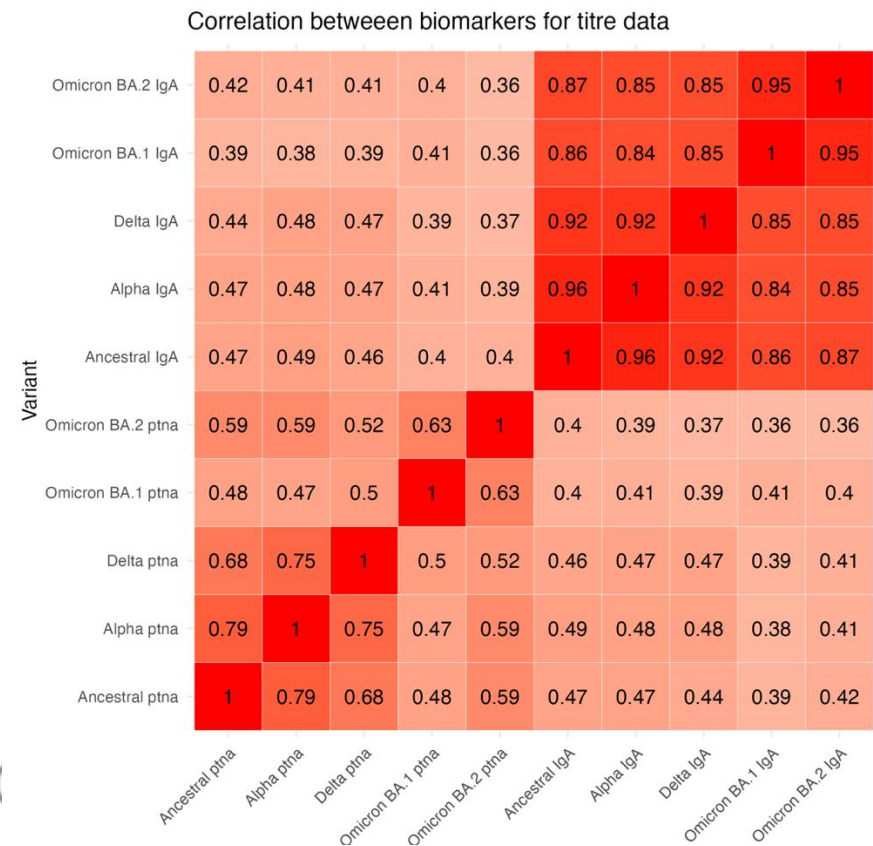
CASE 1: SARS-CoV-2 in The Gambia

TRANSVIR Study (vaccine naïve)

N = 256 people, 308 days, 2 bleeds person,

Two wave; Delta wave and Omicron BA.1 wave

PCR swabbing weekly, CoP against infection (~70% asymptomatic)



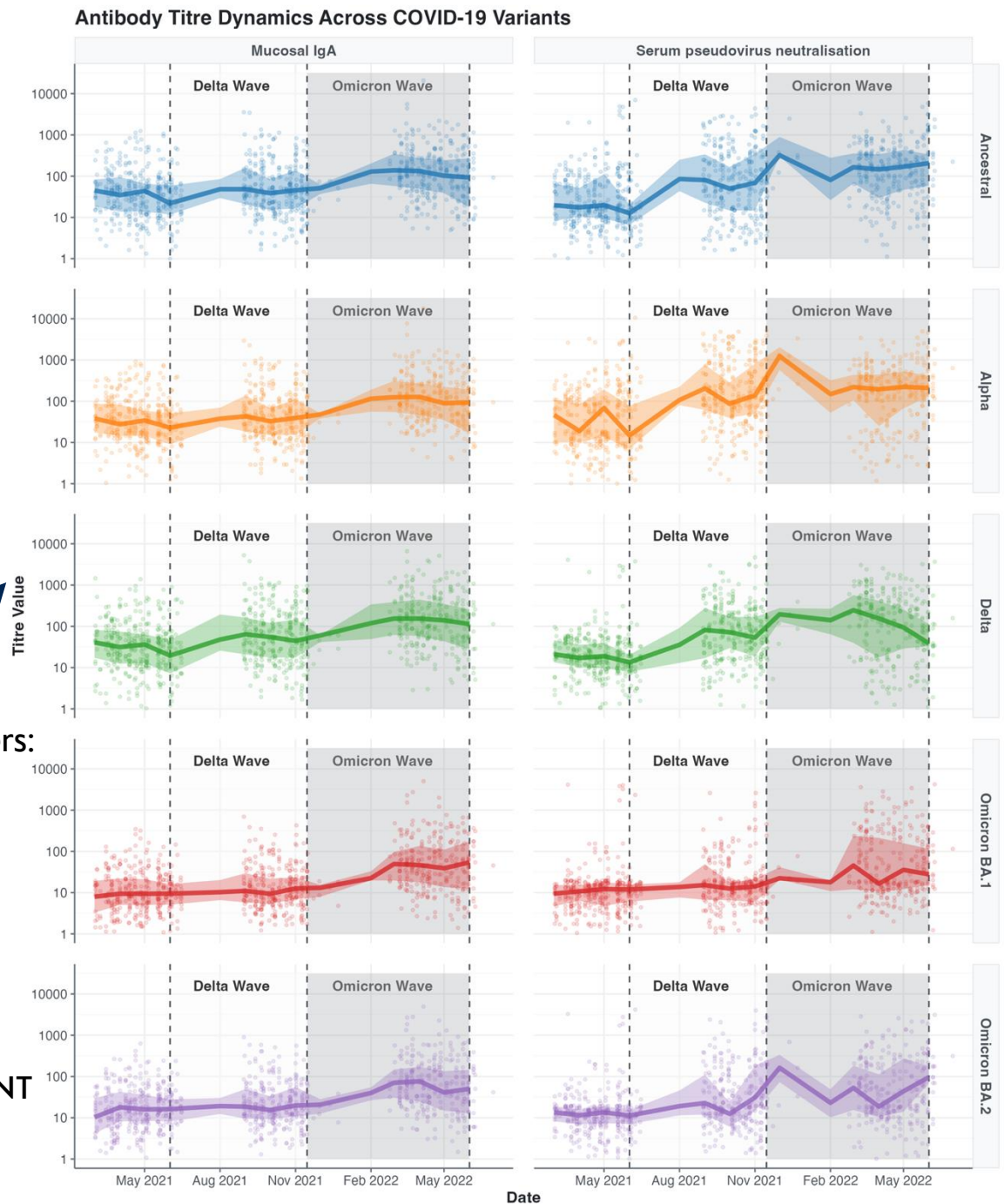
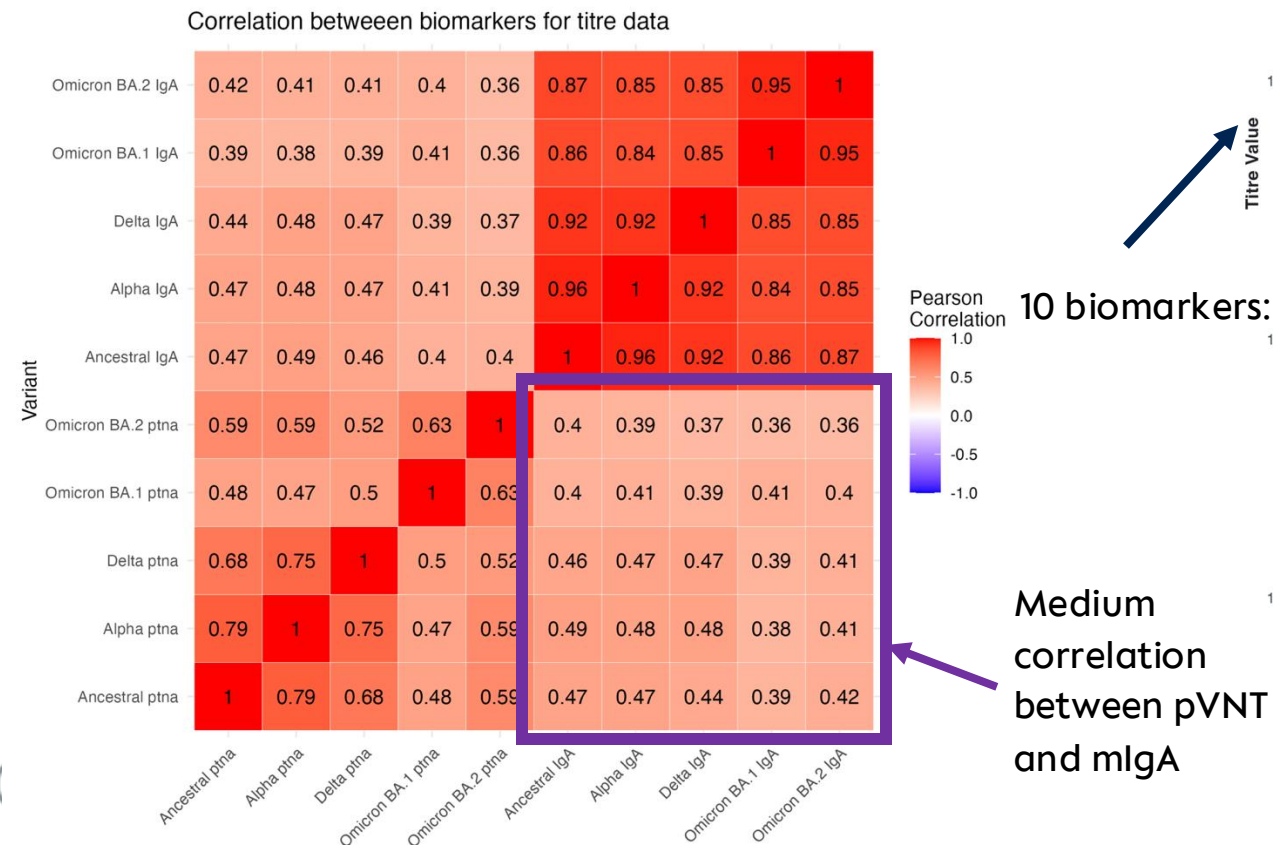
CASE 1: SARS-CoV-2 in The Gambia

TRANSVIR Study (vaccine naïve)

N = 256 people, 308 days, 2 bleeds person,

Two wave; Delta wave and Omicron BA.1 wave

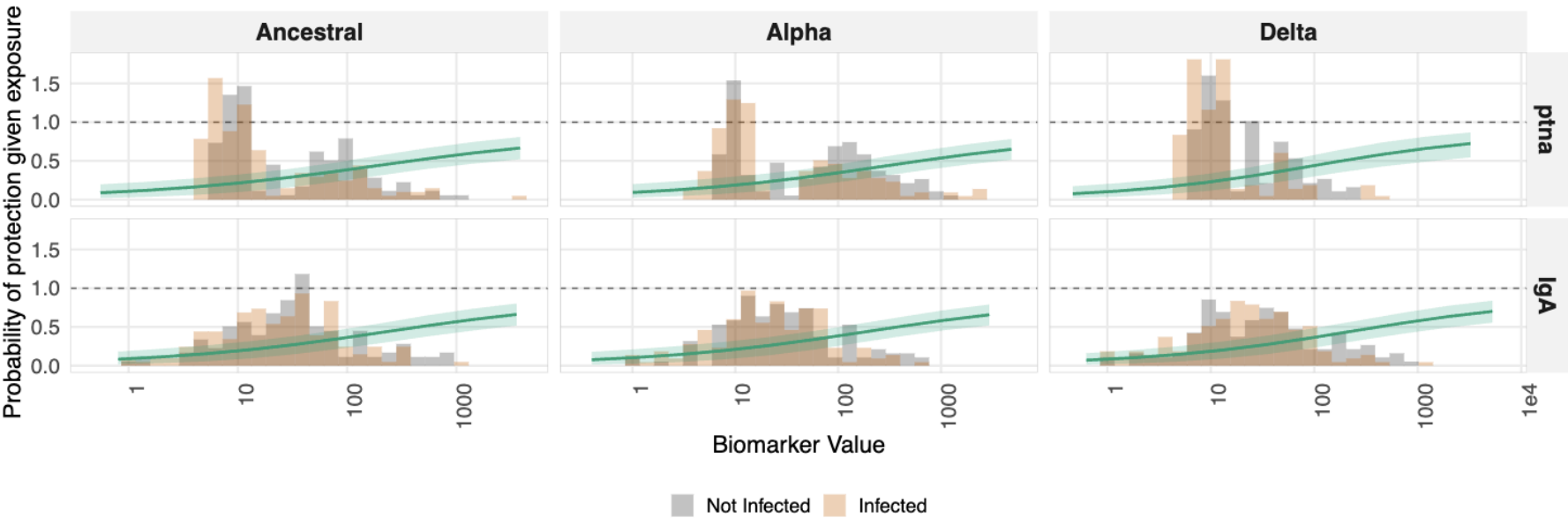
PCR swabbing weekly, CoP against infection (~70% asymptomatic)



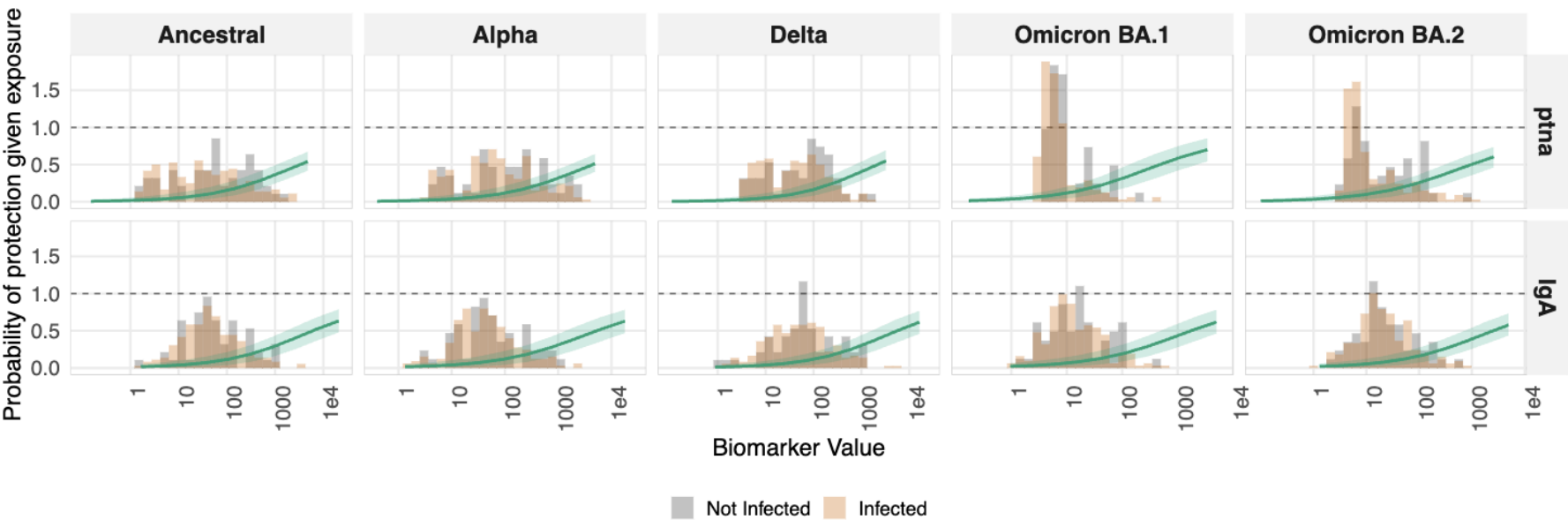
RESULTS FOR SARS-CoV-2

A. Correlates of Protection

Delta wave



Omicron wave



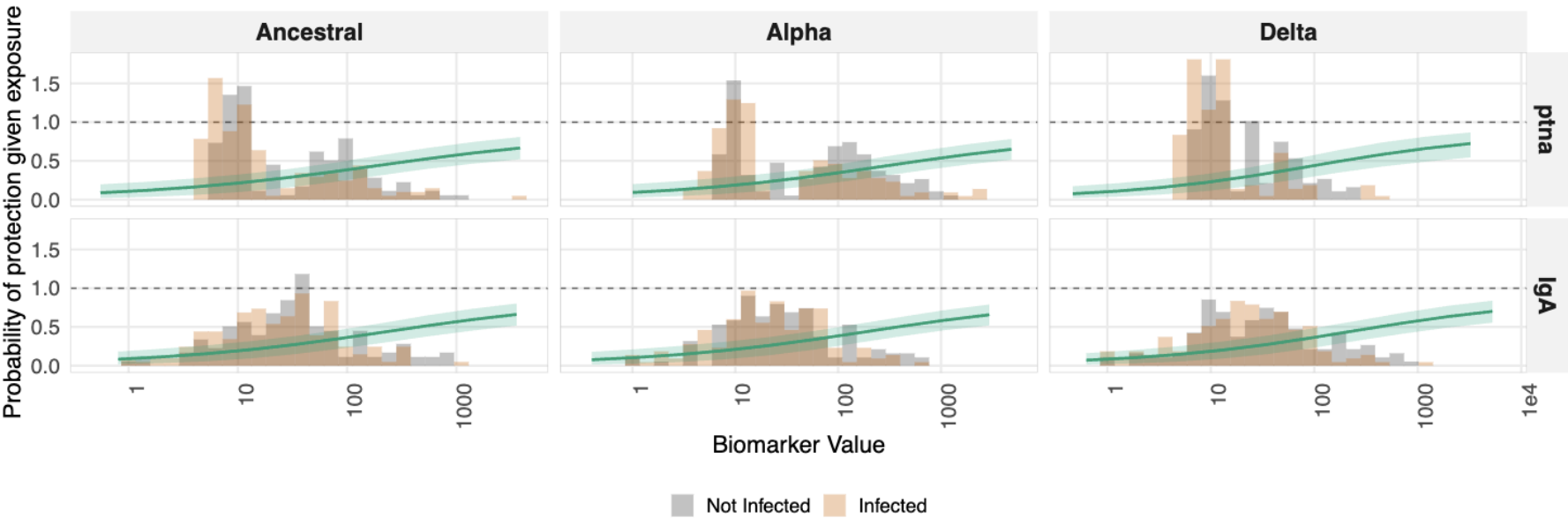
RESULTS FOR SARS-CoV-2

Which of these biomarkers is the best COP?

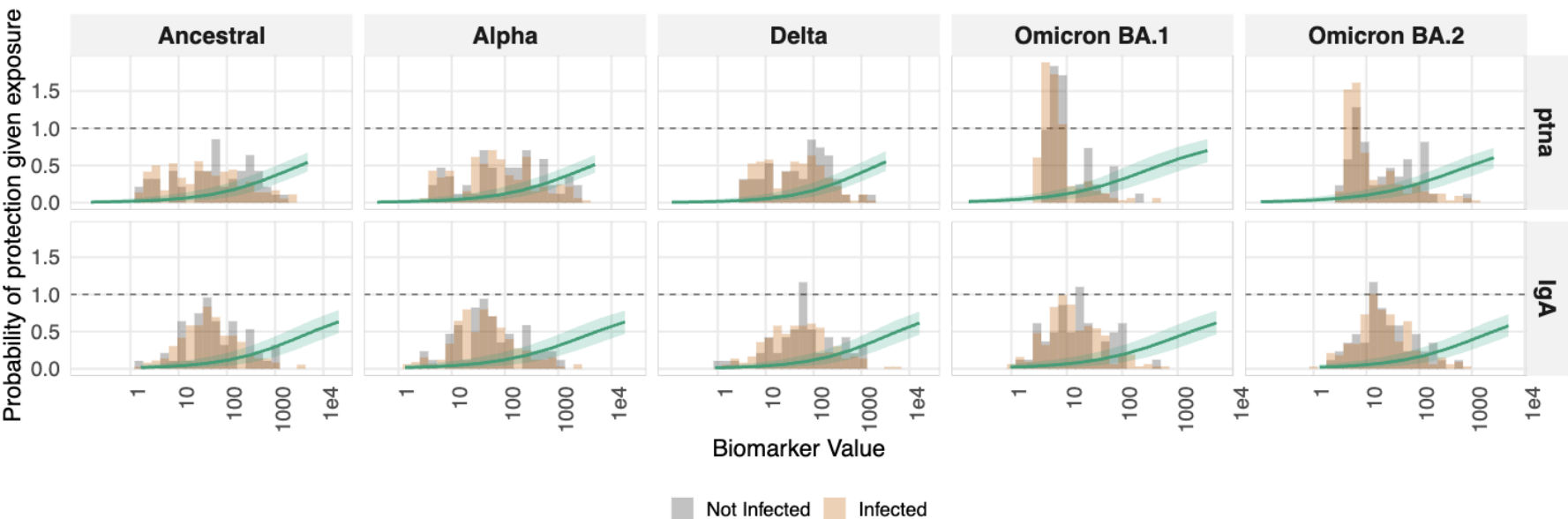
Determine predictive capacity!!

A. Correlates of Protection

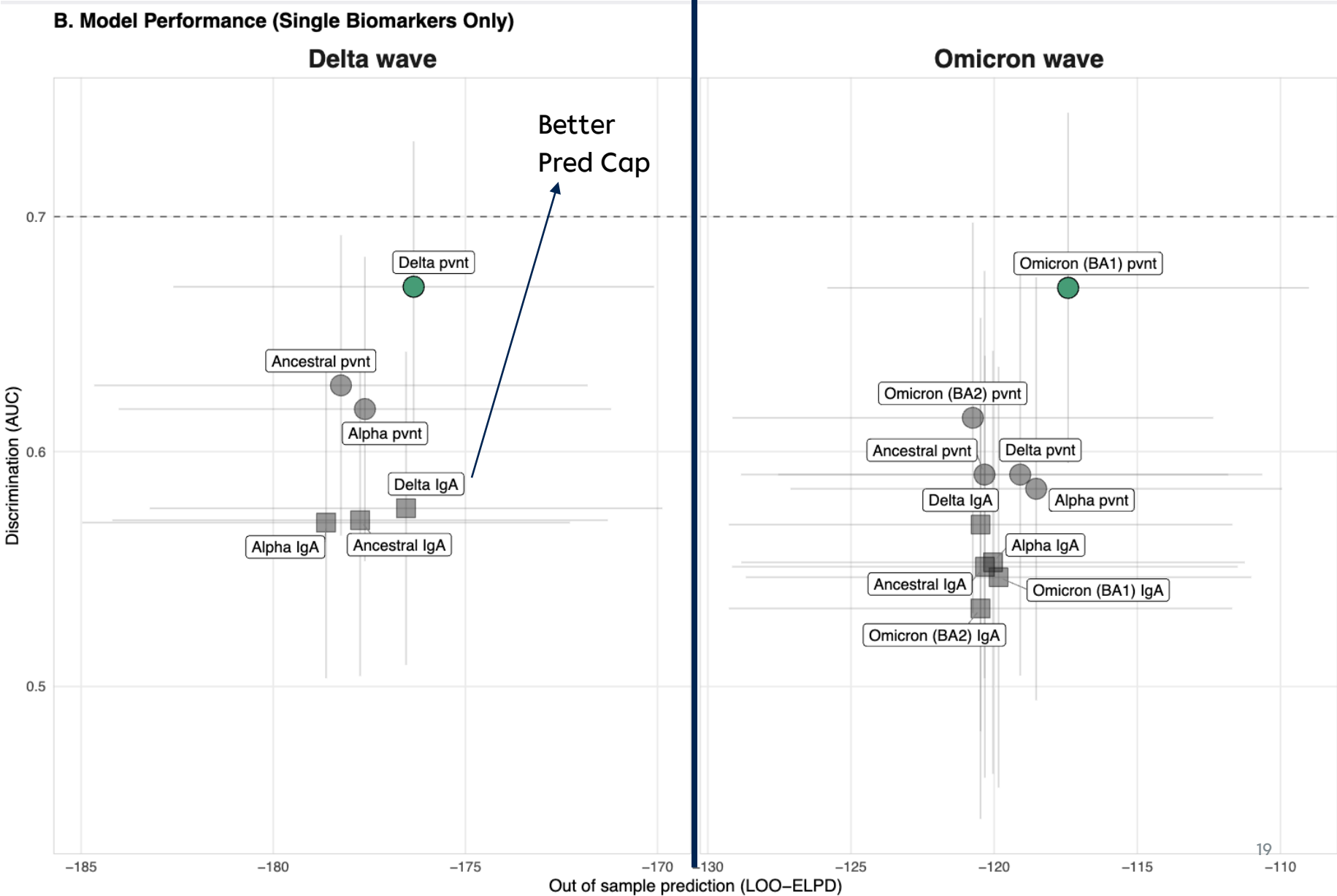
Delta wave



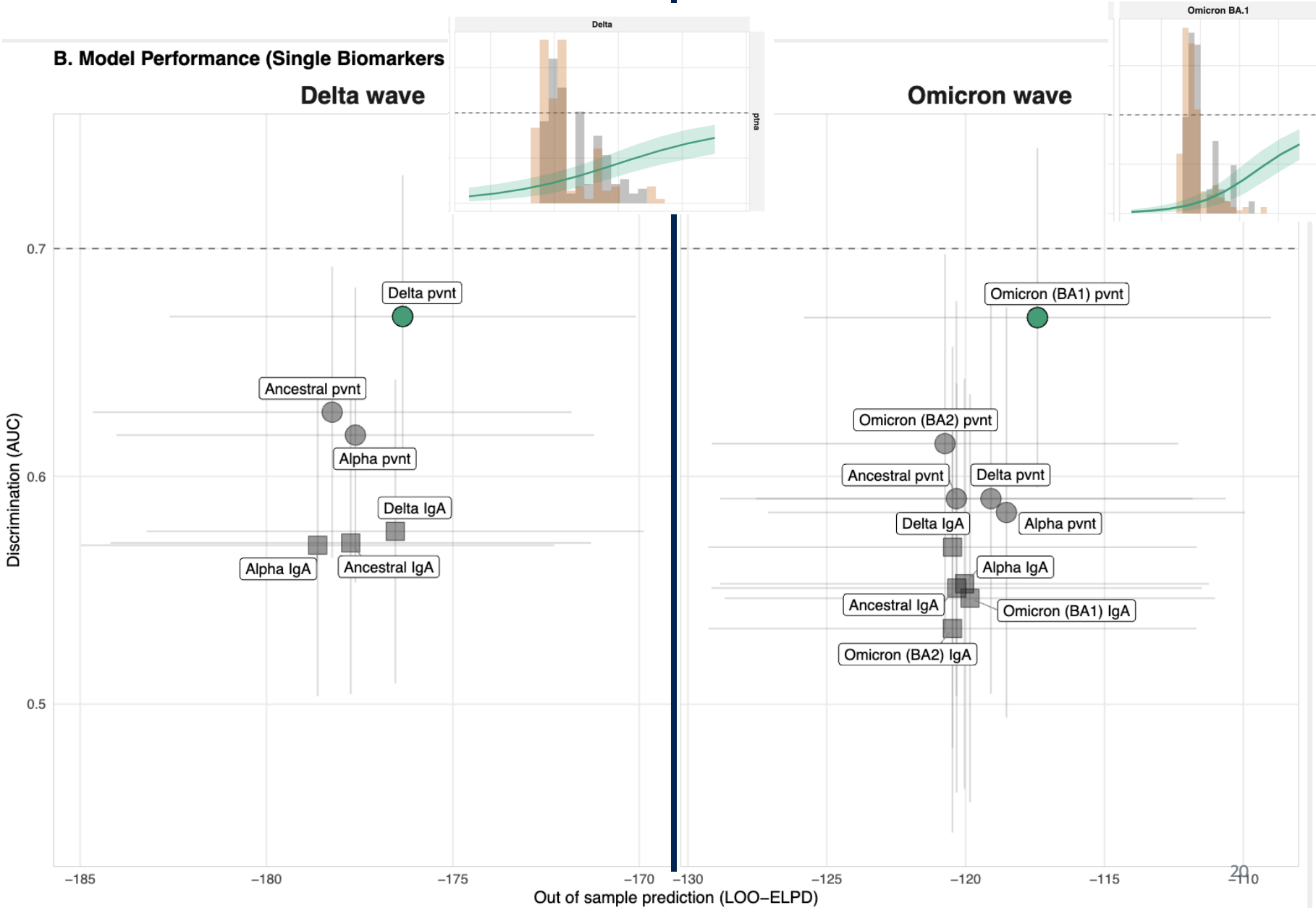
Omicron wave



RESULTS FOR SARS-CoV-2

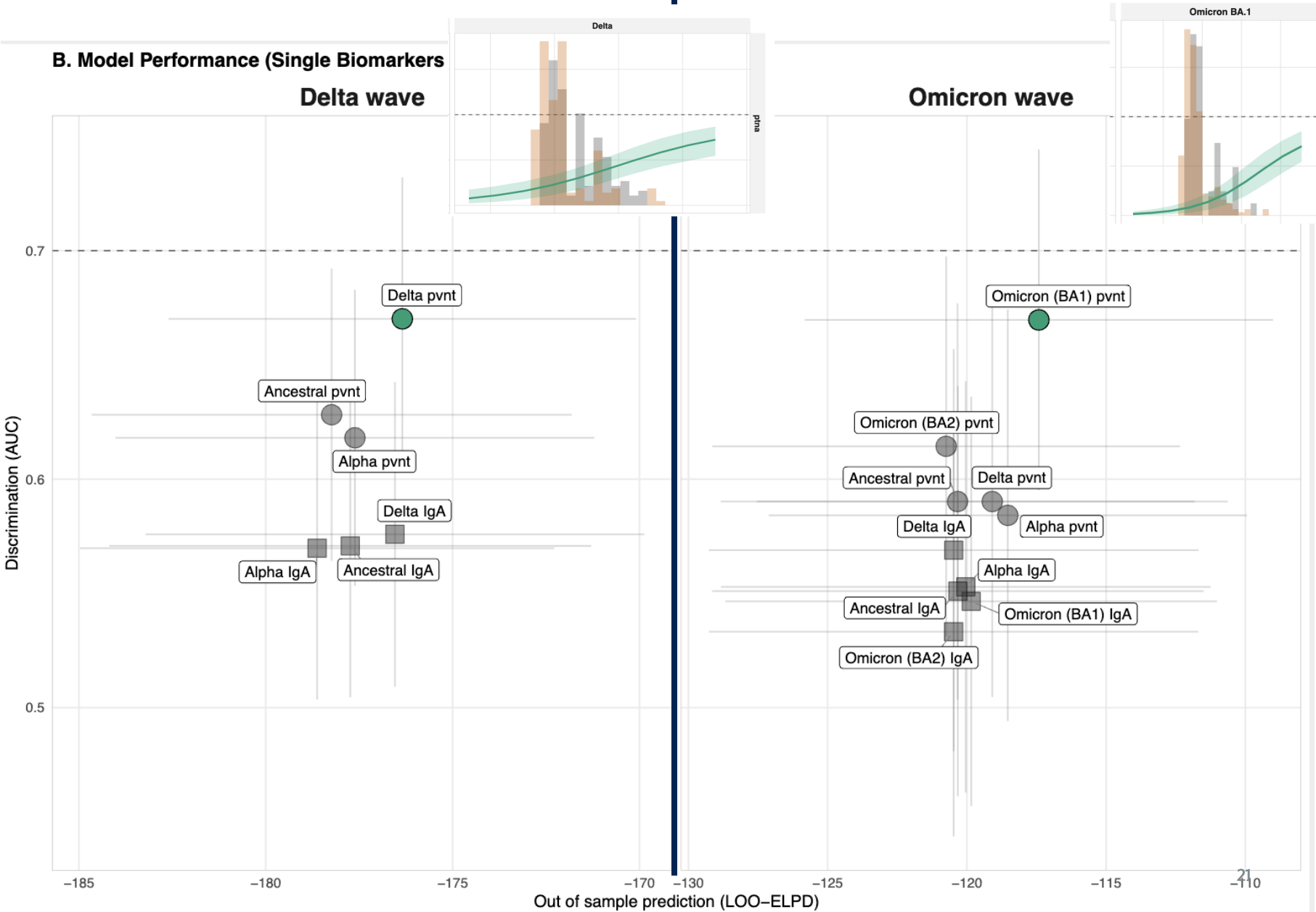


RESULTS FOR SARS-CoV-2



RESULTS FOR SARS-CoV-2

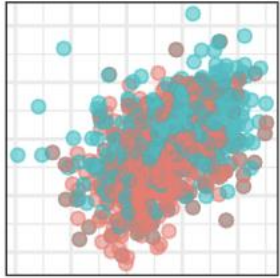
What happens if we look at combining Delta pNTA and Delta mIgA?



RESULTS FOR SARS-CoV-2

Adding mIgA to pTNA decreases predictive capacity!

Why?

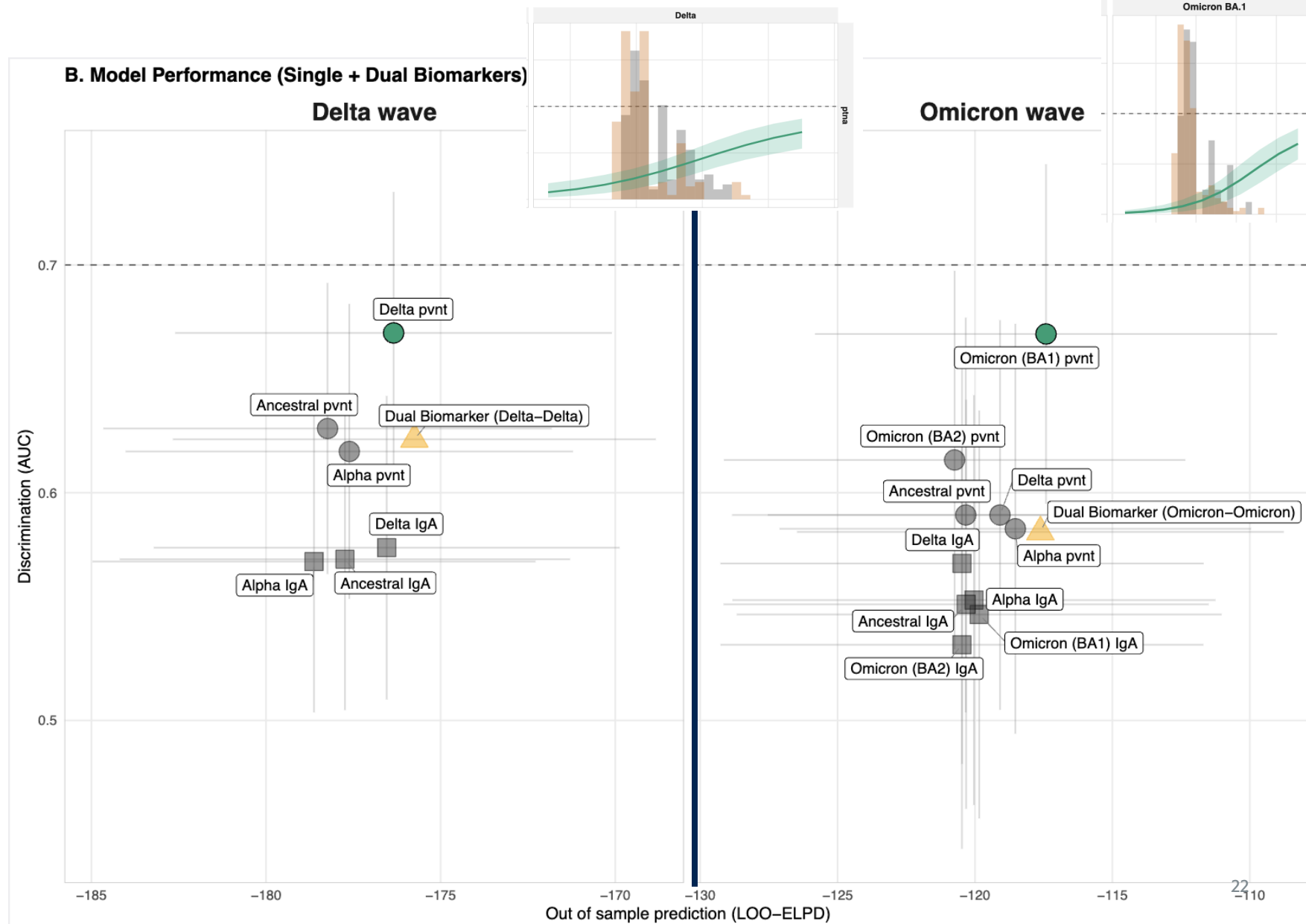


- * Correlation between pTNA and mIgA

- * mIgA very noisy

2 dimensional model overfits—pTNA only better

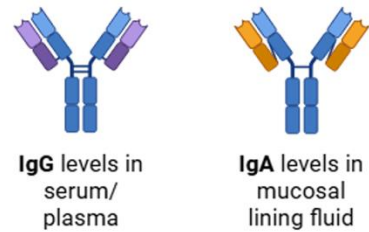
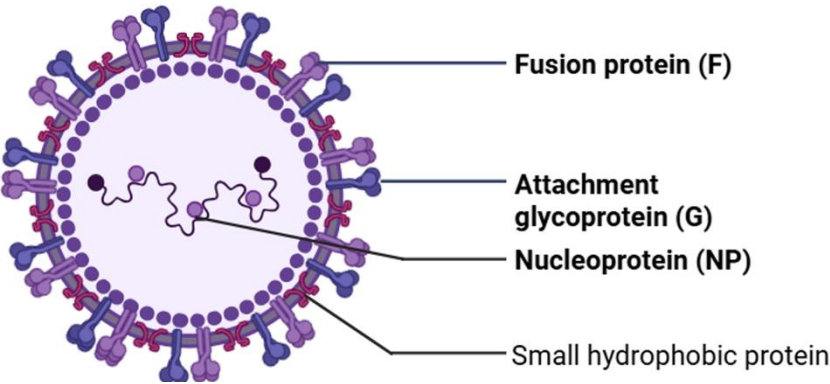
Best to stick to pTNA only
Make sense, pTNA is a functional measure, dominated binding assay



CASE 2: RSV in The Gambia

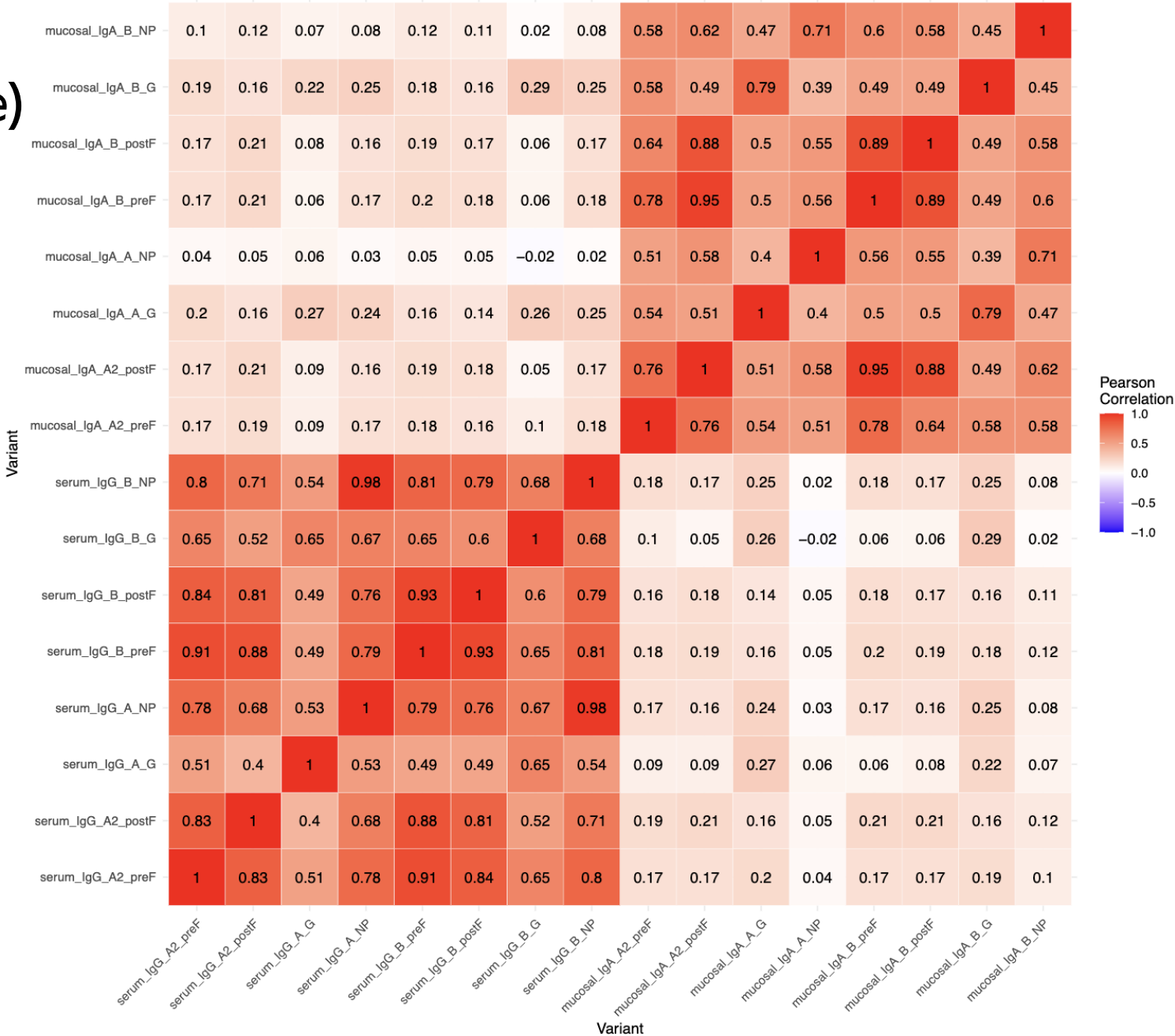
TRANSVIR Study (vaccine naïve)

N = 256 people, 308 days, 2–5 bleeds person



- PreF, PostF, G, NP
- A and B serotype
 - mIgA and sIgG

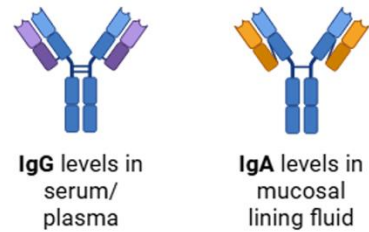
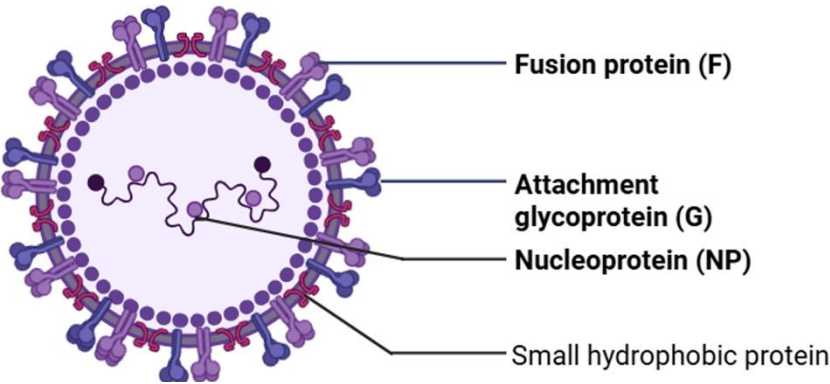
Correlation between biomarkers for titre data



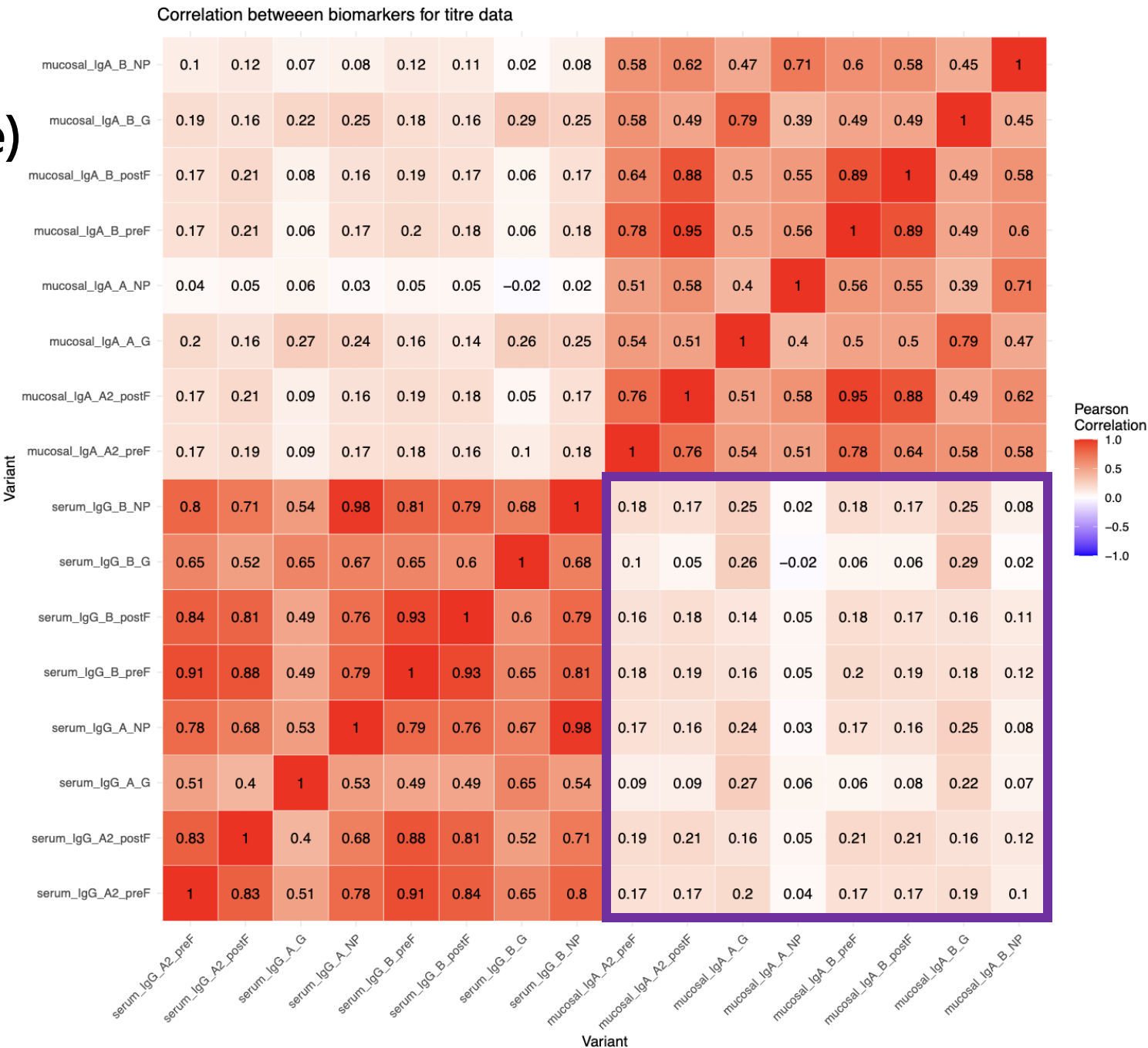
CASE 2: RSV in The Gambia

TRANSVIR Study (vaccine naïve)

N = 256 people, 308 days, 2–5 bleeds person

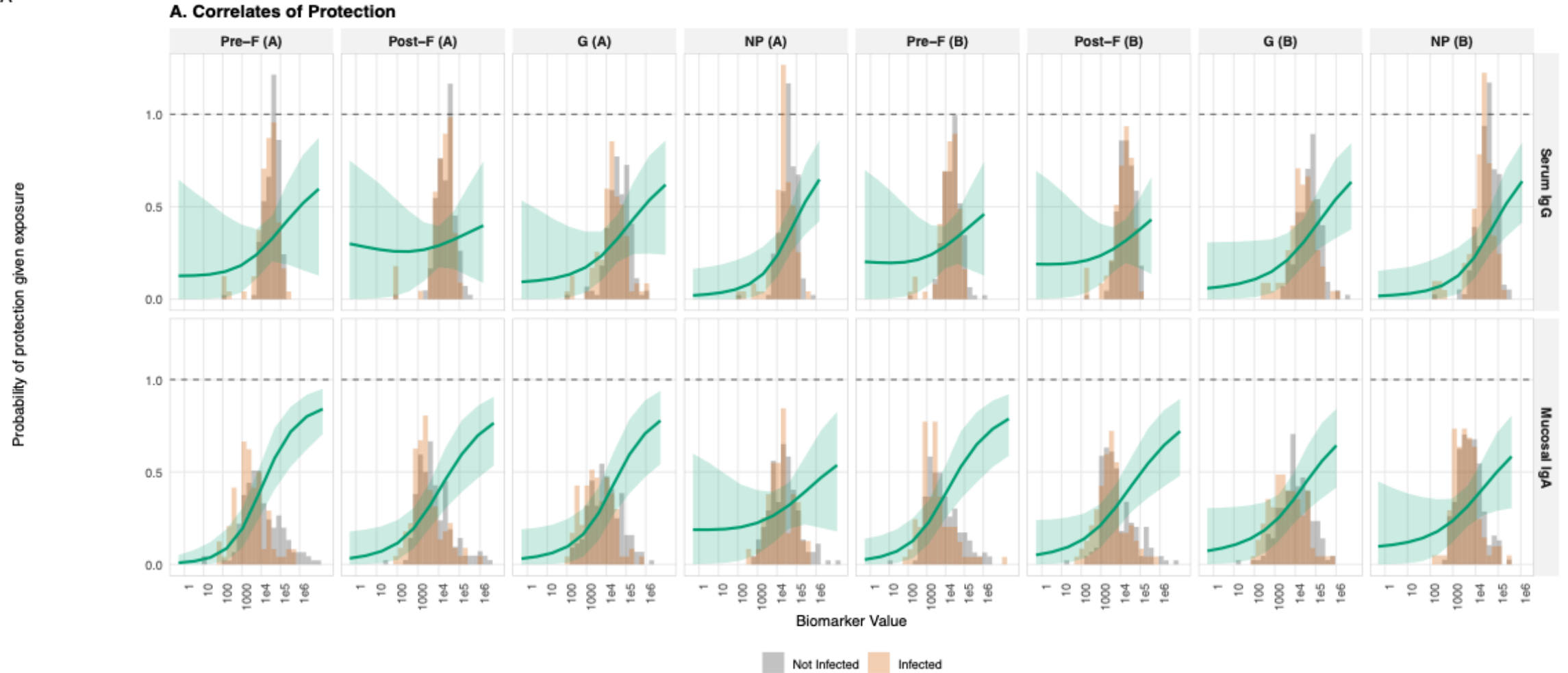


- PreF, PostF, G, NP
- A and B serotype
 - mIgA and sIgG



FITTED COP FOR RSV

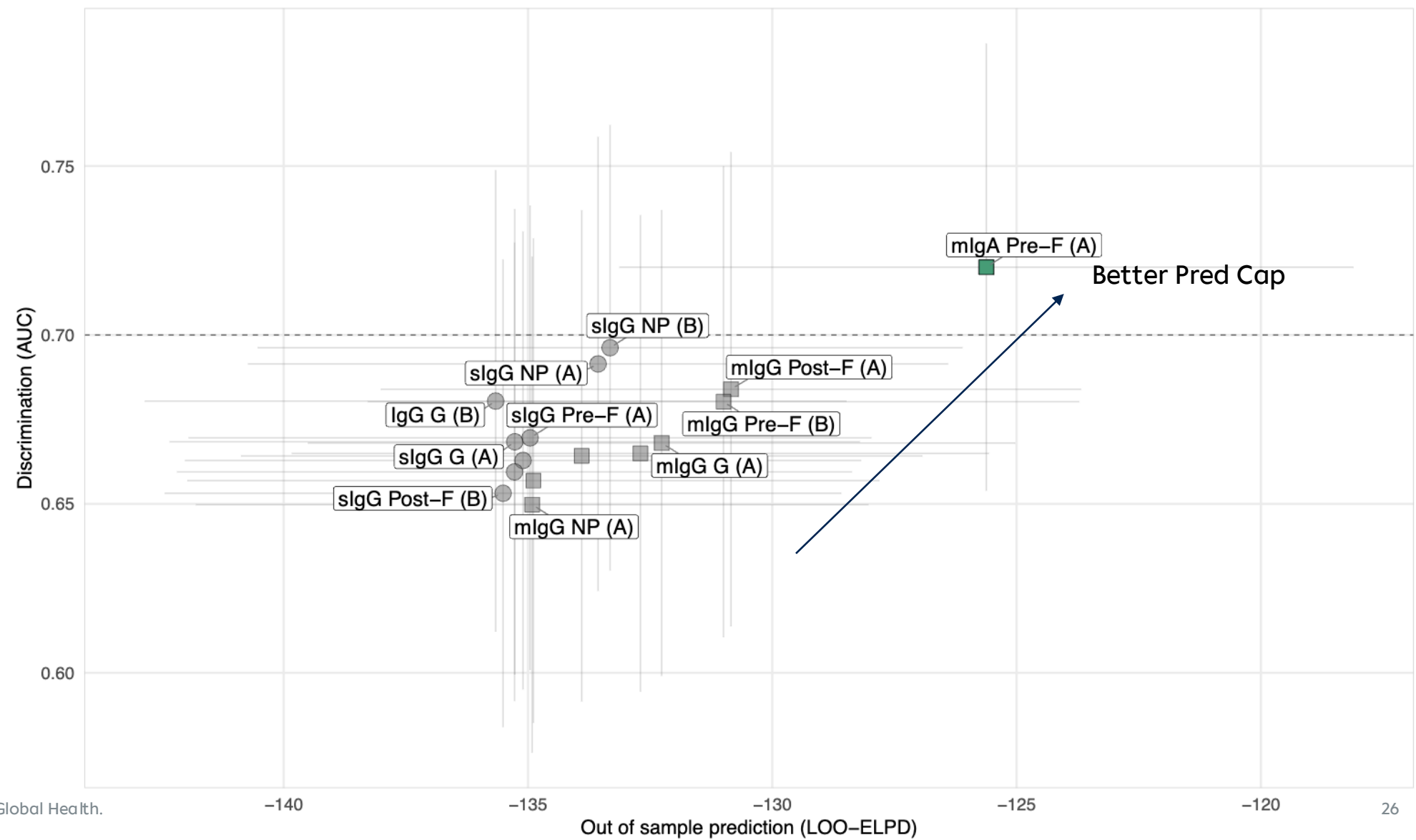
A



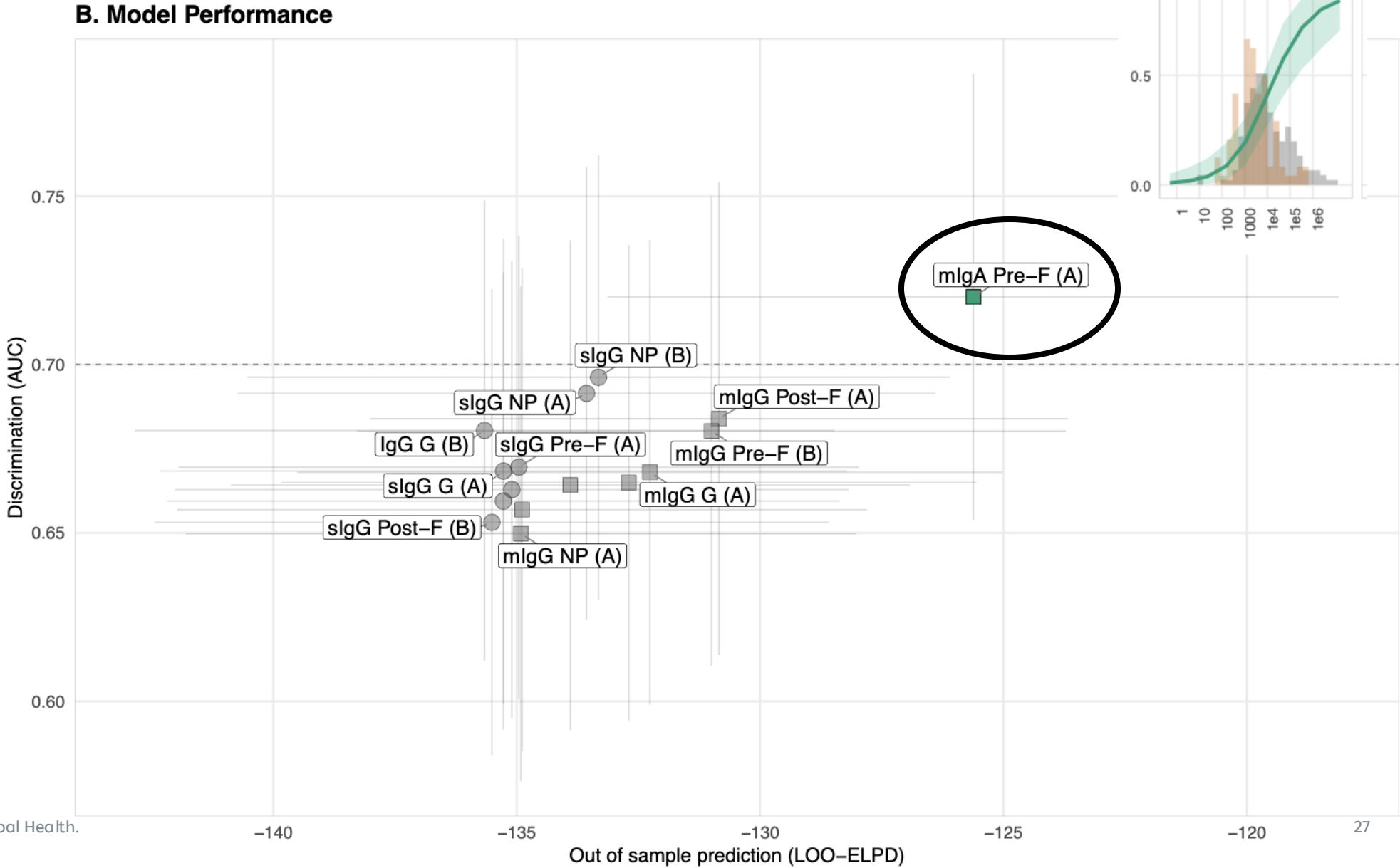
B

BEST PREDICTIVE MODEL FOR COP

B. Model Performance

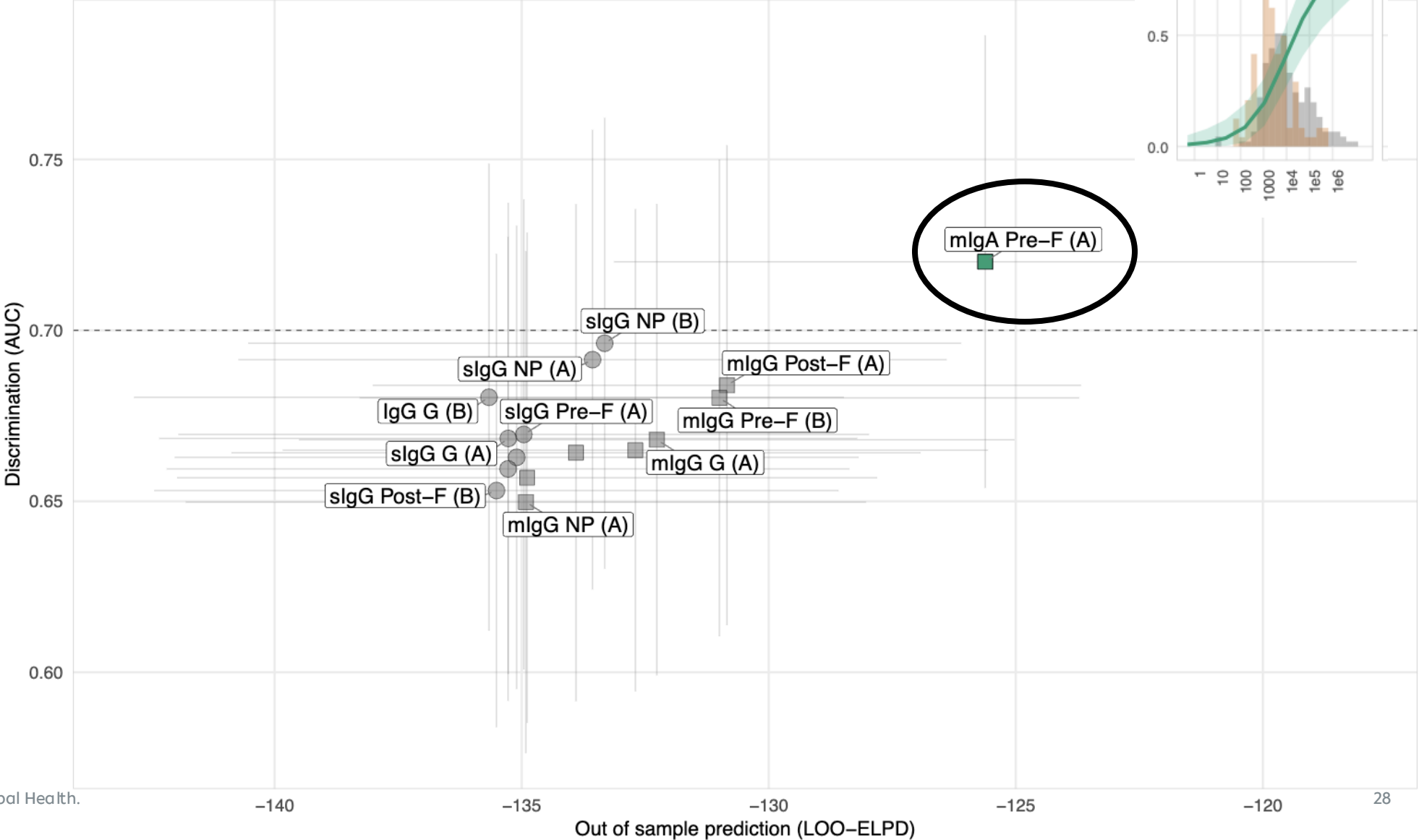


BEST PREDICTIVE MODEL FOR COP



BEST PREDICTIVE MODEL FOR COP

B. Model Performance

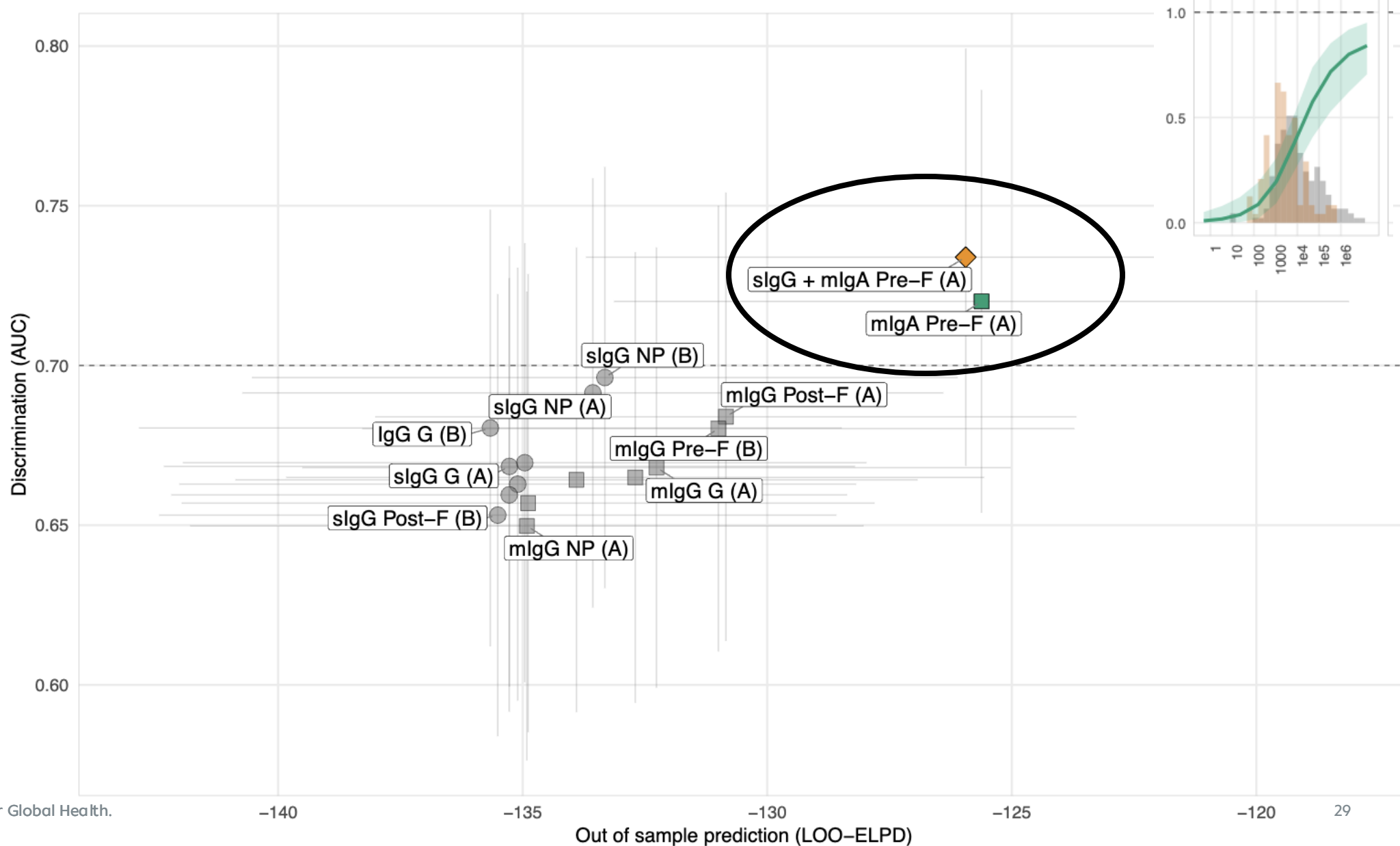


What happens when we add slgG to mlgA?

BEST PREDICTIVE MODEL FOR COP

B. Model Performance

What does
surface look
like?

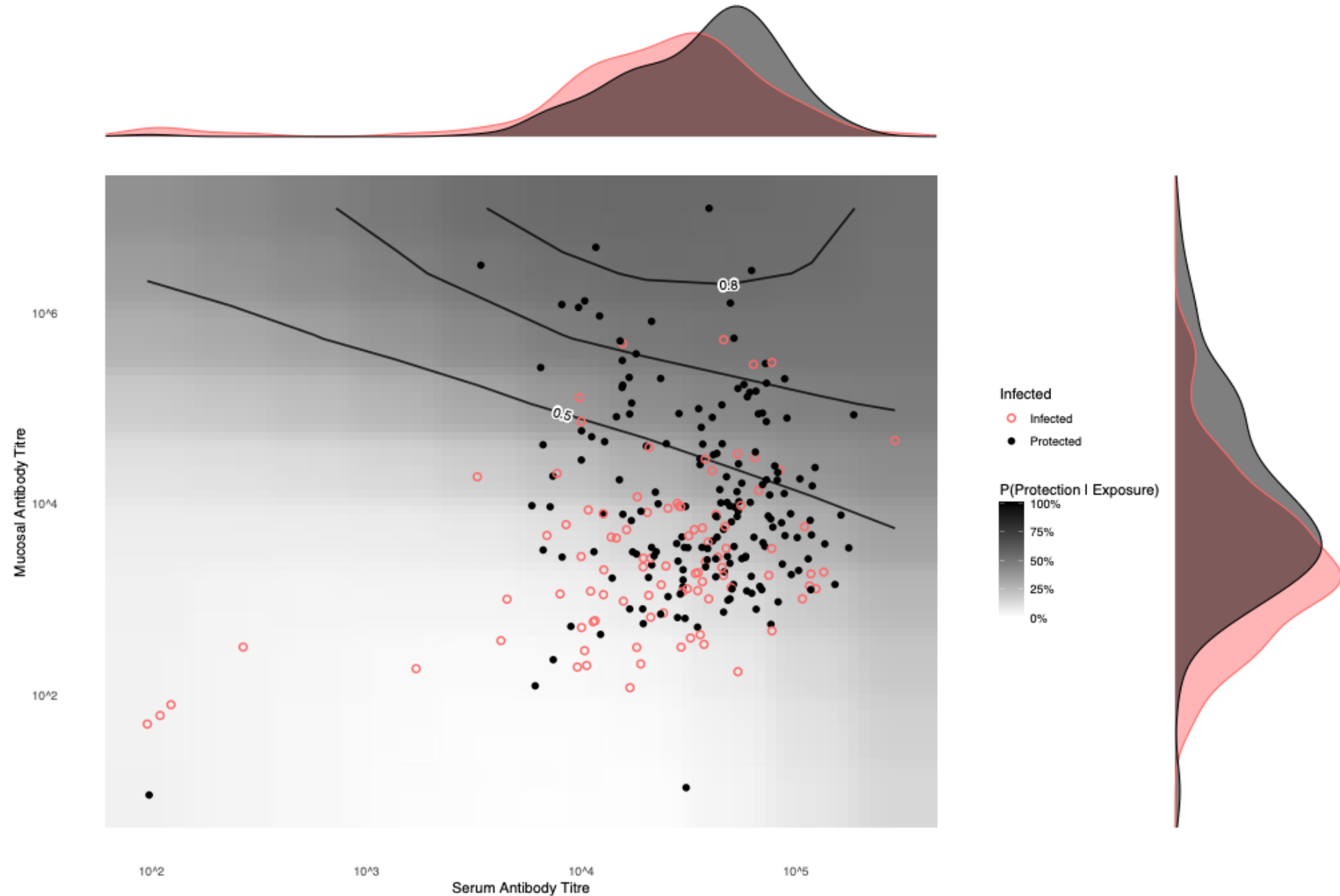


Cowling(?) CoP surface for RSV Pre-F

2D correlate of Protection surface:

Questionable practical use?

Dual Biomarker Protection Surface
Contours show 50%, 70%, 80%, and 90% protection probabilities



DISCUSSION

IMPACT

- Developing robust statistical methods for establishing CoP from natural history studies important;
 - Not enough time/money to run a clinical trial in humans to determine a CoP causally (MoP)
 - A lot of pathogens have no vaccine -> can be used as preliminary work to determine candidate CoP in clinical trials in humans/animals
 - Potential for better CoP using multiple biomarkers
 - Better discrimination + better counterfactual impact

EXTENSIONS

- Add hierarchical effects to logistic function to see how CoP varies across covariates (infection history and/or age)
- Similar stuff using ML; good at discovering unexpected patterns in complex data; blackbox-y so not good for regulatory-acceptable evidence

LIMITATIONS

- Setting and seasonal specific, unsure how well this generalises

CONCLUSIONS

1. We have developed a framework for for CoP; broad application
 - Will be implemented as an *R* package and an online widget
2. We identify the “best” single biomarker form lots of biomarkers
 - **SARS-CoV-2:** Best single biomarker is serum pTNA to Delta for Delta wave, and Omicron BA.1 pTNA to Omicron wave
 - **RSV:** Best single biomarker is mlgA PreF to infection
3. Assessed value of combined biomarker models
 - **SARS-CoV-2:** Adding mlgA binding assay information has worse predictive power
 - **RSV:** *Combing with slgG to PreF has similar predictive capacity, but better AMG (ensuring both biomarker have a four-fold rise)*



ACKNOWLEDGEMENTS

Dr. James Hay
Dr. Sheikh Jarju
Dr. Dawda Jobe
Dr. Rhys Wenlock
Dr. Thushan I de Silva
Prof Adam J Kucharski



LONDON
SCHOOL of
HYGIENE
& TROPICAL
MEDICINE



University of
Sheffield



PANDEMIC
SCIENCES
INSTITUTE

NIHR | National Institute for
Health and Care Research

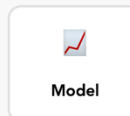
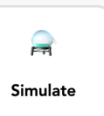
SEROANALYTICS

A directory of free, open-source tools for exploring, modeling and understanding serological data.

GitHub

Docker Hub

How to Use Seroanalytics



Center for Global Health.

-> seroanalytics.org

FOLLOW ME!



david.hodgson@charite.de



LinkedIn: <https://www.linkedin.com/in/dchodgson/>



Bluesky: [dchodge.bsky.social](https://bsky.social/dchodge)

EXTRA SLIDES

MOTIVATION

The Problem:

- Without CoPs => vaccine trials require large sample sizes, long follow-up periods, and are resource-intensive
- Current CoPs (assessed in vaccine trials) rely on single biomarkers (typically serum antibodies), which may miss important aspects of protective immunity.

The Gap:

- Mucosal immunity is the frontline defence for respiratory pathogens, yet (historically) rarely measured in CoP studies
- Rigorous statistical framework needed to compare multiple biomarkers and identify the "best" CoP in a natural history setting
- Limited data on whether combining biomarkers improves prediction of protection

The flowchart illustrates the relationship between exposure and protection, centered around the **Protection Likelihood** model.

Central Model: $Y_i \sim \pi_i \text{Bern}(p_i) + (1 - \pi_i) \text{Bern}(p_{\text{base}})$

Inputs and Associated Models:

- Observational Likelihood:** $S_i \sim N(X_i, \sigma)$. This model uses individual-level antibody kinetics data (Antibody titre, X_i vs Time) to estimate the probability of infection (π_i).
- Exposure model:** $\pi_i(H_i; \alpha_0, \alpha_1)$. This model uses the number of infections in the household to estimate the exposure probability.
- Background risk:** p_{base} . This represents the background risk in the absence of the exposure model.
- Correlate of Protection:** $1 - p_i(x; k, x_0)$. This model uses the probability of protection (Antibody titre vs Probability of protection) to estimate the probability of infection (π_i).

Key Variables and Data Points:

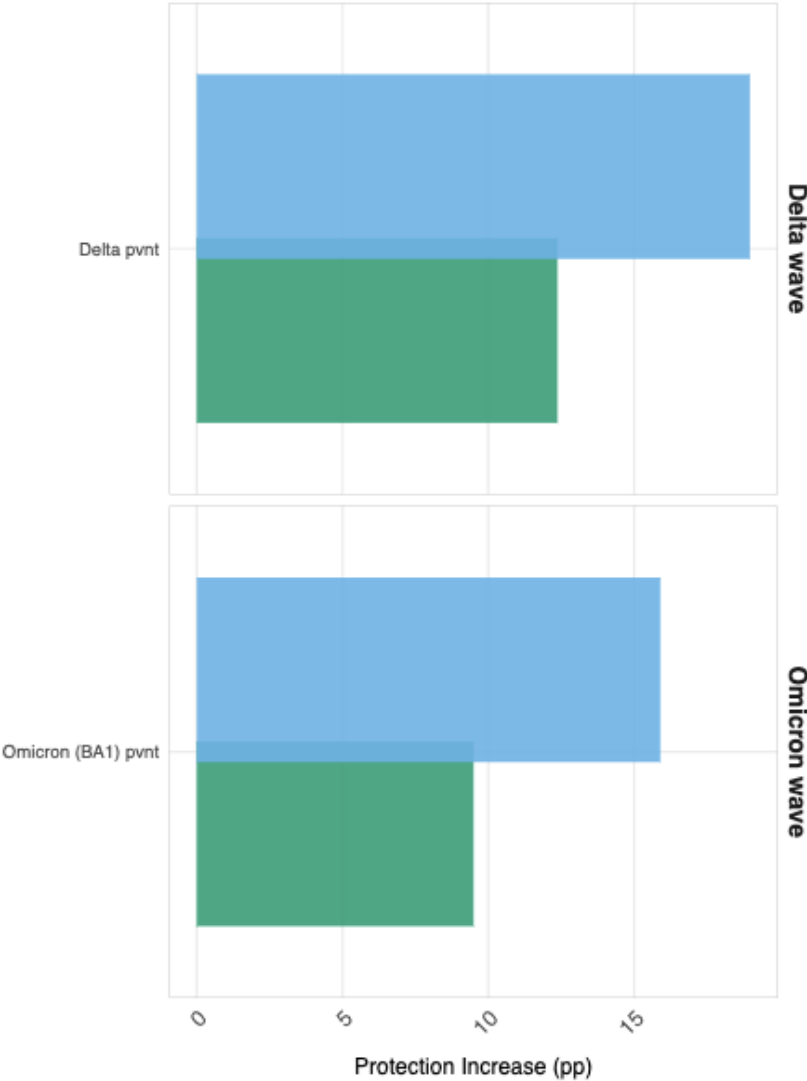
- $Y_i = 1$: infected
- $Y_i = 0$: not infected
- $X_i(T_{\text{inf}})$: Sample titres from fitted kinetics curves from infected individuals at the time of infection.
- $X_i(t^*)$: Sample titres from fitted kinetics curves from non-infected individuals at time t^* .
- π_i : exposure rate
- I : asymptote

The diagram shows how these various models and data points are integrated to estimate the probability of infection and protection, ultimately leading to the central Protection Likelihood model.

RESULTS FOR SARS-CoV-2

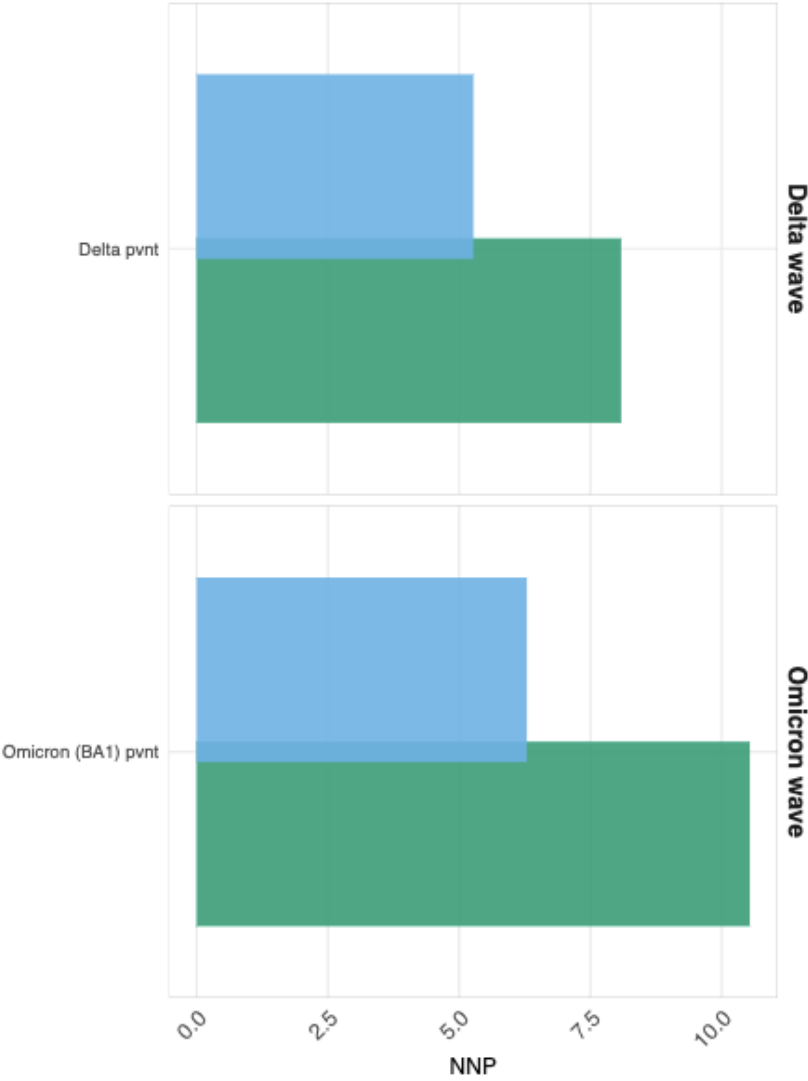
C. Marginal Gain

Average Marginal Gain in protection if titres rose 4-fold

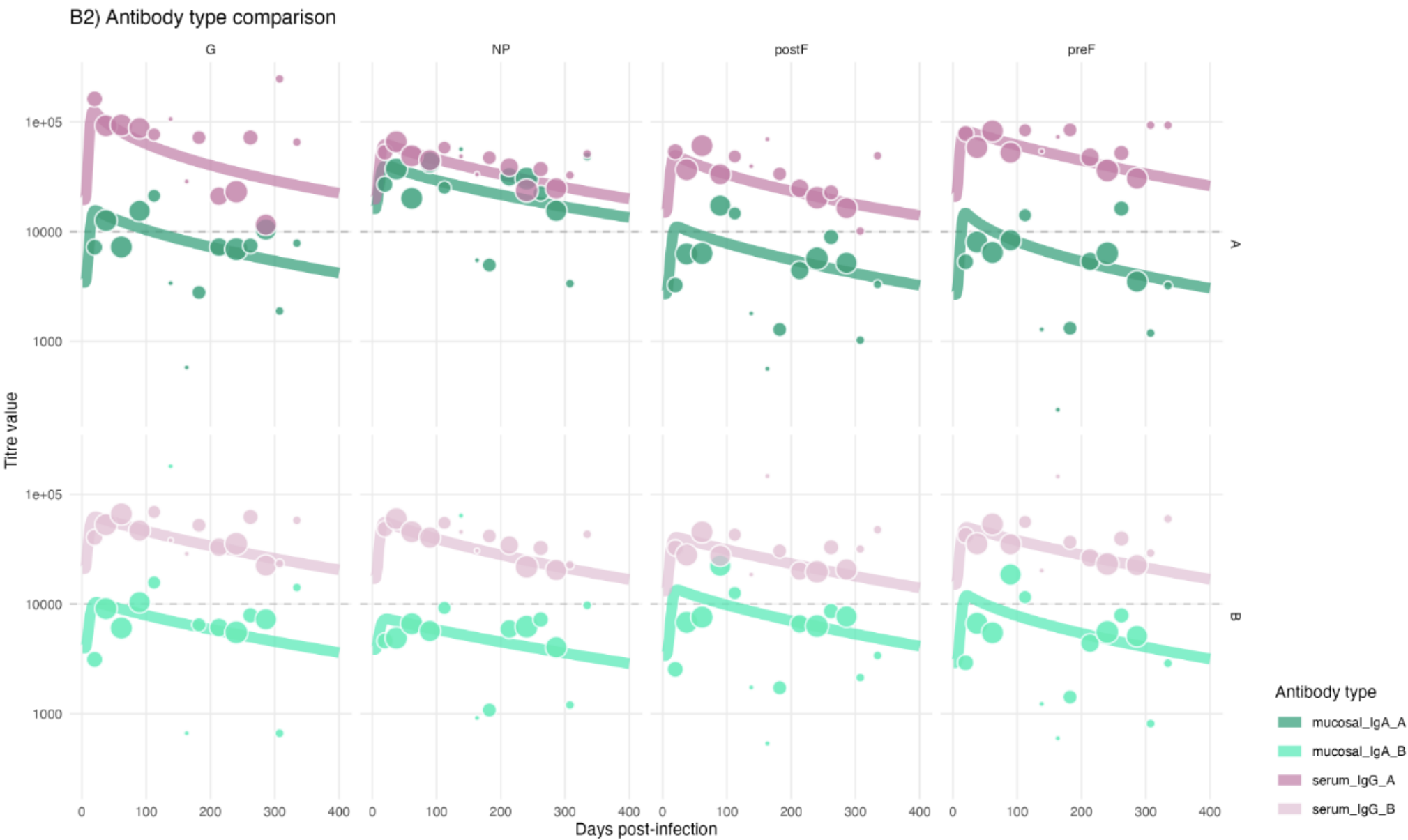


D. Number Needed to Treat

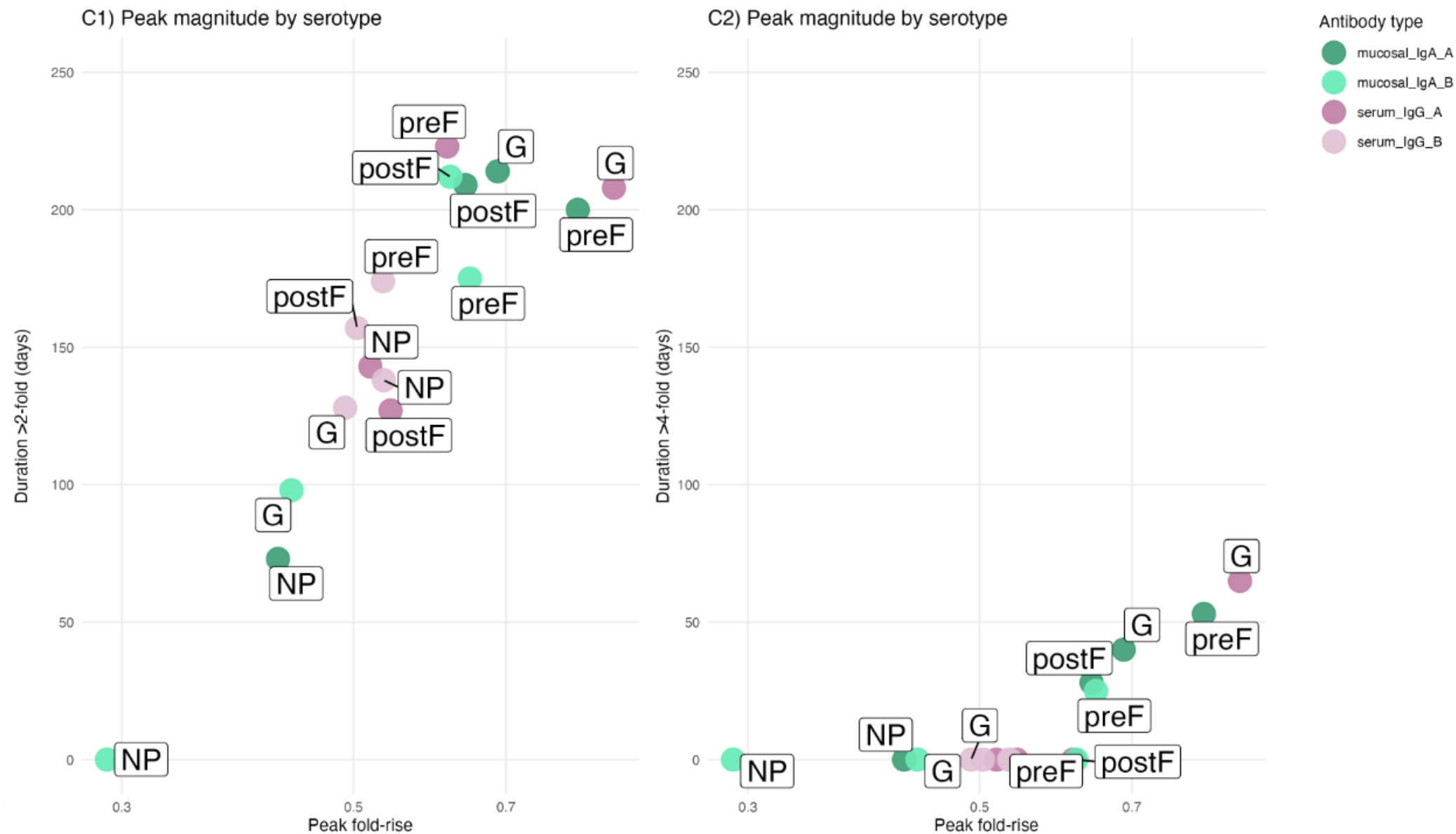
To prevent one infection with 4-fold boost



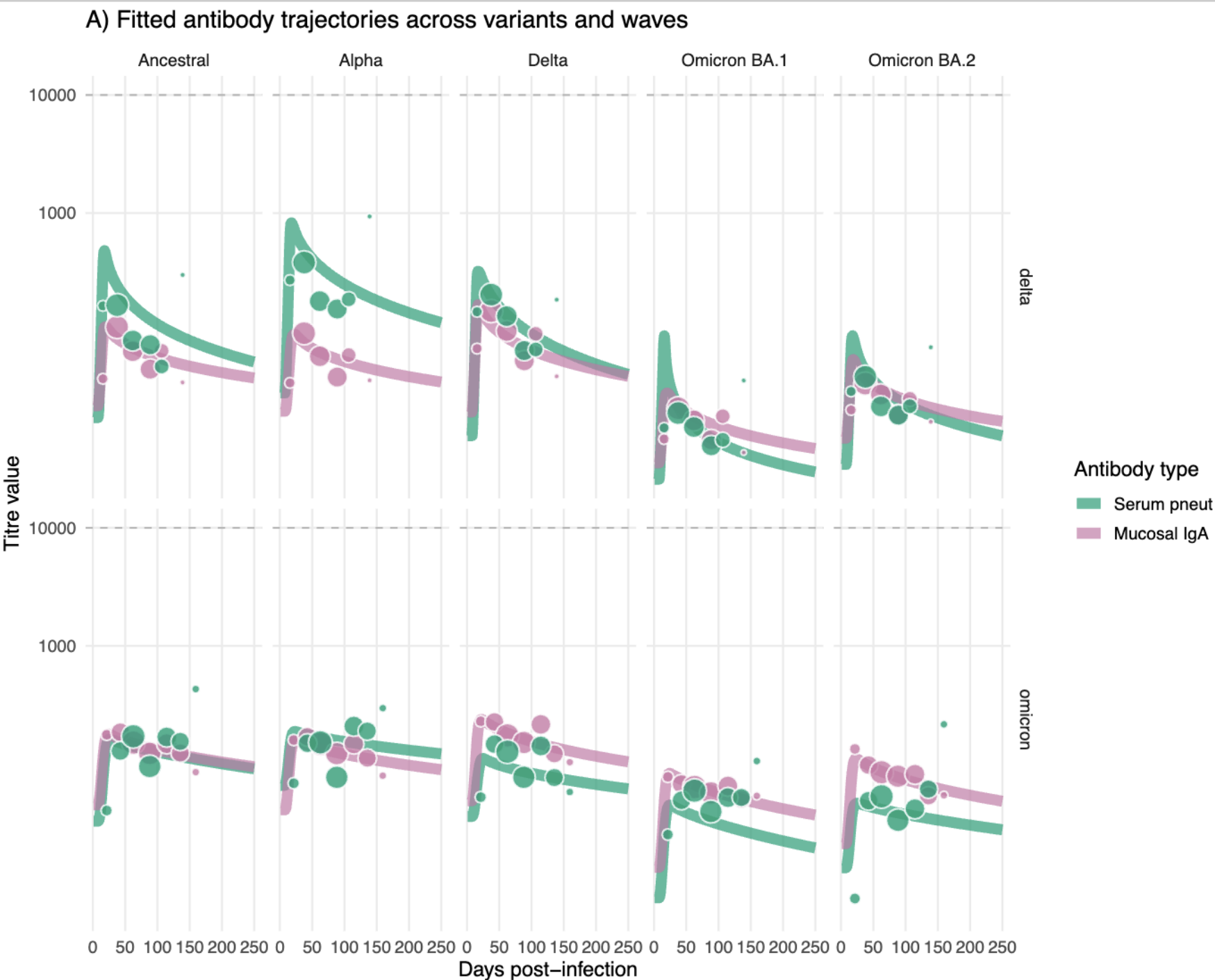
RSV kinetics



RSV kinetics



SARS-CoV-2 Kinetics



SARS-CoV-2 Kinetics

B) Peak magnitude and antibody persistence by variant and wave

