DAEDALUS: economic variables

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Contents

1 Introduction

The objective of the proposed work is to use scenario modelling to ascertain the vulnerability of a country to a hypothetical pandemic across several dimensions. The dimensions of vulnerability we consider here include economic loss, life loss, and education loss. The variables we consider as potential indicators of vulnerability relate to the reliance of the economy on two economic sectors, and the level of digitization and associated capacity to provide home-based work and education.

We simulate hypothetical pandemics caused by one of seven respiratory pathogens, each with a disease profile informed by a past epidemic. We use the integrated epi-econ model DAEDALUS developed in our group for estimating the benefit of pandemic preparedness (P2) (Haw et al. 2022). The scenarios are informed by real-world demographic, societal and economic data for up to 197 countries. We evaluate outcomes for four mitigation strategies ("unmitigated," "adaptive economic closures," "school closures," and "elimination").

The impacts we project are losses to life, to education, and to GDP. We assess the impacts of the four variables of interest on the outcomes using value-of-information methods in order to identify which variables most influence outcomes, and in what circumstances.

2 Methods

2.1 Scenarios

The seven pathogen profiles include influenza and coronaviruses, and are based on past epidemics. Influenza virus profiles correspond to pandemics of the years 1918, 1957 and 2009. Coronavirus profiles correspond to SARS-CoV-1 and SARS-CoV-2, with three profiles: one, corresponding to variants that predated the variant-of-concern nomenclature (which we label "pre-Alpha"), and one each for the Delta and Omicron variants.

The four mitigation strategies are "unmitigated," "adaptive economic closures," "school closures," and "elimination." In the unmitigated strategy, no aversive actions are taken. With adaptive economic closures, sectors close according to a pre-specified programme when hospital occupancy approaches its capacity. With school closures, schools remain closed and other economic sectors have reduced operations. With the elimination strategy, stringent economic closures are maintained until case numbers can be contained by a testing programme. All economic configuration profiles are based on GVA profiles observed in 2020 (OECD), where the monthly GVA of a sector relative to its value one year prior is interpreted as the degree to which it was open.

We consider three stylised "countries" and parametrise models using data from constituent countries according to the World Bank income-classification categories:

- LLMIC, using inputs from LICs and LMICs
- MIC, using inputs from LMICs and UMICs
- HIC, using inputs from HICs

2.2 Outcomes

The outcomes of the model are:

1. Number of deaths (by four age groups)
2. GDP loss
3. Education loss

Numbers of deaths are translated into years of life lost (YLL). This takes into account the life expectancy of each person who dies. YLLs are valued using the value of a statistical life, which we estimate as being 160 times GDP per capita (Robinson, Hammitt, and O'Keeffe 2019).

GDP loss is estimated as the total GDP - the sum of GVA across all sectors, scaled by how open they are across the year - divided by the value of GDP when all sectors are completely open all the time.

Education loss takes into account the extent to which schools are closed, as well as the effectiveness of provision for remote learning. We estimate this using internet coverage as a proxy (that is, we do not take into account education that can be delivered by TV or radio). Education loss is valued by taking into consideration life-long earning losses, following (Psacharopoulos, Collis, and Patrinos 2021).

We report these outcomes as a percentage of GDP (for the year prior to the pandemic – here, 2019). All three outcomes (once a valuation is applied) are linear functions of GDP, and therefore results are all comparable across countries. The time horizon in the simulation is one year.

2.3 Modelling

The integrated epi-econ model is used to project economic and epidemic outcomes. The epidemiological model is a population-structured compartmental SEIR model. It takes many inputs, including pathogen natural history parameters (such as R_0, case-fatality rates, etc) and population parameters (such as age structure, contact rates, etc). The economic model takes as input the GVA per sector, which uses the OECD classification of 45 economic sectors. Both models take as input the economic configuration over time: this is the extent to which each sector is open in each period. A sector is open to a maximum amount of 100%, when its full monthly GVA value is realised. If a sector is open to 50%, it contributes 50% of its maximum GVA for that period. In the epidemic model, contacts associated with that sector – between workers, from workers to consumers, and between consumers – are likewise scaled down.

The economic model is very simple: we do not model interdependencies between sectors, and the only way in which country interdependencies are taken into account is via changes to tourism which manifest in the "food and accommodation services" sector (see Section 8.1). We do not model seasonality or allow for sectors to grow (either in GDP or in workforce).

We generate a distribution over outcomes through sampling inputs. This distribution represents a catalogue of synthetic countries whose characteristics are randomly taken from candidate countries. By examining the relationships between inputs and outputs, we can identify the inputs that most drive uncertainty in outputs as encoded by our model or, equivalently, which inputs are the best predictors of the outcome(s), independently of all other variables.

We include uncertainty in as many parameters as possible. We sample from specified distributions, or sample with replacement from a discrete set of candidate options, where the candidate options are the values belonging to countries in the income group.

Parameter distributions are independent of each other (with the exception of loss in tourism, where the size of the sector is related to the fraction of tourism that comes in from abroad (see Section 8.1.3)). This means that any relationships we uncover between input and output within an income group will be causal, and we will not discover any factors that are "indicative" by association. (Between income groups there are many systematic differences in inputs and learning which of those drives the differences in outcomes is part of the ongoing development of the model.)

2.3.1 Data sources

1. Workforce: ILO
2. GVA: OECD
3. Closure configurations: GVA 2020 for UK, Australia, Indonesia (OECD)
4. Contact matrices: (Prem et al. 2021), (Béraud et al. 2015)
5. Work from home: (Gottlieb et al. 2021)
6. Hospital capacity: World Bank / OECD
7. Response time: Blavatnik 2022
8. Testing rate:
9. Testing start time:
10. Mobility: Our World in Data/Wang et al., 2022
11. Life expectancy: IHME?
12. Population:
13. Tourism data: https://www.unwto.org/tourism-data/international-tourism-and-covid-19
14. International tourism: https://www.unwto.org/tourism-statistics/key-tourism-statistics
15. Internet coverage: World Bank
16. Labour share of GDP: (Inklaar and Timmer 2013)

2.4 Value of information

We assess the impacts of four parameters that relate to economic indicators:

1. Agricultural GVA as a proportion of GDP
2. Tourism GVA as a proportion of GDP
3. Proportional of tourism that comes from abroad
4. Internet coverage

We use value-of-information methods to quantify these relationships. Specifically, we estimate the expected value of partial perfect information (EVPPI), which is the expected gain (in terms of reduction of uncertainty in the outcome) of knowing a parameter (or set of parameters) perfectly (Jackson et al. 2021). Equivalently, and in terms of identifying indicators of vulnerability, it tells us which parameters best predict the outcome.

Value of information is a decision-theoretic quantity. We estimate it using the R package **voi**. Intuitively, EVPPI functions in a similar way to correlation. In the case of a linear relationship between one input and one output, the computation of EVPPI is essentially the same as that of a correlation. EVPPI extends a simple correlation analysis in two ways relevant to the results presented: 1) nonlinear relationships are also captured, and 2) we can assess the EVPPI of a set of parameters. EVPPI allows us

to identify influential parameters. Once identified, relationships between the influential parameter (sets) and outcomes need to be examined independently in order to understand the nature of the relationship.

Finally, we can use mutual information (MI, via the R package **infotheo**) to assess mutual information between inputs and outputs. What MI offers beyond EVPPI is that it takes into account also how *likely* it is that the input parameter occupies a space where it is influential.

3 Results

3.1 Distributions over outcomes

Distributions over costs associated with the first year of an outbreak of SARS-CoV-2 (with parameters corresponding to variants arising before alpha) are shown in Figure **??** for three income levels and four mitigation strategies. Each shape represents the probability density made up of the sampled values for outcomes: the most likely value to take is where the figure is widest. The tip of the tail indicates the highest value sampled, after which point the density is 0.

These distributions show that vulnerability to a pandemic depends on a country's income level together with its mitigation strategy. For example, the elimination strategy appears to have the lowest distribution for overall cost for HICs among all strategies, whereas it appears no lower for MICs and perhaps higher for LLMICs. This will be because of the factors that vary systematically across countries of different income levels. Likewise, the heavier tails in the distributions for YLLs for HICs is likely due to the age distributions in HICs being heavier in older ages. These cross-country differences are one of the focuses of the development of the model.

"If a hypothetical low- or lower-middle income country that relies to 3% on tourism for their national income experienced a pandemic with a similar profile to the Spanish Flu, what would be the number of deaths, the loss in GDP, and the loss of in-person schooling were the country to rely on an elimination strategy? What would the impact be if the country relied to 6% on tourism?"

At 3%, life-year loss is expected to be 8.06% of GDP (95%PI 0, 57.45). Education loss is expected to be 30.42% of GDP (95%PI 1.69, 72.67). GDP loss is expected to be 15.94% of GDP (95%PI 2.44, 25.31).

At 6%, life-year loss is expected to be 7.39% of GDP (95%PI 0, 50.1). Education loss is expected to be 30.41% of GDP (95%PI 2.12, 73.83). GDP loss is expected to be 17.67% of GDP (95%PI 3.36, 27.12).

Here, the uncertainty in model results swamps the difference in expected values across all outcomes.

3.2 Value of information

The value of information associated with a number of parameters for all costs considered is shown in Figure 1. The costs are listed down the y axis. Parameters and parameter groups are along the x axis. Colours indicate the extent to which uncertainty in the input(s) are driving uncertainty in the outcome, with lighter colours representing greater impact.

The first four items on the x axis are the four independent variables: size of the agriculture sector, size of the food and accommodation services sector, fraction of tourism coming from abroad, and internet coverage. While the two parameters driving tourism are impactful on GDP loss, particularly for strategies light on economic closures, they have little impact on total costs. (This relationship is also driven by the distribution of the food and accommodation sector contribution to GVA: the mutual information appears a more balanced metric (Figure **??**).) Meanwhile, internet coverage has modest impacts, particularly on education loss and for strategies that employ school closures.

The EVPPI (and MI) for tourism is high, particularly for lower-income countries because tourism can make up a large part of GDP, and particularly for strategies light on economic closure because then the only sector suffering a shortfall is the Food and accommodation services sector.

The next two items on the x axis are parameter groups. First, both sectors. Second, both tourism parameters. The grouping of parameters shows their combined impact on outcomes, which can be greater than the sum of their individual impacts.

The next columns do not correspond to the "independent variables" of interest but might be expected to influence outcomes: fraction of population who are school age, fraction of population who are in the oldest age group, population size, rate of testing, GDP, R_0 and maximum hospital capacity. R_0 in particular drives a lot of uncertainty in costs, primarily through YLLs.

The final four items on the x axis are groups of variables: both age groups; two social-distancing parameters; hospital capacity, the fraction of the population aged 65 and over, and R_0; and testing parameters, response time, and R_0.

Some distributions in Figure **??** are bimodal. For example, GDP loss under the Economic Closures strategy have peaks in density close to zero and also far from zero, with a low-density region in between. Here, in some samples (low GDP loss), the epidemic was not severe enough to warrant closures. This could be because R_0 was low, because hospital capacity was high, or both. Similarly, under the Elimination strategy, there is an area of high density at higher costs where the strategy does not work: due to R_0 being high, and/or the capacity to test being low, case numbers are not brought low enough and severe economic closures persist throughout, leading to high GDP loss.

These relationships are identified in the value-of-information analyses: the last two columns show value of information for R_0, fraction of population aged 65 and over and hospital capacity combined, and R_0, testing parameters and social-distancing parameters combined. These variables together explain much of the variance in GDP loss for the Economic Closures and Elimination strategies, respectively.
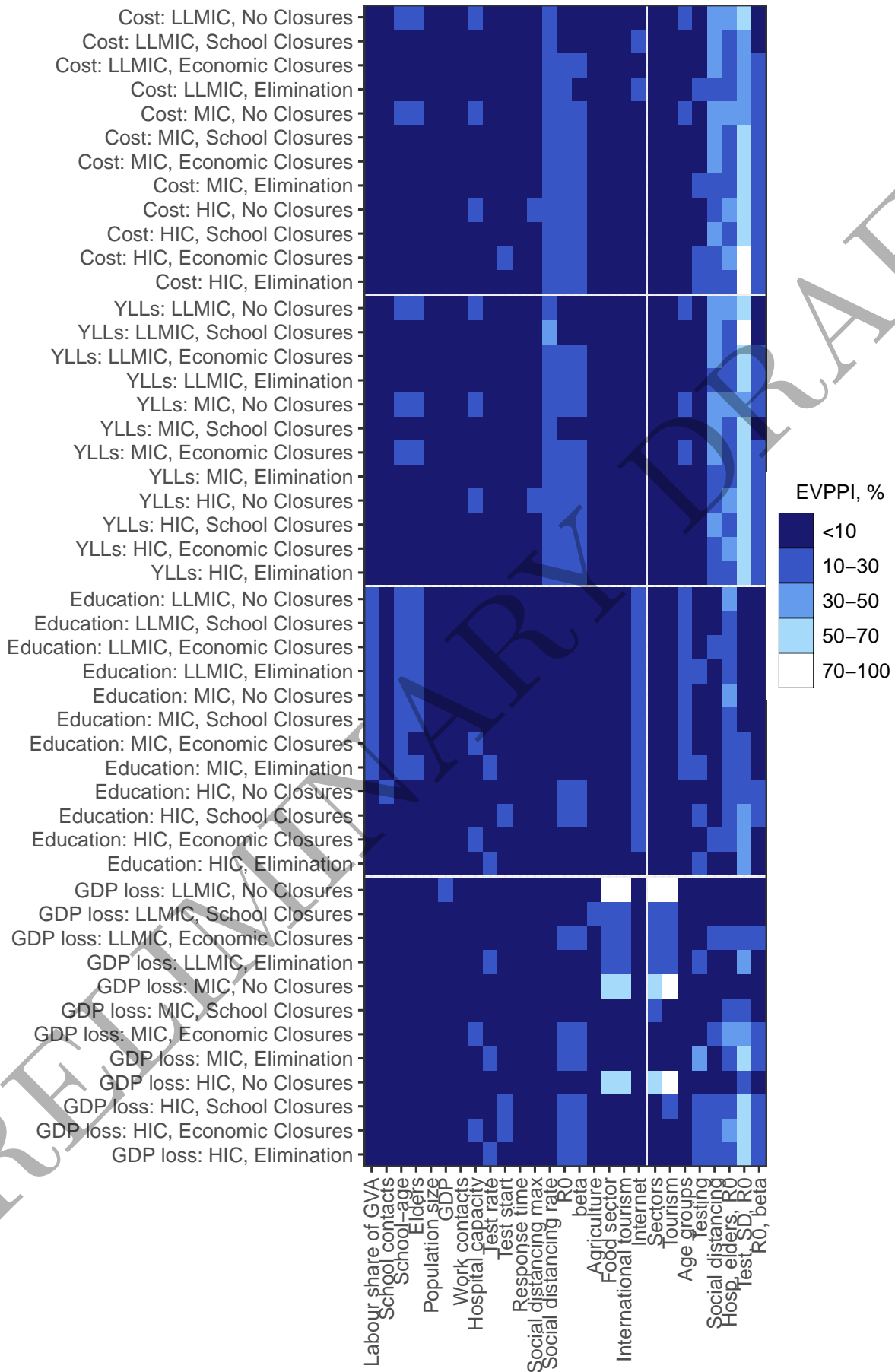
Figure 1: Value of information for pre-Alpha variants of SARS-CoV-2. First four columns: individual parameters of interest (agricultural sector as % of GDP, Food and accommodation services sector as % of GDP, international tourism as % of toursim, internet coverage). Next two columns: pairs of parameters of interest (both sectors, both tourism-related parameters). Next 11 columns: other random variables (fraction of population school age, fraction of population age 65 and over, population size, GDP, hospital capacity, testing rate, testing start time, government response time, social distancing minimum, social distancing responsiveness to case numbers, R_0). Final four columns: combinations of random variables (both age fractions, both social distancing parameters, hospital capacity + elders population + R_0, testing parameters + social distancing parameters + R_0).

To understand the relationship between a parameter and an outcome, e.g. whether the relationship is linear and increasing or decreasing, whether it is nonlinear, whether it is driven by extreme values, they must be plotted against each other. Likewise, a relationship between a parameter pair and an outcome can be plotted, e.g. Figure 4: for middle-income countries in a pre-Alpha SARS-CoV-2 pandemic with the "No Closures" strategy, GDP loss is greatest when both the food and accommodation services GVA as fraction of GDP and international tourism as a fraction of tourism are high.
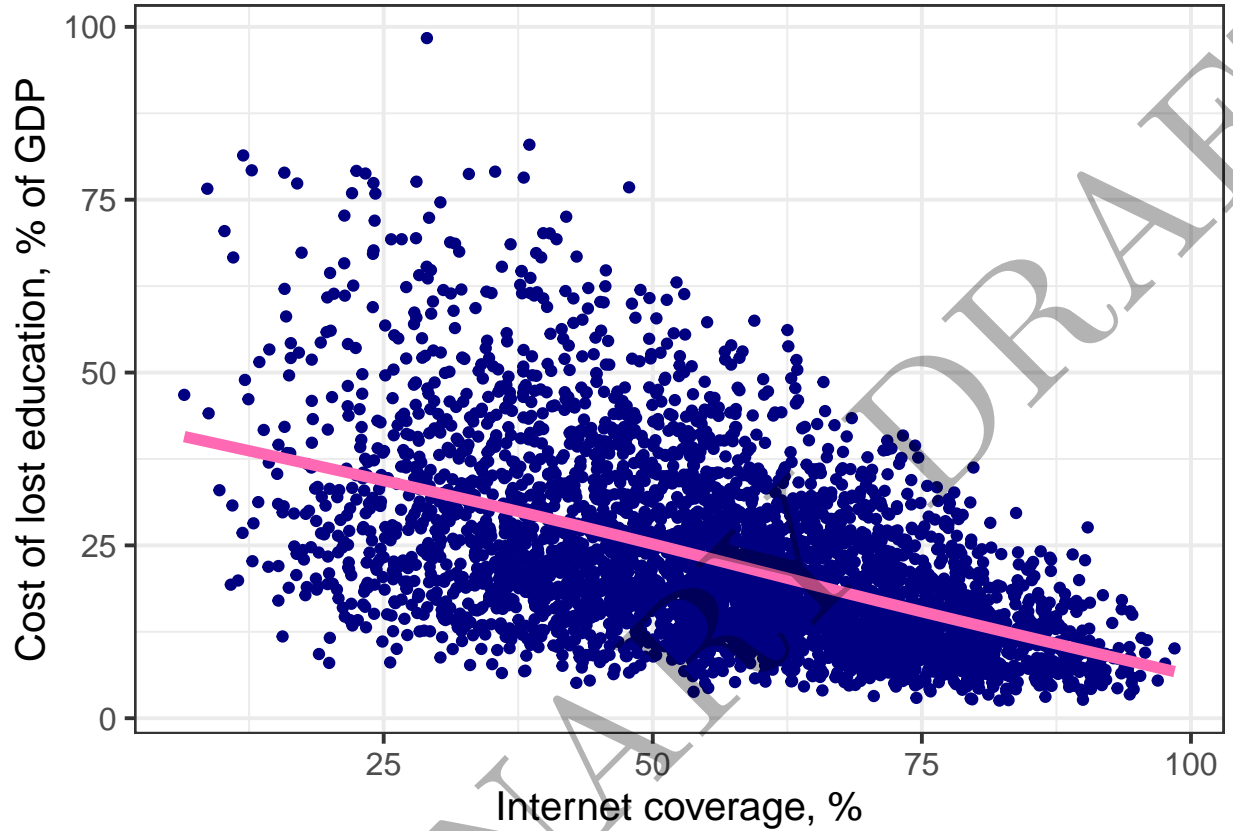

Figure 2: Relationship between internet coverage and education losses for middle-income countries in a Delta SARS-CoV-2 pandemic with the "School Closures" strategy.
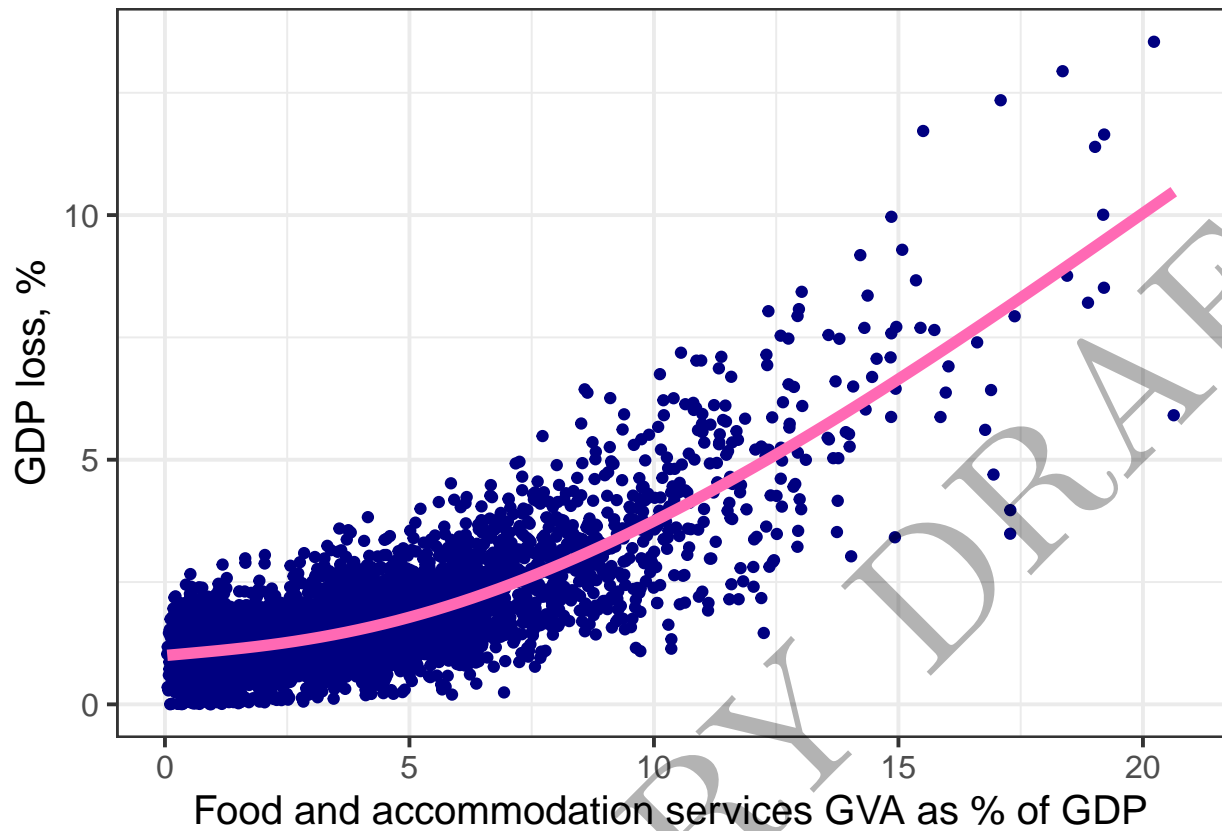
Figure 3: Relationship between the "tourism sector" size and GDP loss for middle-income countries in a pre-Alpha SARS-CoV-2 pandemic with the "No Closures" strategy.
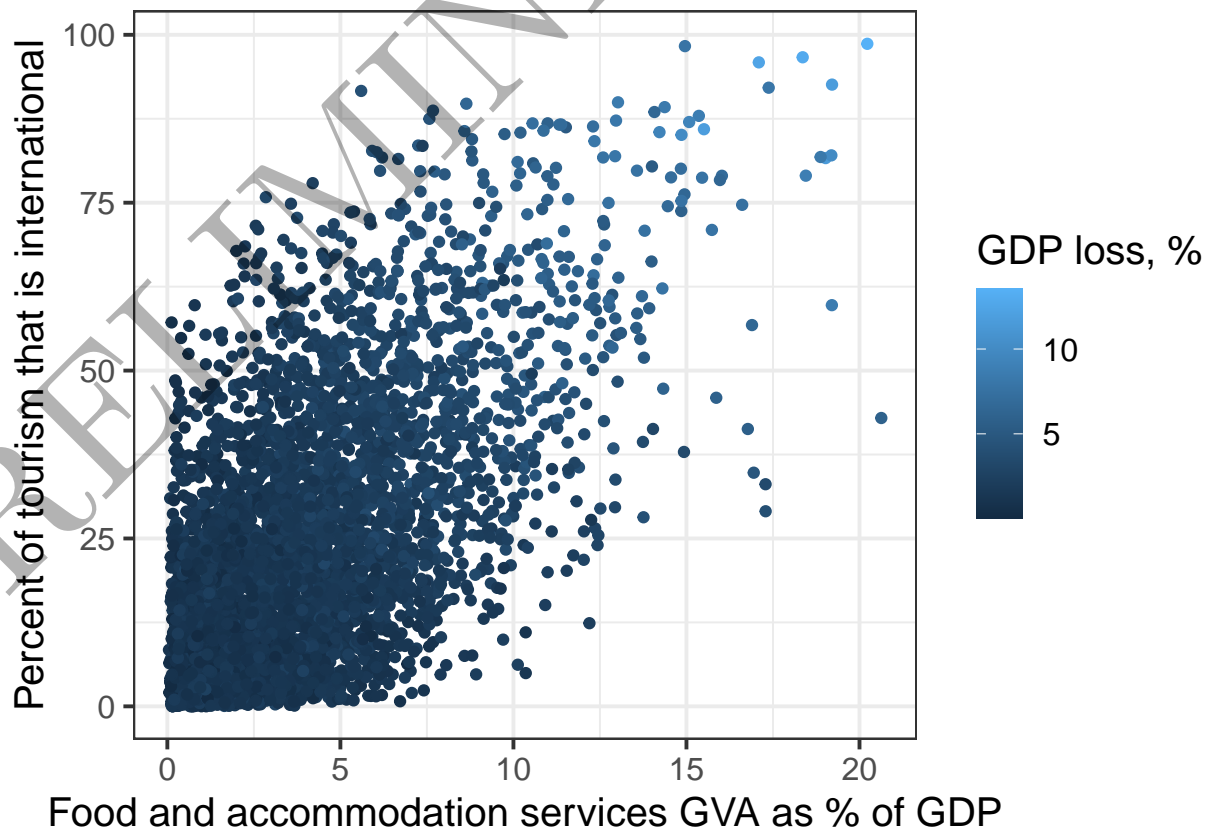

Figure 4: Relationship between tourism parameters and GDP loss for middle-income countries in a pre-Alpha SARS-CoV-2 pandemic with the "No Closures" strategy.

4 Conclusions

Using simulation modelling, we have projected distributions of epidemic losses – of life, GDP, and education – for seven pathogenic profiles, four stylised mitigation strategies, and three levels of country income. We assessed what the impact is of four economic variables in our model: fraction of GDP from the agriculture sector, fraction of GDP from the food and accommodation services sector, fraction of tourism that comes from abroad, and internet coverage.

We found that the tourism-related variables impacted GDP loss for the No Closure strategy, which is because GDP losses will be suffered only in this sector when there is no mandated closure. This means the GDP loss will depend on the extent to which the economy is depending on this sector. We found that Education losses depend to some extent on internet coverage, because our model assumes that internet access can be used to mitigate losses by enabling remote learning. We found little effect of the size of the agricultural sector.

In parallel, we present a selection of other model parameters, including those related to demography (e.g. the fraction of the population who are of school age), to the economy (e.g. GDP), to the health system (e.g. hospital capacity), to the pandemic response (e.g. the rate of testing), and to the pathogen (e.g. the basic reproductive number, R_0). We found that these variables – in combinations up to four – account for much of the variability in outcomes.

4.1 The modelling framework

Ours is a mechanistic simulation model. The model encodes complex relationships between demographic, epidemic and economic variables. With simulation, it allows us to explore outcomes as consequences of inputs using information- and decision-theoretic methods. Modelling allows *in silico* experimentation, which is crucial for questions pertaining to rare events with small and confounded datasets, as cross-sectional country data are. The model allows us to ask questions about cause and effect that cannot be asked in reality and rarely can be inferred from observational data.

The challenge we face with modelling, then, is to be confident that our model mimics reality, or at least captures the elements with which we are concerned.

4.2 The economic model

We have used a simple economic model that allows us to estimate GDP loss in a year assuming that sector closures follow mandates. The mandates we use are schematic and representative of GVA profiles seen in different countries in 2020.

The economic model is static, and does not take into account any dynamics such as feedback, changes to demand, supply and supply chains, changes in international trade, or any macroeconomic factors. As such, to model longer-term economic impacts (apart from the impact of lost education) is beyond the scope of this model.

For example, Figure 5 shows the relationship between GDP loss in the first year (2020) and GDP loss in the second year (2021) following the outbreak of COVID-19. There is heterogeneity in losses in the first year, but also in whether or not the economy recovers in the second year, and to what extent. The recovery is arguably a more important phenomenon to capture than initial losses, and it is not something that can be captured by our economic model. However, a model of recovery / future losses would include initial loss as an input, which our model could provide.

(confirm with Patrick) GVA for a sector is reduced as a consequence of illness and death of workers, but not due to a reduction in demand (e.g. private/final consumption).
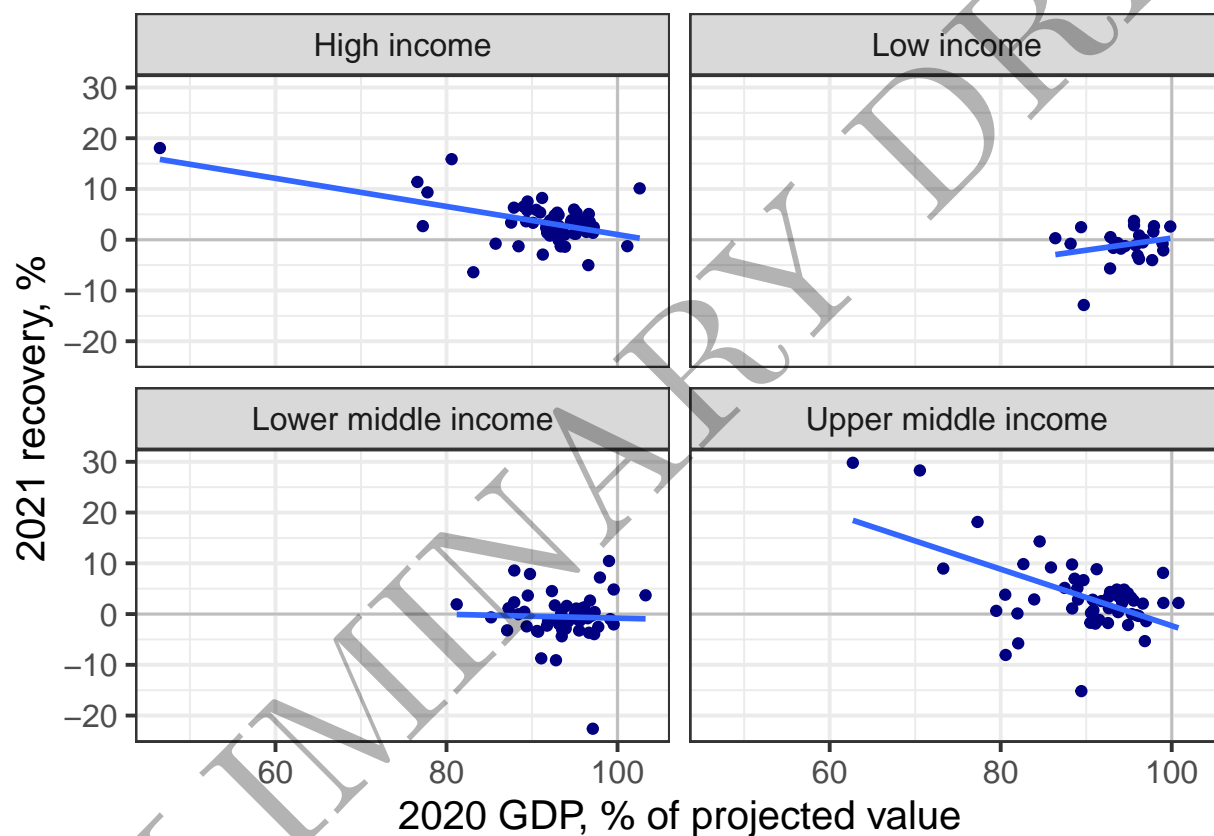
Figure 5: GDP loss and recovery. On the x axis is the GDP of 2020 relative to its 2019 projected value (IMF). On the y axis is 2021 GDP relative to its 2019 projected value relative to the same value for 2020 (ratio of ratios). x values below 100 represent a loss in the year 2020. y values above 0 represent recovery (i.e. growth exceeded what was expected in 2019); y values equal to zero represent a fixed level of loss; y values less than zero represent increasing loss.

5   References

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6 Pathogen profiles

Table 1: Pathogen profiles.

	SARS	Flu2009	Flu1957	Flu1918	CovidWT	CovidOM	CovidDE
IHR, ages 0-4, %	5.8	0.47	0.09	12	0.0016	0.0033	0.003
IHR, ages 5-9, %	5.8	0.18	0.09	2.1	0.0016	0.0033	0.003
IHR, ages 10-14, %	5.8	0.18	0.09	2.6	0.041	0.059	0.075
IHR, ages 15-19, %	5.8	0.18	0.09	5.3	0.041	0.059	0.075
IHR, ages 20-24, %	8.2	0.18	0.09	9.1	1	0.83	1.9
IHR, ages 25-29, %	8.2	0.38	0.09	16	1	0.83	1.9
IHR, ages 30-34, %	8.2	0.38	0.09	13	3.4	2	6.3
IHR, ages 35-39, %	8.2	0.38	0.09	12	3.4	2	6.3
IHR, ages 40-44, %	30	0.38	0.09	8.8	4.2	1.6	7.9
IHR, ages 45-49, %	30	0.38	2.3	6.4	4.2	1.6	7.9
IHR, ages 50-54, %	30	0.71	2.3	8.8	8.2	2.1	15
IHR, ages 55-59, %	30	0.71	2.3	6.3	8.2	2.1	15
IHR, ages 60-64, %	87	0.71	2.3	16	12	3.1	22
IHR, ages 65-69, %	87	1	18	22	12	3.1	22
IHR, ages 70-74, %	87	1	18	26	17	6.1	31
IHR, ages 75-79, %	87	1	18	26	17	6.1	31
IHR, ages 80-+, %	60	1	18	26	18	11	34
IFR, ages 0-4, %	1.5	0.018	0.0067	1.5	0.0016	0.0033	0.003
IFR, ages 5-9, %	1.5	0.0074	0.0067	0.27	0.0016	0.0033	0.003
IFR, ages 10-14, %	1.5	0.0074	0.0067	0.32	0.007	0.01	0.013
IFR, ages 15-19, %	1.5	0.008	0.0067	0.66	0.007	0.01	0.013
IFR, ages 20-24, %	2.1	0.008	0.0067	1.1	0.031	0.025	0.057
IFR, ages 25-29, %	2.1	0.02	0.0067	2	0.031	0.025	0.057
IFR, ages 30-34, %	2.1	0.02	0.0067	1.7	0.084	0.048	0.16
IFR, ages 35-39, %	2.1	0.02	0.0067	1.5	0.084	0.048	0.16
IFR, ages 40-44, %	7.7	0.02	0.0067	1.1	0.16	0.06	0.3
IFR, ages 45-49, %	7.7	0.043	0.17	0.8	0.16	0.06	0.3
IFR, ages 50-54, %	7.7	0.043	0.17	1.1	0.6	0.15	1.1
IFR, ages 55-59, %	7.7	0.043	0.17	0.78	0.6	0.15	1.1
IFR, ages 60-64, %	22	0.043	0.17	2.1	1.9	0.5	3.6
IFR, ages 65-69, %	22	0.66	1.3	2.8	1.9	0.5	3.6
IFR, ages 70-74, %	22	0.66	1.3	3.3	4.3	1.6	7.9
IFR, ages 75-79, %	22	0.66	1.3	3.3	4.3	1.6	7.9
IFR, ages 80-+, %	15	0.66	1.3	3.3	7.8	4.8	14
Probability asymptomatic	0.87	0.67	0.67	0.67	0.6	0.6	0.6
Latent period	4.6	1.1	1.1	1.1	4.6	4	4
Time to recovery (asymptomatic)	2.1	2.5	2.5	2.5	2.1	2.1	2.1
Time to recovery (symptomatic)	4	2.5	2.5	2.5	4	4	4
Time to hospitalisation	3.8	2.5	2.5	2.5	4	4	4
Time to recovery (hospital)	23	5	5	5	12	5.5	7.6
Time to death	20	5	5	5	12	5.5	7.6
Immunity waning	360	360	360	360	360	360	360
Reduced infectivity asymptomatic	0.58	0.58	0.58	0.58	0.58	0.58	0.58
R0	1.8	1.6	1.8	2.5	2.9	5.9	5.1

7 Economic configurations

Table 2: Economic configurations used to implement strategies.
Values are the openness of the sector expressed as a percentage.
Elimination values are taken from Australia. Lockdown and Economic Closures values are taken from the UK. School Closures
values are taken from Indonesia.

Sector	Elimination	Lockdown	Economic Closures	Lockdown (School Closures)	School Closures
Agriculture, hunting, forestry	100	86	88	100	100
Fishing and aquaculture	100	86	88	100	100
Mining and quarrying, energy producing products	100	90	91	67	79
Mining and quarrying, non-energy producing products	100	90	91	100	100
Mining support service activities	100	90	91	100	100
Food products, beverages and tobacco	100	70	94	100	100
Textiles, textile products, leather and footwear	98	70	94	89	92
Wood and products of wood and cork	98	70	94	100	95
Paper products and printing	98	70	94	100	98
Coke and refined petroleum products	88	70	94	87	88
Chemical and chemical products	88	70	94	100	100
Pharmaceuticals, medicinal chemical and botanical products	88	70	94	100	100
Rubber and plastics products	88	70	94	87	100
Other non-metallic mineral products	88	70	94	92	89
Basic metals	100	70	94	100	100
Fabricated metal products	100	70	94	90	100
Computer, electronic and optical equipment	100	70	94	90	100
Electrical equipment	100	70	94	90	100
Machinery and equipment, nec	100	70	94	89	95
Motor vehicles, trailers and semi-trailers	100	70	94	66	82
Other transport equipment	100	70	94	66	82
Manufacturing nec; repair and installation of machinery and equipment	98	70	94	98	100
Electricity, gas, steam and air conditioning supply	97	89	100	94	94
Water supply; sewerage, waste management and remediation activities	97	92	98	100	100
Construction	94	56	92	95	95
Wholesale and retail trade; repair of motor vehicles	100	64	100	92	97
Land transport and transport via pipelines	100	63	82	83	100
Water transport	100	63	82	81	98
Air transport	18	63	82	16	42
Warehousing and support activities for transportation	91	63	82	64	91

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Sector	Elimination	Lockdown	Economic Closures	Lockdown (School Closures)	School Closures
Postal and courier activities	91	63	82	64	91
Accommodation and food service activities	92	10	85	77	91
Publishing, audiovisual and broadcasting activities	100	88	91	100	100
Telecommunications	100	88	91	100	100
IT and other information services	100	88	91	100	100
Financial and insurance activities	100	94	96	100	100
Real estate activities	100	98	98	100	100
Professional, scientific and technical activities	100	85	92	90	95
Administrative and support services	90	66	80	90	95
Public administration and defence; compulsory social security	100	100	100	96	100
Education	100	10	100	10	10
Human health and social work activities	100	75	92	100	100
Arts, entertainment and recreation	94	55	71	90	96
Other service activities	94	54	83	90	96
Activities of households as employers; undifferentiated goods- and services-producing activities of households for own use	94	49	53	90	96

8 Methodological developments specific to this application

This work is based on a model currently under development. In this section we detail features added specifically to address the question of what is the impact of certain parameters on outcomes as encoded by our model.

8.1 Impact of tourism

8.1.1 Food and accommodation services sector

As there is no "tourism" sector in the 45-sector classification we are using, to model the impact of changes to tourism, we identify the "Food and accommodation services" sector with tourism. This is imperfect. The correlation of their % contributions to GDP is 0.64 and the order of magnitude is similar (1 to 7% vs 2 to 10% of GDP). The other two sectors considered (Air transport and Arts, entertainment and recreation) have little correlation with tourism in terms of % of GDP. (See Figure 6.)
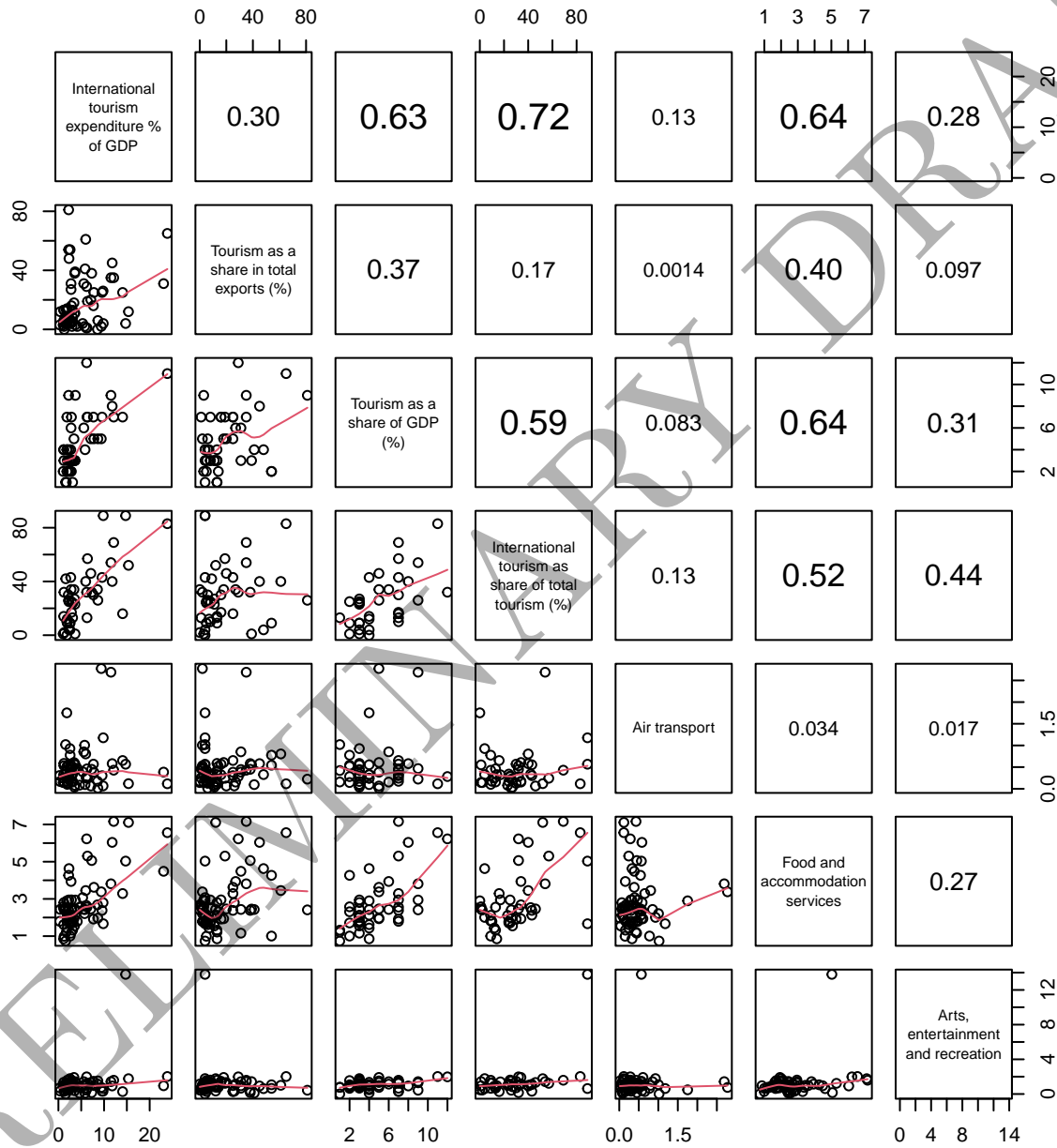
Figure 6: Correlations between tourism-related data. First: https://www.unwto.org/tourism-statistics/key-tourism-statistics. Second to fourth: https://www.unwto.org/tourism-data/international-tourism-and-covid-19. Fifth to seventh: OECD.

8.1.2 Sector shrinkage as a result of the pandemic

For many countries, tourism was reduced not because of domestic mandates but because of reduced international travel. Therefore, the fraction of tourism that comes from abroad is a factor that can determine the impact of a pandemic on a country's GDP potentially independently of what happens within the country. (A useful model extension would be to include some dependence on country factors, e.g. case numbers.)

We model mitigation via business closures, which are mandated by sector. We represent openness with values x which range from 0 to 1, 1 representing maximum openness. To capture the impact of reduced international travel, we set the maximum openness of the food and accommodation services sector to be limited by international tourism as:

$$x_\tau = \min\{\hat{x}_\tau, 1 + y(z - 1)\}$$

where $\hat{x}_\tau$ is the openness of the sector at time τ according to the schedule (i.e. the mitigation strategy), y is the proportion of tourism that is international, and z is the fraction international tourism reduces to as a consequence of the pandemic. I.e. the tourism remaining is the domestic $(1 - y)$ plus that that comes in from abroad (yz).

Therefore, the contribution of the GVA of the food and accommodation services sector is limited either by the pandemic, or by the mitigation measures - whichever is lower.

8.1.3 Loss of international tourists

We model the distribution of z using data from 2020 (Figure 7, bottom-right plot). We fit to it a log-normal distribution, and find mean value -1.39 and standard deviation 0.39 (Figure 8). We use these values as inputs for all country models.
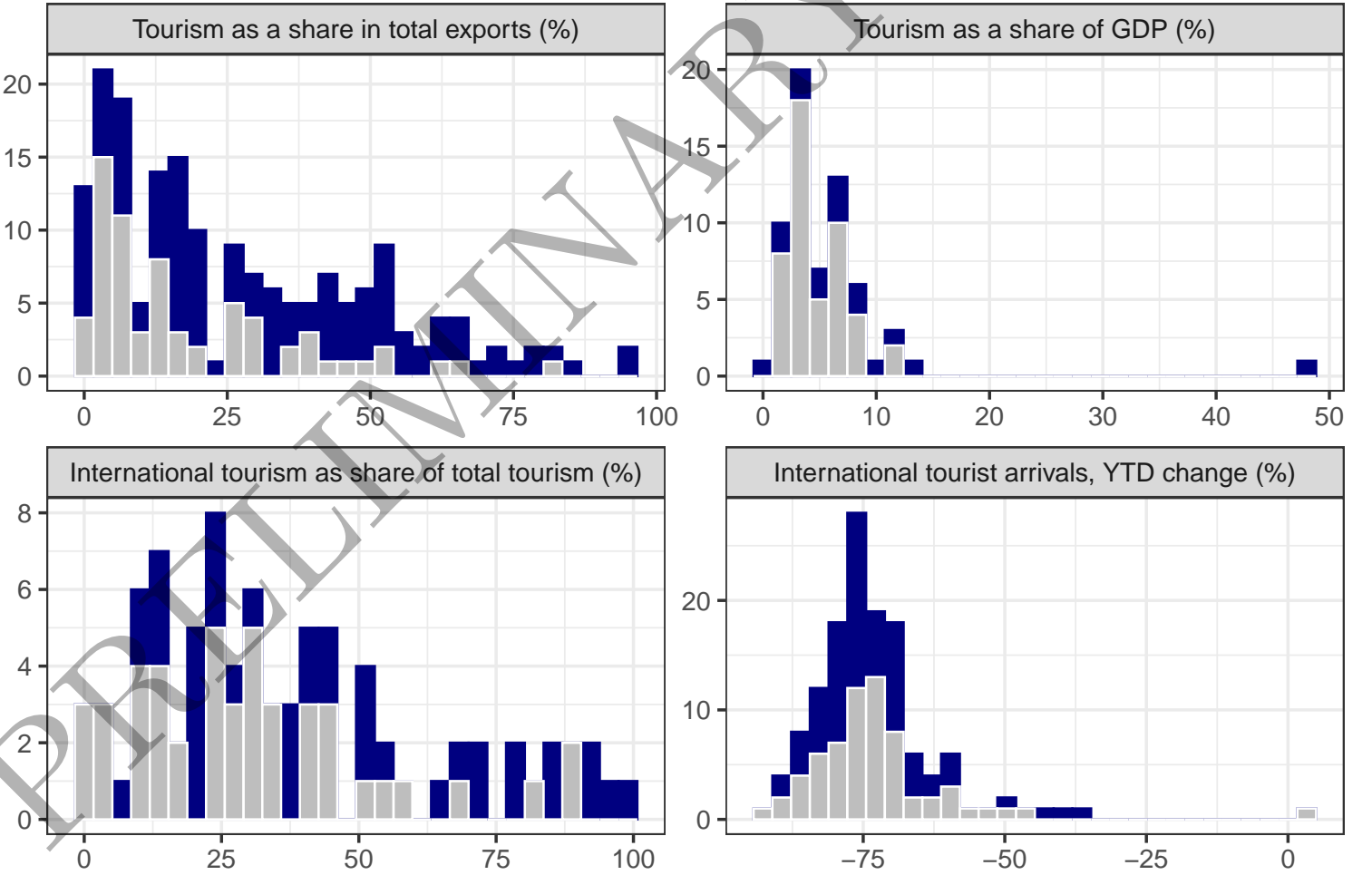

Figure 7: Distributions of tourism-related data from https://www.unwto.org/tourism-data/international-tourism-and-covid-19. In grey are the subset of countries for which we have GVA data by sector.
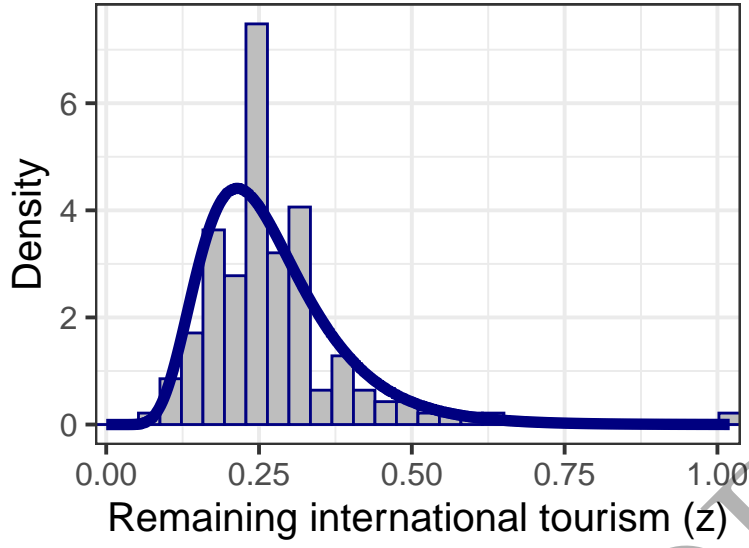
Figure 8: Fit of log-normal distribution to loss-of-tourism data.

8.1.4 Dependence on international tourism

We model y as a function of the share of GDP that comes from the sector. Note that the data we have for this are biased towards high-income countries.

We write

$$y \sim \text{Beta}(\alpha(u), \beta(u))$$

where u is the fraction of GDP coming from the Food and accommodation sector. We learn three parameters p_1, p_2 and p_3 to best fit the relationship between u and y in countries we have observations for:

$$p_1 = \alpha(u) + \beta(u)$$

$$p_2 u + p_3 = \frac{\alpha(u)}{\alpha(u) + \beta(u)}$$

Here, p_1 controls the variance of the distribution and p_2 and p_3 the linear relationship between u and y. Using an optimisation routine in R we find $p_1 = 5.93$, $p_2 = 3.66$ and $p_3 = 0.099$. Results are shown in Figure 9. We use these values as inputs for all country models.
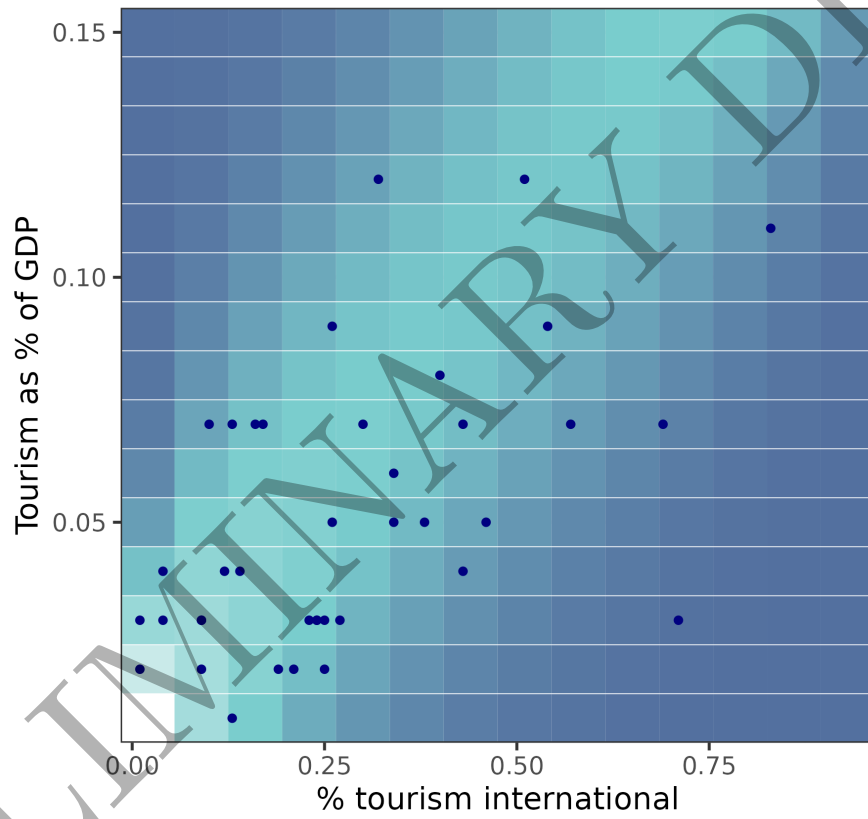
Figure 9: Predicting the percentage of tourism that comes from abroad as a function of the size of the sector. Each row represents a beta distribution whose mean is determined by the size of the sector (u). Blue points show the data we have available (grey bars in Figure 7).

8.2 Sampling sector sizes

To learn about the impacts of changes to sector sizes, we use the following process to sample a baseline economic configuration.

1. Sample a population distribution from all countries (within income group)
2. Sample new values for the population proportions of the Food and accommodation services and Agricultural workforces from uniform distributions bounded by the limits of the dataset
3. Scale the remaining sectors up or down proportionally to match the original total population size.

8.3 Impact of sector sizes

The distribution of people among sectors of the workforce impacts the numbers of contacts made. In order to propagate these influences through the model, we sample a null distribution of contacts from the generating model and save the corresponding average number of candidate infectees (CI, where CI $= R_0/\beta$). Separately, we define a distribution over R_0, e.g. a normal distribution with its stated mean value and a coefficient of variation of 0.1. (E.g. for H1N1, with mean 1.58, the standard deviation given 95% interval {1.34, 2.04} is 0.18 which is a coefficient of variation of 0.11 (Fraser et al. 2009).) Then, for each simulation, we compute the quantile of the CI distribution corresponding to the contacts generated, and select the corresponding quantile from the R_0 distribution. Shown illustratively in Figure 10.
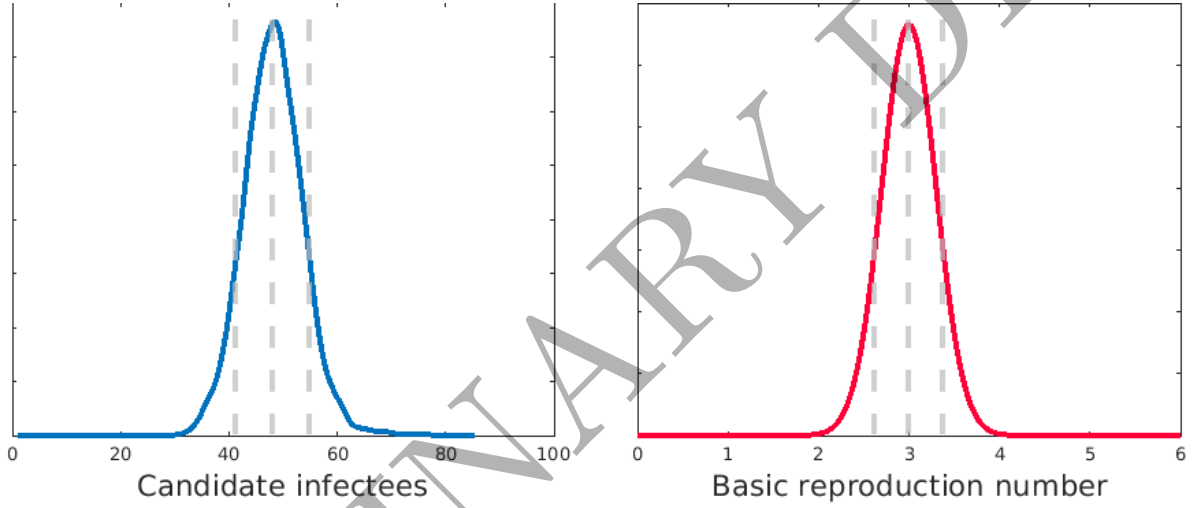

Figure 10: The number of candidate infectees is mapped to the basic reproduction number R_0 via matching quantiles from the simulated null distribution (left) to the parametric distribution (right). 10, 50 and 90% quantiles shown.

8.4 Internet infrastructure

For each sector in each country, we have the 90% interval for the proportion of people who can work from home from (Gottlieb et al. 2021). We assume that the value we sample within the range is related to internet infrastructure, so that a low value in one sector implies low values in all sectors. We:

- Take the subset of countries in the income group (LLMIC / MIC / HIC)
- Take the minimum of the lower bounds by sector (5%)
- Take the maximum of the upper bounds by sector (95%)
- Sample from a uniform distribution between these bounds, taking the same quantile for each sector
- Use the same quantile again for internet coverage in computing the effectiveness of remote learning

8.4.1 Remote teaching

For the value of a year of education, we use the method of (Psacharopoulos, Collis, and Patrinos 2021). The loss due to school closure is

$$L = \text{PV} \cdot Y \cdot \alpha \cdot r \cdot S \cdot \beta$$

where PV is the present value of lost earnings:

$$\text{PV} = \frac{1 - (1 + d)^{-n}}{d}$$

for discount rate $d = 0.03$ and expected number of years of work $n = 45$. Y is mean annual earnings, α is the fraction of the year schools are closed:

$$\alpha = \frac{1}{12} \sum_{\tau=1}^{12} 1 - x_{ed,\tau,}$$

$r = 0.08$ is the rate of return for one year, S is the total number of students, and β is the proportion of students affected. We take $\beta = 1 - 0.86I$ to be the complement fraction of internet coverage I (Figure 11) multiplied by 0.86, to match values for the Philippines: it has 43% internet coverage and effectiveness of remote education was estimated to be 37% (National Economic and Development Authority 2021).
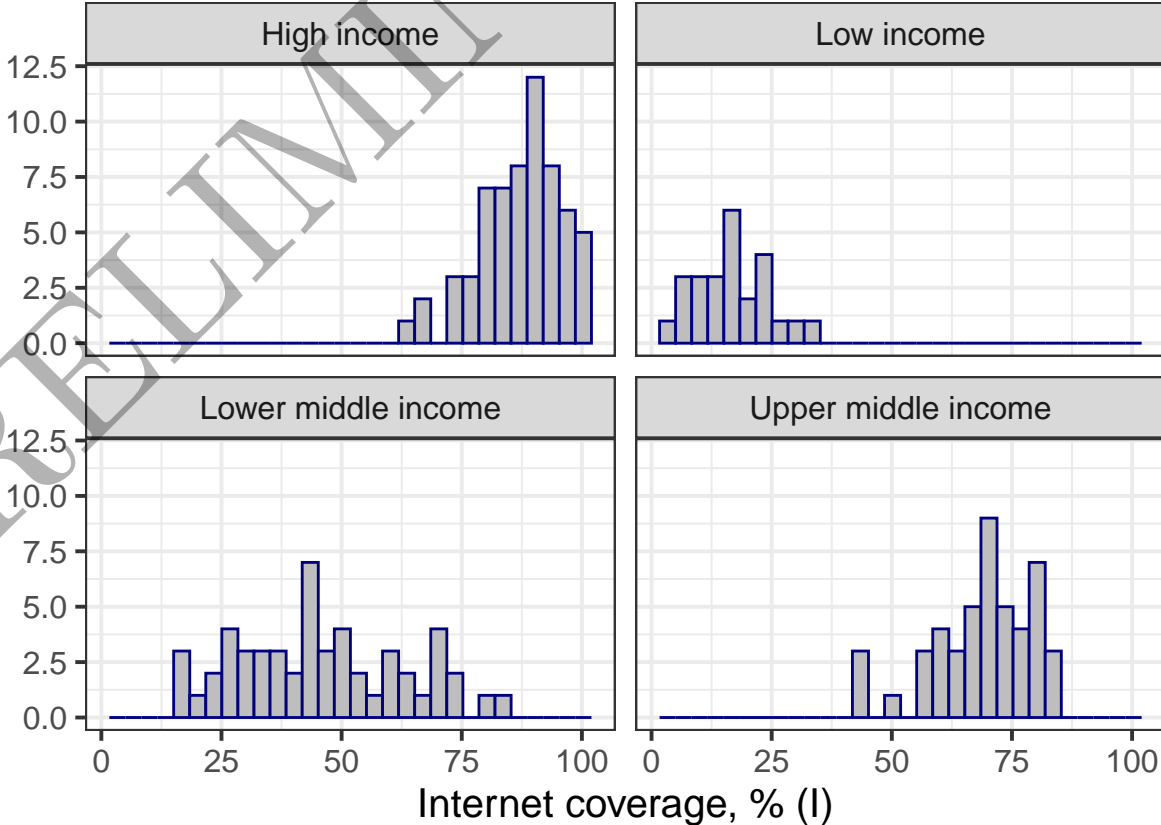

Figure 11: Internet access by income level. World Bank data for 2019.

We model the Figure 11 values with Beta distributions. For LLMICs, we have parameters 1.78 and 3.11. For MICs, we have parameters 3.77 and 2.91. For HICs, we have parameters 9.57 and 1.39.

We estimate the average annual income per working-age adult as the total GVA multiplied by the fraction of GVA that goes to labour divided by the number of working-age adults. For the fraction of GVA that goes to labour we use PWT estimates from 2011 (Figure 12). (This correction might lead us to underestimate the impact of education: perhaps GNI per working-age adult is better than average income among working-age adults. E.g. suppose Country A and Country B have the same GVA and the same number of workers, where GVA = labour compensation + capital. And suppose Country A splits its GVA between labour and capital with ratio 1:2, and Country B with ratio 2:1. Then the value of education in Country B is twice that in Country A, because we are only counting the income contribution to the economy. If we wanted to estimate the impact on the economy, we should use the whole GVA, not just the labour share.)

Figure 12: Fraction of GVA that goes to labour (PWT, 2011).

We model these values with Beta distributions. For LLMICs, we have parameters 5.09 and 4.51. For MICs, we have parameters 6.29 and 6.54. For HICs, we have parameters 7.97 and 6.87.
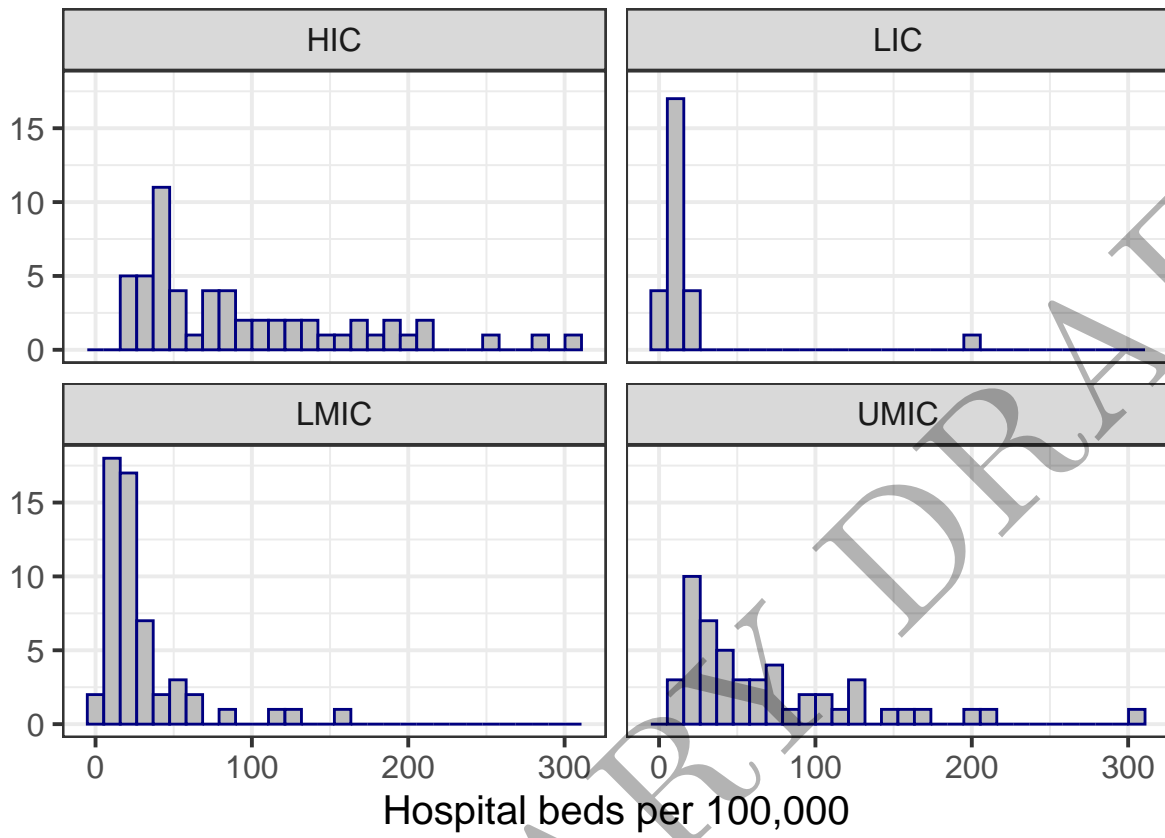
8.5 Hospital capacity

Figure 13: Fraction of GVA that goes to labour (PWT, 2011).

We model these values with gamma distributions. For LLMICs, we have parameters 1.3 and 0.05. For MICs, we have parameters 1.36 and 0.03. For HICs, we have parameters 2.05 and 0.02.

9 Distributions over outcomes: other six pathogens

	virus	strategy	igroup	variable	value

1 Influenza 2009 No Closures LLMIC deaths 1.145571e+00 2 Influenza 2009 School Closures LLMIC deaths 6.126833e-01 3 Influenza 2009 Economic Closures LLMIC deaths 6.862834e-01 4 Influenza 2009 Elimination LLMIC deaths 1.048459e-01 5 Influenza 1957 No Closures LLMIC deaths 3.698098e+00 6 Influenza 1957 School Closures LLMIC deaths 1.427621e+00 7 Influenza 1957 Economic Closures LLMIC deaths 1.616415e+00 8 Influenza 1957 Elimination LLMIC deaths 4.966748e-01 9 Influenza 1918 No Closures LLMIC deaths 1.466405e+02 10 Influenza 1918 School Closures LLMIC deaths 6.310012e+01 11 Influenza 1918 Economic Closures LLMIC deaths 3.376272e+01 12 Influenza 1918 Elimination LLMIC deaths 2.169010e+01 13 SARS-CoV-2 Omicron No Closures LLMIC deaths 3.534815e+01 14 SARS-CoV-2 Omicron School Closures LLMIC deaths 2.635241e+01 15 SARS-CoV-2 Omicron Economic Closures LLMIC deaths 1.978978e+01 16 SARS-CoV-2 Omicron Elimination LLMIC deaths 1.781380e+01 17 SARS-CoV-2 pre-Alpha No Closures LLMIC deaths 4.740673e+01 18 SARS-CoV-2 pre-Alpha School Closures LLMIC deaths 2.118879e+01 19 SARS-CoV-2 pre-Alpha Economic Closures LLMIC deaths 1.073414e+01 20 SARS-CoV-2 pre-Alpha Elimination LLMIC deaths 7.799863e+00 21 SARS-CoV-2 Delta No Closures LLMIC deaths 1.955870e+02 22 SARS-CoV-2 Delta School Closures LLMIC deaths 1.315232e+02 23 SARS-CoV-2 Delta Economic Closures LLMIC deaths 7.880909e+01 24 SARS-CoV-2 Delta Elimination LLMIC deaths 7.642155e+01 25 SARS-CoV-1 No Closures LLMIC deaths 8.853427e+00 26 SARS-CoV-1 School Closures LLMIC deaths 2.190366e+00 27 SARS-CoV-1 Economic Closures LLMIC deaths 9.870361e-01 28 SARS-CoV-1 Elimination LLMIC deaths 4.355187e-02 29 Influenza 2009 No Closures MIC deaths 1.066545e+00 30 Influenza 2009 School Closures MIC deaths 7.458421e-01 31 Influenza 2009 Economic Closures MIC deaths 8.044419e-01 32 Influenza 2009 Elimination MIC deaths 1.038811e-01 33 Influenza 1957 No Closures MIC deaths 4.503307e+00 34 Influenza 1957 School Closures MIC deaths 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6.533462e+00 163 SARS-CoV-2 Delta Economic Closures HIC education 4.380271e+00 164 SARS-CoV-2 Delta Elimination HIC education 6.325396e+00 165 SARS-CoV-1 No Closures HIC education 3.557667e-04 166 SARS-CoV-1 School Closures HIC education 6.490323e-02 167 SARS-CoV-1 Economic Closures HIC education 3.079367e-02 168 SARS-CoV-1 Elimination HIC education 4.431569e-01 169 Influenza 2009 No Closures LLMIC gdp 1.682499e+00 170 Influenza 2009 School Closures LLMIC gdp 1.792317e+00 171 Influenza 2009 Economic Closures LLMIC gdp 2.585431e+00 172 Influenza 2009 Elimination LLMIC gdp 8.208215e+00 173 Influenza 1957 No Closures LLMIC gdp 1.869668e+00 174 Influenza 1957 School Closures LLMIC gdp 3.145469e+00 175 Influenza 1957 Economic Closures LLMIC gdp 5.996930e+00 176 Influenza 1957 Elimination LLMIC gdp 1.014088e+01 177 Influenza 1918 No Closures LLMIC gdp 3.292143e+00 178 Influenza 1918 School Closures LLMIC gdp 7.008917e+00 179 Influenza 1918 Economic Closures LLMIC gdp 1.874795e+01 180 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gdp 1.257458e+01 236 Influenza 1918 Elimination HIC gdp 1.246893e+01 237 SARS-CoV-2 Omicron No Closures HIC gdp 2.272870e+00 238 SARS-CoV-2 Omicron School Closures HIC gdp 5.138172e+00 239 SARS-CoV-2 Omicron Economic Closures HIC gdp 1.101240e+01 240 SARS-CoV-2 Omicron Elimination HIC gdp 1.760223e+01 241 SARS-CoV-2 pre-Alpha No Closures HIC gdp 1.550117e+00 242 SARS-CoV-2 pre-Alpha School Closures HIC gdp 3.786188e+00 243 SARS-CoV-2 pre-Alpha Economic Closures HIC gdp 9.772921e+00 244 SARS-CoV-2 pre-Alpha Elimination HIC gdp 9.419443e+00 245 SARS-CoV-2 Delta No Closures HIC gdp 5.192008e+00 246 SARS-CoV-2 Delta School Closures HIC gdp 8.405246e+00 247 SARS-CoV-2 Delta Economic Closures HIC gdp 1.970848e+01 248 SARS-CoV-2 Delta Elimination HIC gdp 2.408650e+01 249 SARS-CoV-1 No Closures HIC gdp 8.216844e-01 250 SARS-CoV-1 School Closures HIC gdp 8.632028e-01 251 SARS-CoV-1 Economic Closures HIC gdp 9.619379e-01 252 SARS-CoV-1 Elimination HIC gdp 4.034601e+00

Table 3: Results for all scenarios shown. Mean values and 95% prediction intervals.)

Virus	Strategy	Income group	Total costs	YLLs	Education	GDP
Influenza 2009	No Closures	LLMIC	2.9 (0, 11.1)	1.1 (0, 4.9)	0.1 (0, 0.2)	1.7 (0, 8.1)
Influenza 2009	School Closures	LLMIC	9.2 (0, 55.8)	0.6 (0, 1.7)	6.7 (0, 51.3)	1.8 (0, 9.5)
Influenza 2009	Economic Closures	LLMIC	4.3 (0, 20.8)	0.7 (0, 1.8)	1.1 (0, 9.1)	2.6 (0, 12.6)
Influenza 2009	Elimination	LLMIC	20 (1.2, 80)	0.1 (0, 1.2)	11.7 (0.1, 58.8)	8.2 (0.2, 25.1)
Influenza 1957	No Closures	LLMIC	5.7 (0.7, 19.2)	3.7 (0, 15.3)	0.1 (0, 0.3)	1.9 (0.2, 8.6)
Influenza 1957	School Closures	LLMIC	26.3 (0.4, 77.1)	1.4 (0, 3.9)	21.7 (0, 70.1)	3.1 (0.2, 13.5)
Influenza 1957	Economic Closures	LLMIC	11.4 (0.4, 37.6)	1.6 (0, 3.7)	3.8 (0, 21.3)	6 (0.2, 17.2)
Influenza 1957	Elimination	LLMIC	26.1 (2.2, 83.9)	0.5 (0, 2.5)	15.4 (0.2, 62.6)	10.1 (0.4, 27)
Influenza 1918	No Closures	LLMIC	150.2 (22.1, 415.5)	146.6 (19.9, 410.6)	0.2 (0, 0.8)	3.3 (0.5, 11.3)
Influenza 1918	School Closures	LLMIC	114 (29.8, 318)	63.1 (1.1, 263.6)	43.9 (11.9, 94.2)	7 (1.6, 23)
Influenza 1918	Economic Closures	LLMIC	79.3 (24.3, 229.2)	33.8 (1, 159.7)	26.8 (1.4, 74.2)	18.7 (9.1, 31.1)
Influenza 1918	Elimination	LLMIC	82.1 (16.4, 229)	21.7 (0.3, 159.2)	38.8 (5.1, 91.7)	21.6 (5.8, 34.8)
SARS-CoV-2 Omicron	No Closures	LLMIC	39.2 (10.8, 104.6)	35.3 (7.8, 99.3)	0.5 (0.1, 1.1)	3.4 (1.2, 11.3)
SARS-CoV-2 Omicron	School Closures	LLMIC	75.7 (19.9, 141.5)	26.4 (4.5, 84.7)	42.5 (5.9, 94.6)	6.9 (1.8, 21)
SARS-CoV-2 Omicron	Economic Closures	LLMIC	54.2 (17.8, 137.3)	19.8 (3.3, 65.7)	19.4 (2.3, 66.4)	15 (3.9, 31.6)
SARS-CoV-2 Omicron	Elimination	LLMIC	82.4 (14.8, 145.8)	17.8 (1.8, 65.1)	41.3 (1.7, 93.7)	23.3 (1.8, 35.9)
SARS-CoV-2 pre-Alpha	No Closures	LLMIC	50.3 (9, 146.2)	47.4 (6.9, 143.5)	0.2 (0, 0.6)	2.6 (0.6, 9.1)
SARS-CoV-2 pre-Alpha	School Closures	LLMIC	60.1 (14.7, 145.8)	21.2 (0.1, 102.4)	33.2 (6.7, 73)	5.7 (1.4, 19)
SARS-CoV-2 pre-Alpha	Economic Closures	LLMIC	49.8 (14.3, 120.5)	10.7 (0.1, 60.6)	23.6 (3.1, 58)	15.5 (7.3, 25.7)
SARS-CoV-2 pre-Alpha	Elimination	LLMIC	56.5 (6.2, 123.2)	7.8 (0, 60.1)	31.2 (1.8, 74.9)	17.5 (3.2, 28.7)
SARS-CoV-2 Delta	No Closures	LLMIC	201.7 (29.7, 461.4)	195.6 (26.5, 454.4)	0.4 (0.1, 0.9)	5.7 (1.3, 13.7)
SARS-CoV-2 Delta	School Closures	LLMIC	185 (42.9, 412.2)	131.5 (3.8, 368.5)	43.8 (12, 94.1)	9.6 (3.2, 26.8)
SARS-CoV-2 Delta	Economic Closures	LLMIC	141.5 (43.4, 330.2)	78.8 (2.5, 265.8)	39 (9.5, 87.2)	23.7 (14.2, 35.6)
SARS-CoV-2 Delta	Elimination	LLMIC	145.3 (51, 330.4)	76.4 (1.5, 265.8)	43.8 (11.9, 94)	25.1 (16.3, 36.1)
SARS-CoV-1	No Closures	LLMIC	10.4 (0, 91.5)	8.9 (0, 89.8)	0 (0, 0.1)	1.5 (0, 8)
SARS-CoV-1	School Closures	LLMIC	6.7 (0, 52.4)	2.2 (0, 25.4)	2.7 (0, 25.5)	1.8 (0, 9.1)
SARS-CoV-1	Economic Closures	LLMIC	5.4 (0, 33.3)	1 (0, 7.8)	1.8 (0, 16.7)	2.6 (0, 12.4)
SARS-CoV-1	Elimination	LLMIC	20.6 (1.5, 80.2)	0 (0, 0)	12.1 (0.3, 60.2)	8.5 (0.8, 25.4)

Virus	Strategy	Income group	Total costs	YLLs	Education	GDP
Influenza 2009	No Closures	MIC	2.1 (0, 6.6)	1.1 (0, 3.9)	0 (0, 0.2)	0.9 (0, 4.4)
Influenza 2009	School Closures	MIC	3.5 (0, 25.4)	0.7 (0, 2.4)	1.8 (0, 20.7)	1 (0, 5)
Influenza 2009	Economic Closures	MIC	2.4 (0, 12.4)	0.8 (0, 2.5)	0.3 (0, 2.7)	1.3 (0, 8.7)
Influenza 2009	Elimination	MIC	11.8 (1.5, 49.4)	0.1 (0, 1.5)	5 (0.1, 29.9)	6.7 (0.5, 22)
Influenza 1957	No Closures	MIC	5.7 (0.2, 18.5)	4.5 (0, 17.2)	0.1 (0, 0.2)	1.1 (0.2, 4.6)
Influenza 1957	School Closures	MIC	14 (0.2, 43.4)	2.1 (0, 5.7)	9.6 (0, 37.3)	2.4 (0.1, 8.5)
Influenza 1957	Economic Closures	MIC	8.6 (0.2, 24.3)	2.4 (0, 6)	1.5 (0, 9.1)	4.7 (0.1, 14.5)
Influenza 1957	Elimination	MIC	13.6 (2.1, 50)	0.9 (0, 4.2)	5.5 (0.1, 29.7)	7.1 (0.3, 22.9)
Influenza 1918	No Closures	MIC	142.3 (24.7, 406.2)	139.9 (23.4, 402.7)	0.1 (0, 0.5)	2.3 (0.4, 6.5)
Influenza 1918	School Closures	MIC	88.3 (21.8, 254.4)	59.7 (1.9, 219.4)	22.7 (6.2, 56.2)	5.9 (1.9, 15.3)
Influenza 1918	Economic Closures	MIC	67.9 (18.7, 156.4)	40.4 (1.7, 114.1)	11.4 (0.6, 39.7)	16.1 (7.5, 26.8)
Influenza 1918	Elimination	MIC	53.7 (11, 147.8)	18.9 (0.7, 96)	16.9 (1.5, 50.4)	17.9 (4, 29.9)
SARS-CoV-2 Omicron	No Closures	MIC	40.6 (9.9, 117.9)	37.9 (7.6, 115.3)	0.3 (0.1, 0.7)	2.4 (1.1, 6.6)
SARS-CoV-2 Omicron	School Closures	MIC	55.5 (12.2, 117.4)	29 (6.5, 89.2)	20.8 (0.9, 55)	5.7 (1.4, 14.8)
SARS-CoV-2 Omicron	Economic Closures	MIC	42.5 (13.4, 107.6)	22.4 (6, 62.9)	7.5 (0.6, 31.5)	12.5 (2.6, 27)
SARS-CoV-2 Omicron	Elimination	MIC	59 (10.6, 111.8)	19.4 (3.7, 61.3)	19.2 (0.3, 52.6)	20.4 (1.1, 31.1)
SARS-CoV-2 pre-Alpha	No Closures	MIC	51.6 (0.5, 165.6)	49.7 (0, 163)	0.1 (0, 0.4)	1.8 (0.3, 5.3)
SARS-CoV-2 pre-Alpha	School Closures	MIC	42.7 (0.3, 124.5)	21.8 (0, 102.8)	16.1 (0, 42.7)	4.8 (0.3, 12.8)
SARS-CoV-2 pre-Alpha	Economic Closures	MIC	35.9 (0.3, 91.7)	12.5 (0, 55)	10.4 (0, 31.4)	13 (0.3, 22)
SARS-CoV-2 pre-Alpha	Elimination	MIC	35.2 (2.4, 92.1)	7.4 (0, 53.9)	13.5 (0.3, 42.5)	14.3 (1.9, 24.6)
SARS-CoV-2 Delta	No Closures	MIC	244.2 (32.8, 581.5)	239.2 (31.1, 574.2)	0.2 (0, 0.6)	4.9 (1.2, 9.5)
SARS-CoV-2 Delta	School Closures	MIC	182.6 (33.8, 461.1)	151.2 (9.2, 433.5)	22.6 (6.2, 56)	8.8 (3.5, 19.8)
SARS-CoV-2 Delta	Economic Closures	MIC	128.5 (36.6, 330.6)	88.5 (6.3, 290)	18.5 (2.9, 48.4)	21.5 (11, 30.8)
SARS-CoV-2 Delta	Elimination	MIC	129.6 (41.2, 330.6)	83.4 (3.8, 289.7)	22.5 (6.2, 55.8)	23.7 (16, 31.7)
SARS-CoV-1	No Closures	MIC	8.5 (0, 91.9)	7.6 (0, 91.5)	0 (0, 0)	0.8 (0, 4.3)
SARS-CoV-1	School Closures	MIC	4.2 (0, 35.1)	2.1 (0, 23.2)	1 (0, 11.1)	1 (0, 5.1)
SARS-CoV-1	Economic Closures	MIC	3.4 (0, 23.7)	1.2 (0, 11.6)	0.7 (0, 7.3)	1.5 (0, 8.5)
SARS-CoV-1	Elimination	MIC	11.7 (1.4, 49.3)	0 (0, 0)	5 (0.1, 30)	6.7 (1.1, 22)
Influenza 2009	No Closures	HIC	2.3 (0, 6)	1.3 (0, 3.9)	0 (0, 0)	0.9 (0, 3.7)
Influenza 2009	School Closures	HIC	2.2 (0, 8.4)	1.2 (0, 3.7)	0.2 (0, 3.7)	0.8 (0, 3.7)
Influenza 2009	Economic Closures	HIC	2.2 (0, 8.4)	1.2 (0, 3.7)	0 (0, 0.3)	0.9 (0, 6.3)
Influenza 2009	Elimination	HIC	4.8 (1.8, 15)	0.4 (0, 3.4)	0.5 (0, 3)	4 (0.3, 12.2)
Influenza 1957	No Closures	HIC	7.6 (0.1, 17.1)	6.5 (0, 16)	0 (0, 0.1)	1.1 (0.1, 4)
Influenza 1957	School Closures	HIC	9.5 (0.1, 19.8)	3.8 (0, 8.8)	3.3 (0, 11.3)	2.4 (0.1, 6.1)
Influenza 1957	Economic Closures	HIC	9.9 (0.1, 19.3)	4.7 (0, 9.4)	0.3 (0, 1.8)	4.8 (0.1, 12.3)
Influenza 1957	Elimination	HIC	7.4 (2.2, 17.7)	2.4 (0, 8.7)	0.6 (0, 3.2)	4.3 (0.3, 13)
Influenza 1918	No Closures	HIC	134.8 (27.2, 366.1)	132.7 (26, 362.3)	0 (0, 0.1)	2.1 (0.4, 5.5)

Virus	Strategy	Income group	Total costs	YLLs	Education	GDP
Influenza 1918	School Closures	HIC	69.3 (15.6, 155.8)	57.6 (5.4, 141.2)	6.6 (2.3, 14.5)	5.1 (2.7, 9.6)
Influenza 1918	Economic Closures	HIC	69 (16.6, 136.4)	54.6 (4.9, 120)	1.9 (0.2, 8.1)	12.6 (6.8, 24.6)
Influenza 1918	Elimination	HIC	35.2 (9.8, 77.1)	19.8 (2.6, 54.4)	2.9 (0.3, 11.1)	12.5 (3.8, 28.3)
SARS-CoV-2 Omicron	No Closures	HIC	54.2 (15.5, 137.5)	51.9 (13.8, 134.2)	0.1 (0, 0.2)	2.3 (1.1, 5.6)
SARS-CoV-2 Omicron	School Closures	HIC	53.3 (18.2, 113.2)	42.2 (12.4, 99.9)	6 (0.1, 14.2)	5.1 (1.1, 9.7)
SARS-CoV-2 Omicron	Economic Closures	HIC	47.6 (19.7, 91.7)	35.3 (11.8, 71)	1.3 (0.1, 6.5)	11 (1.1, 24.1)
SARS-CoV-2 Omicron	Elimination	HIC	50.7 (17.3, 93.1)	28.5 (8.2, 62.7)	4.5 (0.1, 12.6)	17.6 (1.1, 29.7)
SARS-CoV-2 pre-Alpha	No Closures	HIC	54.2 (0.1, 187.2)	52.6 (0, 185.1)	0 (0, 0.1)	1.6 (0.1, 4.4)
SARS-CoV-2 pre-Alpha	School Closures	HIC	29.4 (0.1, 95.4)	21.8 (0, 83.4)	3.8 (0, 11.1)	3.8 (0.1, 8.1)
SARS-CoV-2 pre-Alpha	Economic Closures	HIC	27.8 (0.1, 69.9)	16.1 (0, 49.1)	2 (0, 7)	9.8 (0.1, 20.9)
SARS-CoV-2 pre-Alpha	Elimination	HIC	19 (2.1, 63.8)	7.5 (0, 38.7)	2.1 (0.1, 8.7)	9.4 (1.9, 23.6)
SARS-CoV-2 Delta	No Closures	HIC	383.2 (46, 759.6)	377.9 (44.4, 751.6)	0.1 (0, 0.1)	5.2 (1, 9.7)
SARS-CoV-2 Delta	School Closures	HIC	246.3 (32.6, 558.3)	231.3 (20.3, 538.7)	6.5 (2.3, 14.3)	8.4 (3.9, 13.9)
SARS-CoV-2 Delta	Economic Closures	HIC	156 (39.4, 358)	131.9 (17.4, 326.4)	4.4 (0.5, 11.8)	19.7 (8.9, 30.4)
SARS-CoV-2 Delta	Elimination	HIC	148 (38.4, 353.5)	117.6 (10.5, 322.6)	6.3 (2, 14.2)	24.1 (12.7, 31.7)
SARS-CoV-1	No Closures	HIC	2.8 (0, 22)	1.9 (0, 20.3)	0 (0, 0)	0.8 (0, 3.6)
SARS-CoV-1	School Closures	HIC	1.5 (0, 11)	0.5 (0, 6.8)	0.1 (0, 0)	0.9 (0, 3.9)
SARS-CoV-1	Economic Closures	HIC	1.4 (0, 11.6)	0.4 (0, 5.9)	0 (0, 0)	1 (0, 5.5)
SARS-CoV-1	Elimination	HIC	4.5 (1.8, 15.1)	0 (0, 0)	0.4 (0, 3.1)	4 (1.7, 12.6)

10 VOI and MI: other six pathogens
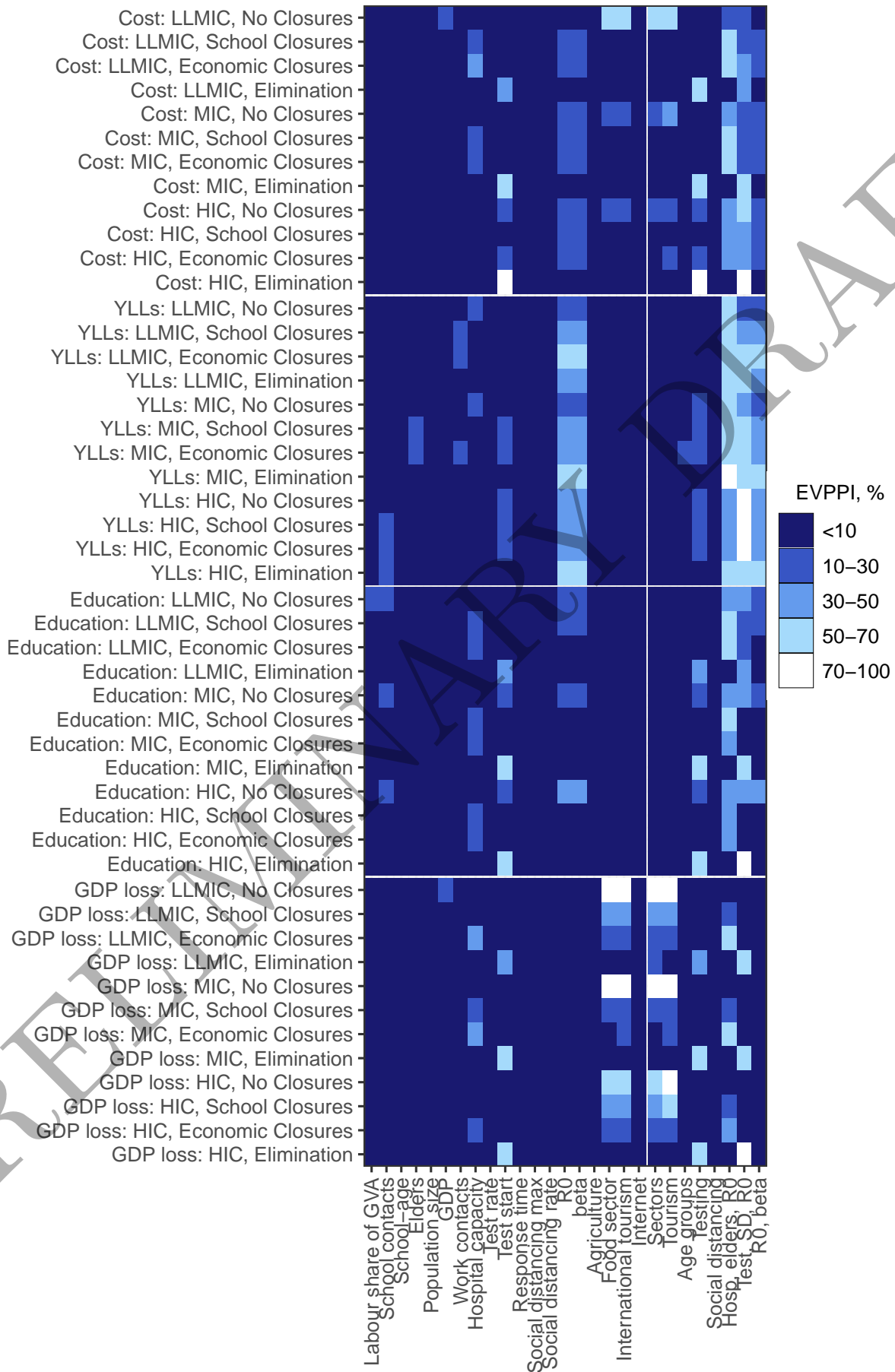
Figure 14: Value of information for Influenza 2009.
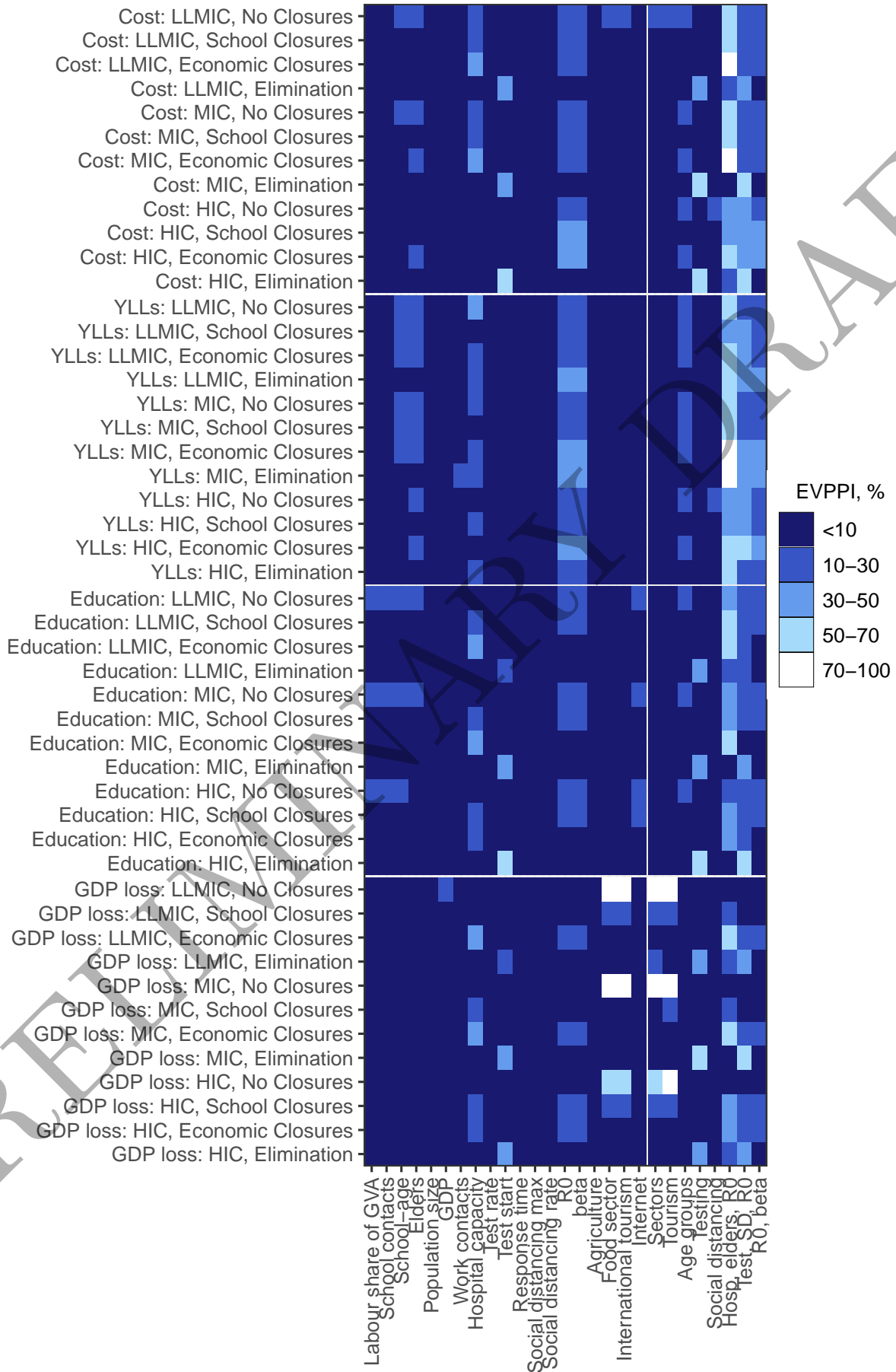
Figure 15: Value of information for Influenza 1957.
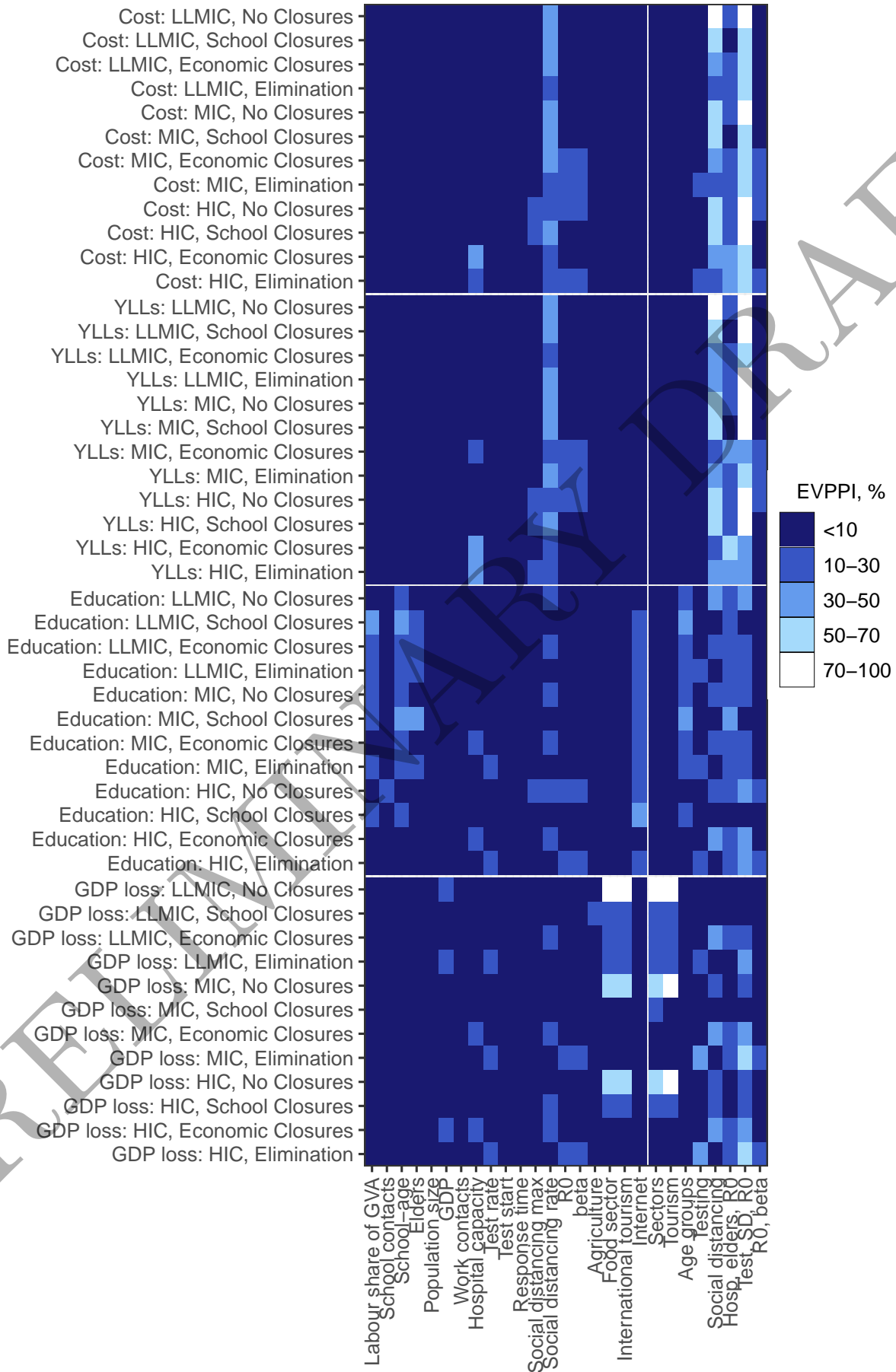
Figure 16: Value of information for Influenza 1918.
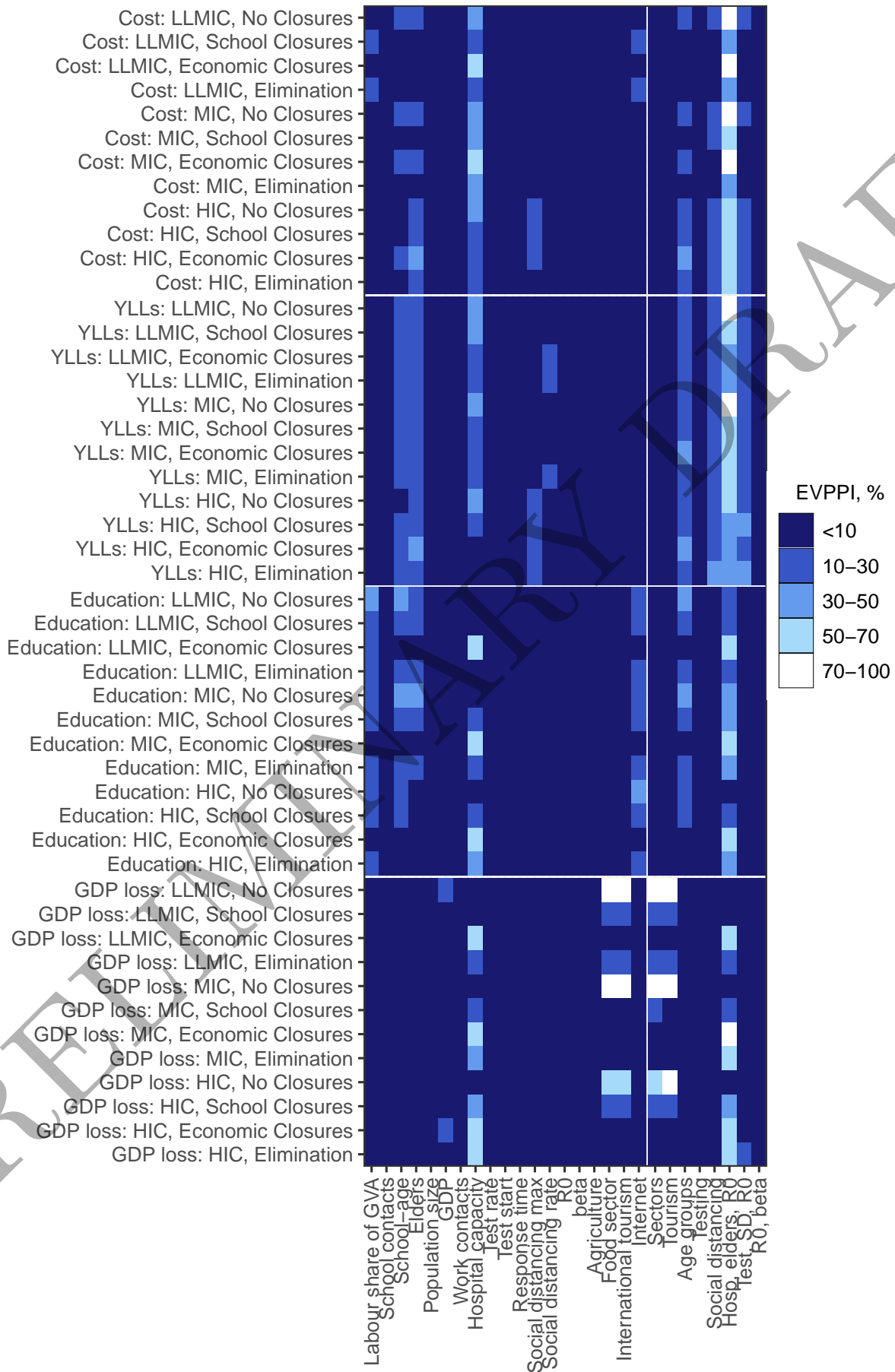
Figure 17: Value of information for Omicron SARS-CoV-2.
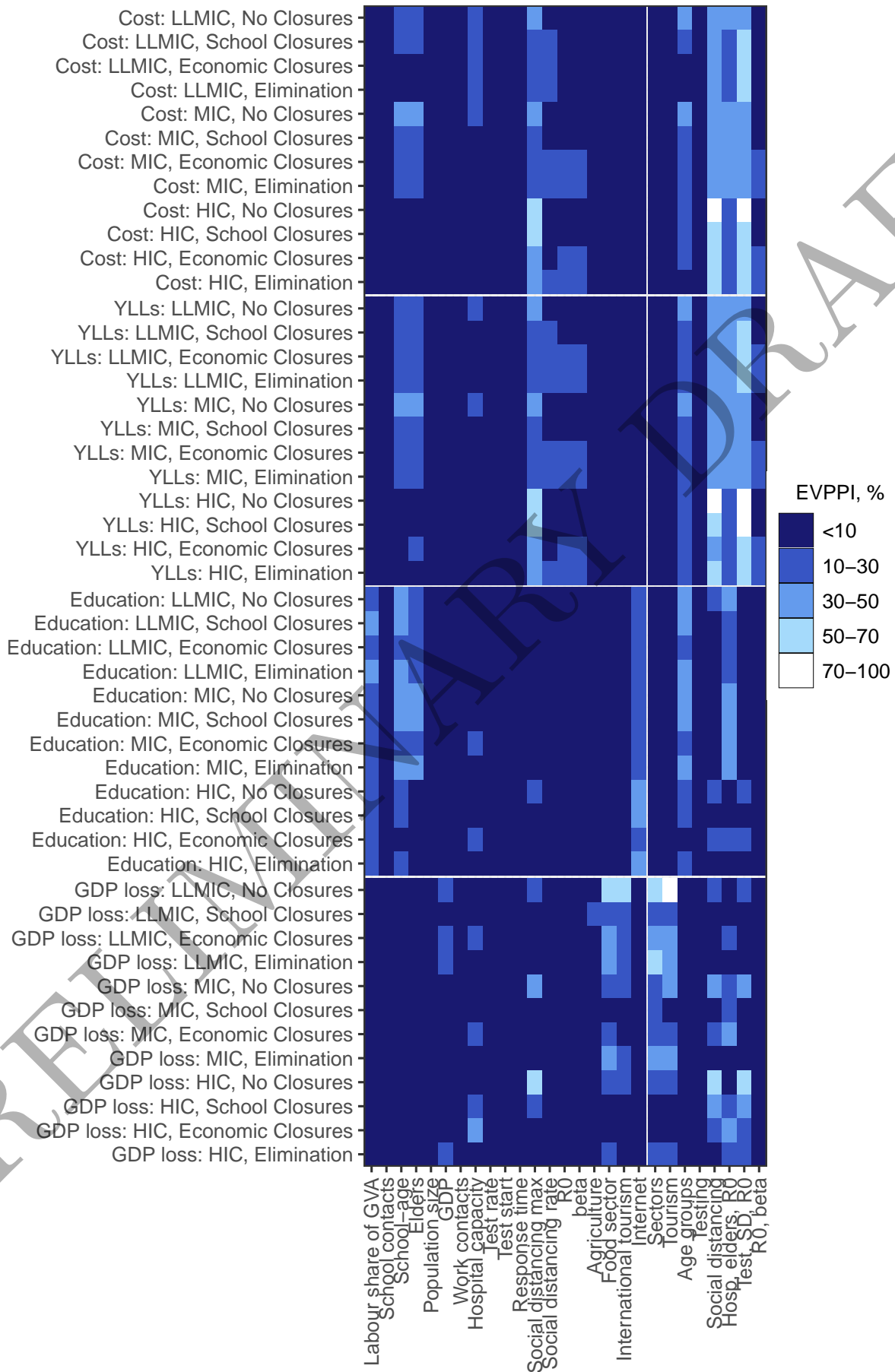
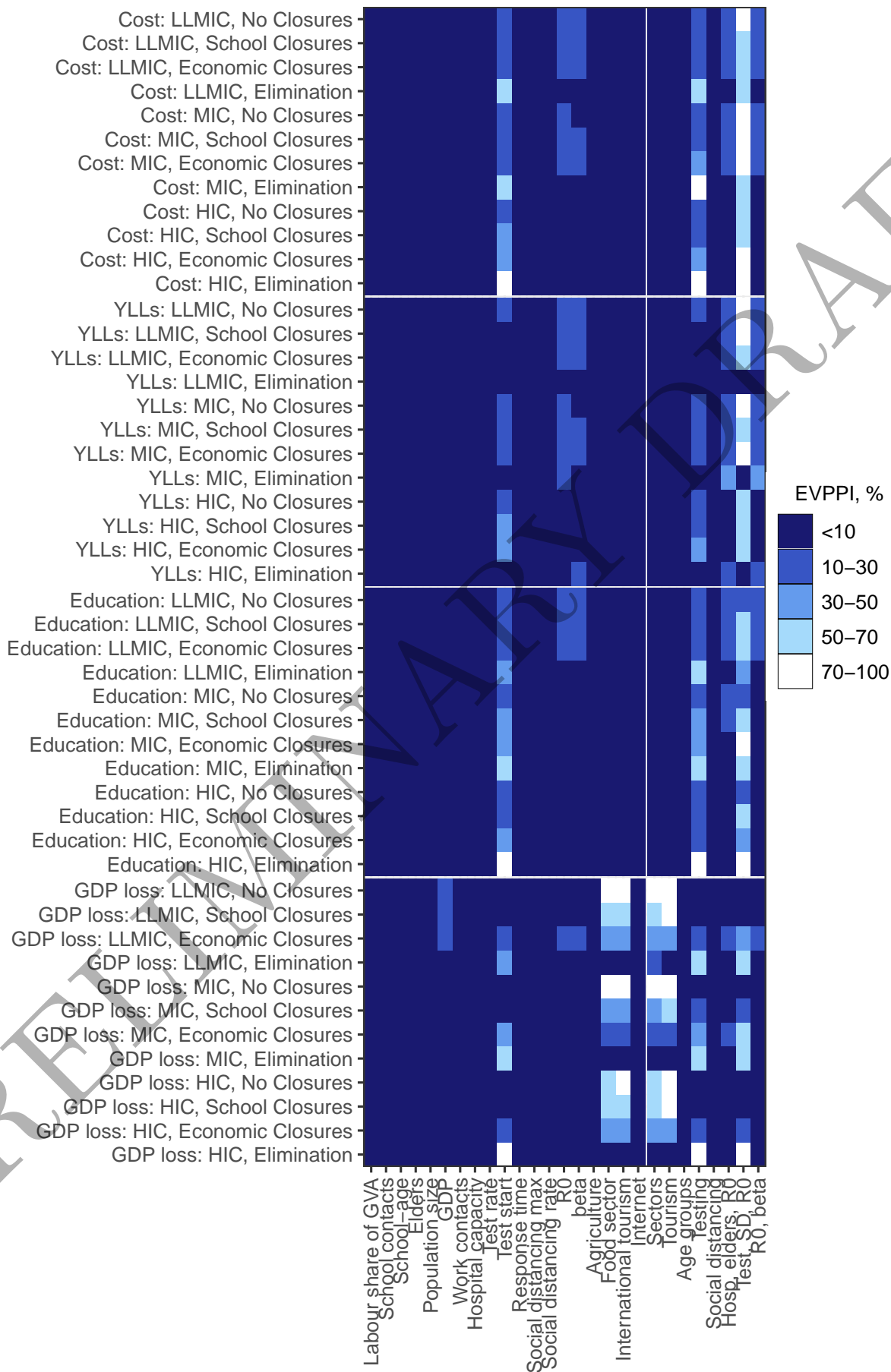Figure 18: Value of information for Delta SARS-CoV-2.

Figure 19: Value of information for SARS-CoV-1.

11 Comparison of model results for SARS-CoV-2 (pre-Alpha) to 2020 data

Our model has not been calibrated to fit any observed economic outcomes in general or for any specific country. However, the distributions for the pre-Alpha profile of SARS-CoV-2 should align to some extent with data pertaining to 2020, as many of the inputs to the model were taken from this period.

11.1 GDP loss
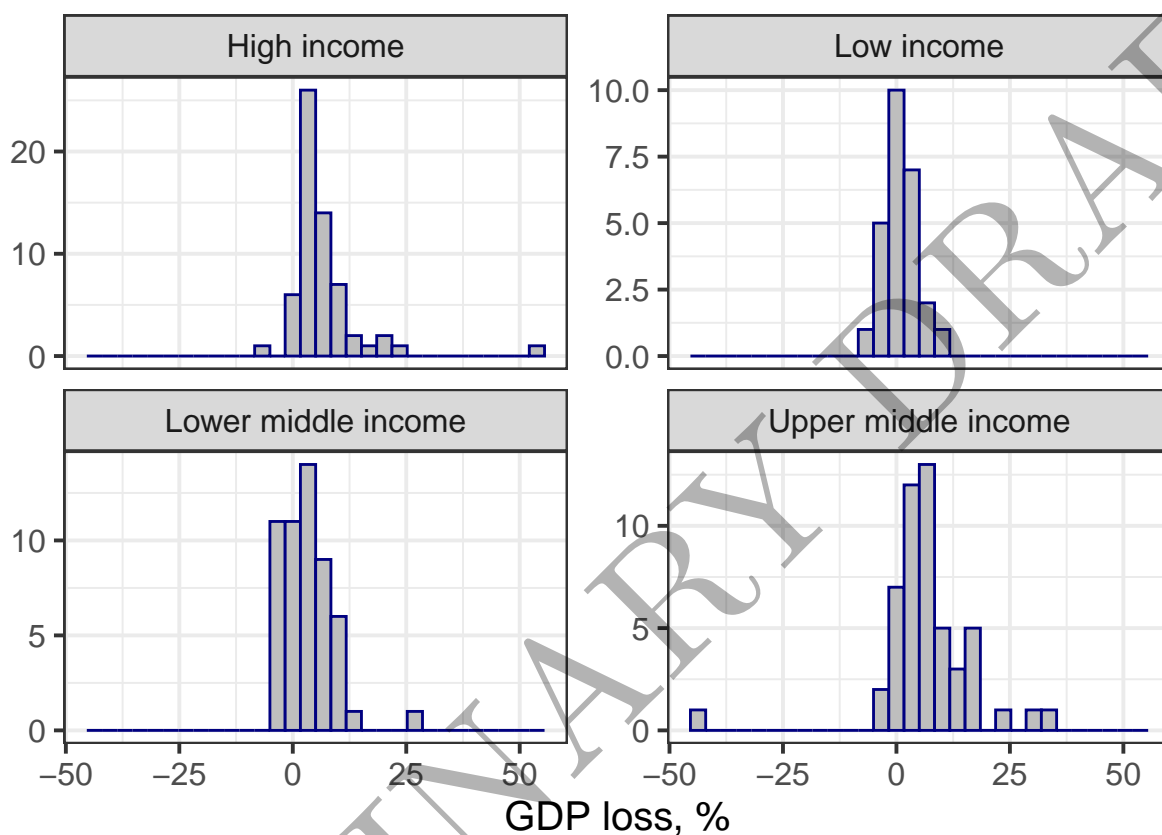
Figure 20: GDP loss: loss in 2020 as a percentage of 2019 GDP (IMF). NB: data are annual, so the loss is for the year starting January 2020. We would prefer to present data for April 2020 to March 2021 but these data are unavailable for most countries. The outlier is Guyana.
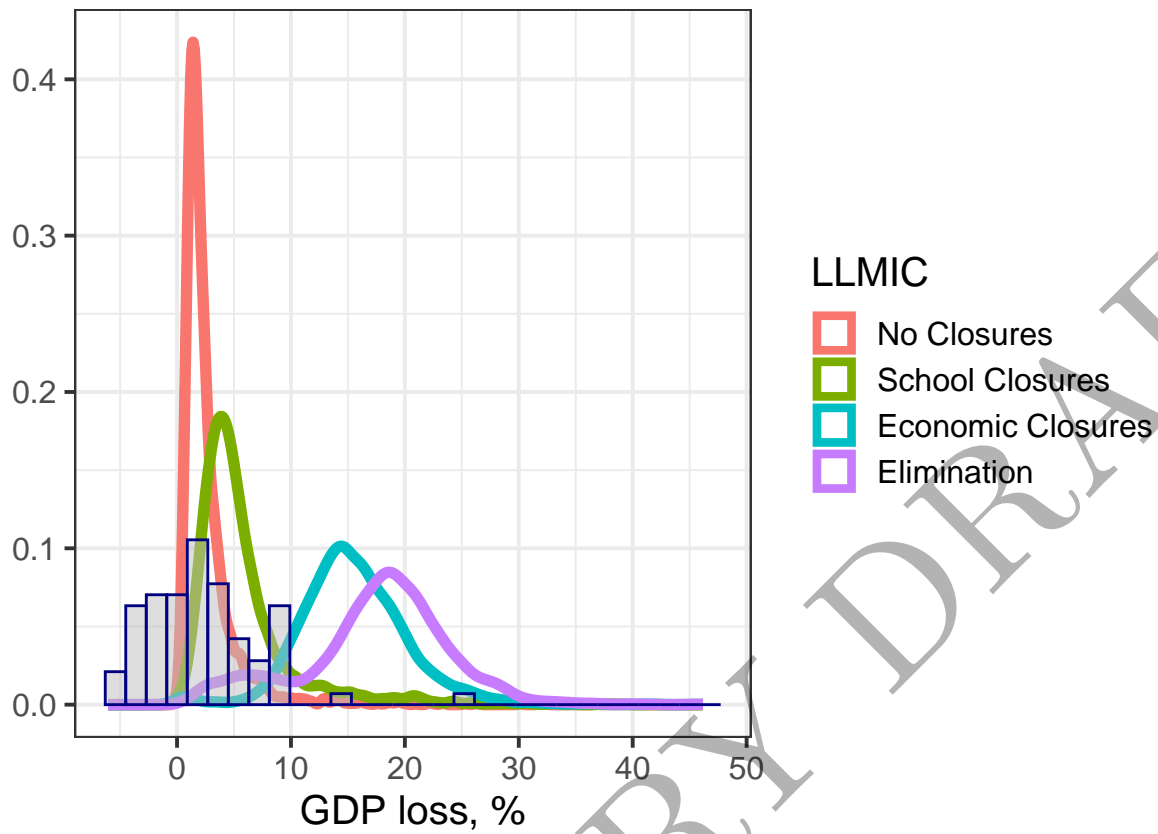
Figure 21: GDP loss: loss in 2020 as a percentage of 2019 GDP (IMF) for low- and lower-middle-income countries with densities from the model shown by strategy. NB: data are annual, so the loss is for the year starting January 2020. We would prefer to present data for April 2020 to March 2021 but these data are unavailable for most countries.
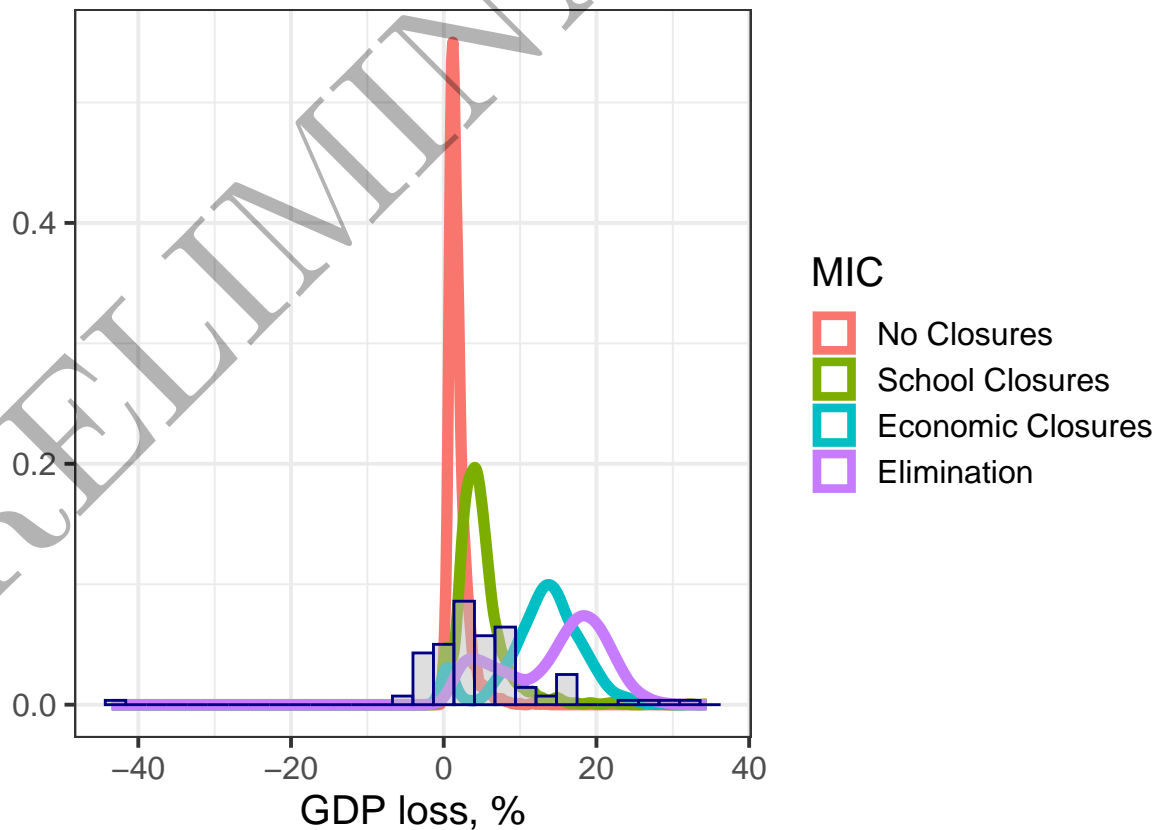
Figure 22: GDP loss: loss in 2020 as a percentage of 2019 GDP (IMF) for upper- and lower-middle-income countries with densities from the model shown by strategy. NB: data are annual, so the loss is for the year starting January 2020. We would prefer to present data for April 2020 to March 2021 but these data are unavailable for most countries. The outlier is Guyana.
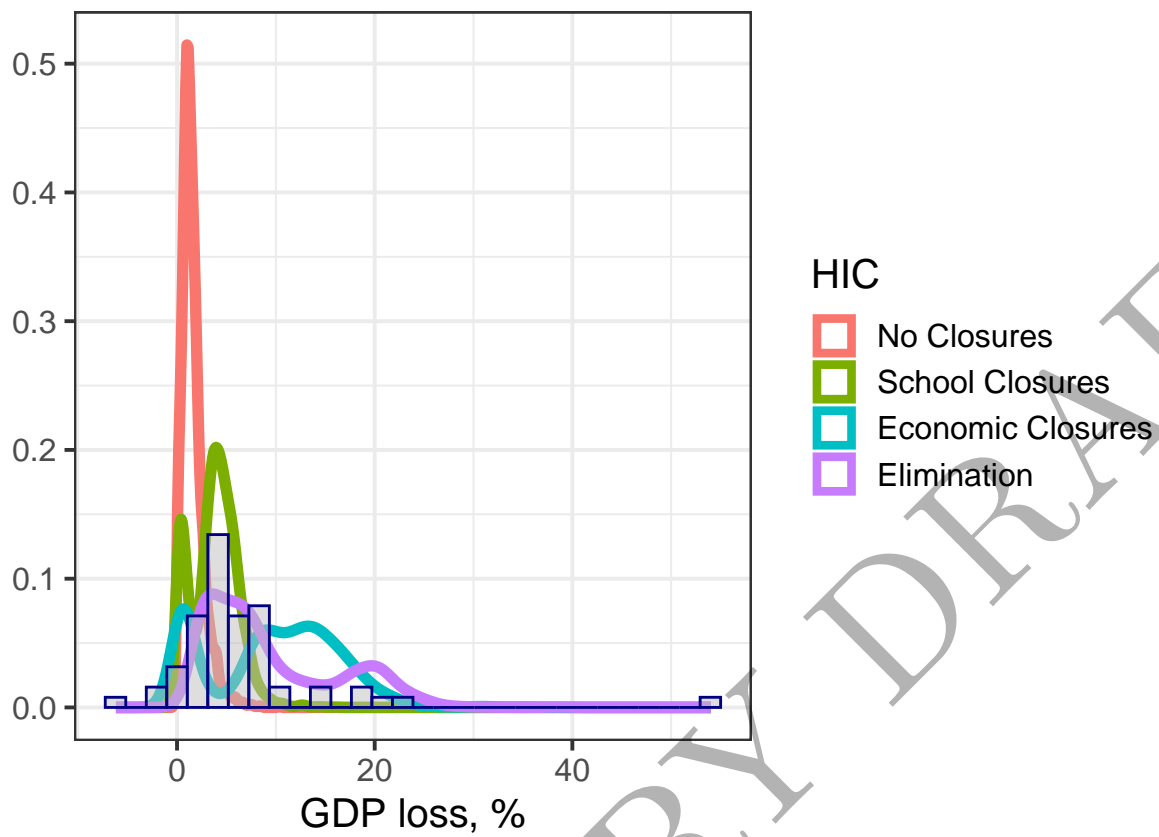
Figure 23: GDP loss: loss in 2020 as a percentage of 2019 GDP (IMF) for high-income countries with densities from the model shown by strategy. NB: data are annual, so the loss is for the year starting January 2020. We would prefer to present data for April 2020 to March 2021 but these data are unavailable for most countries.

11.2 School closure
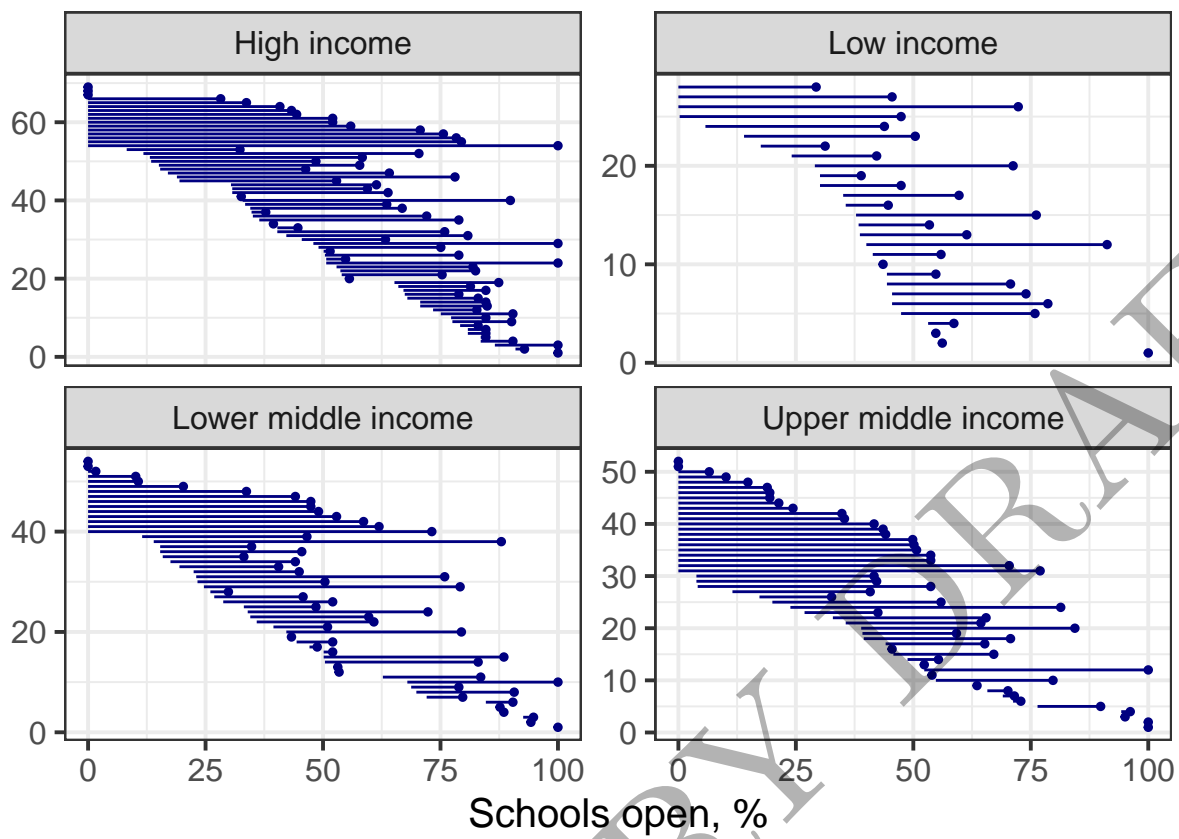
Figure 24: Extent of school closure. Horizontal lines (one per country) show the duration of the first year spent with schools partially closed. The space to the left of the line represents the duration schools were open. The space to the right of the line represents the duration schools were closed. (UNESCO)

11.3 Value of lives lost
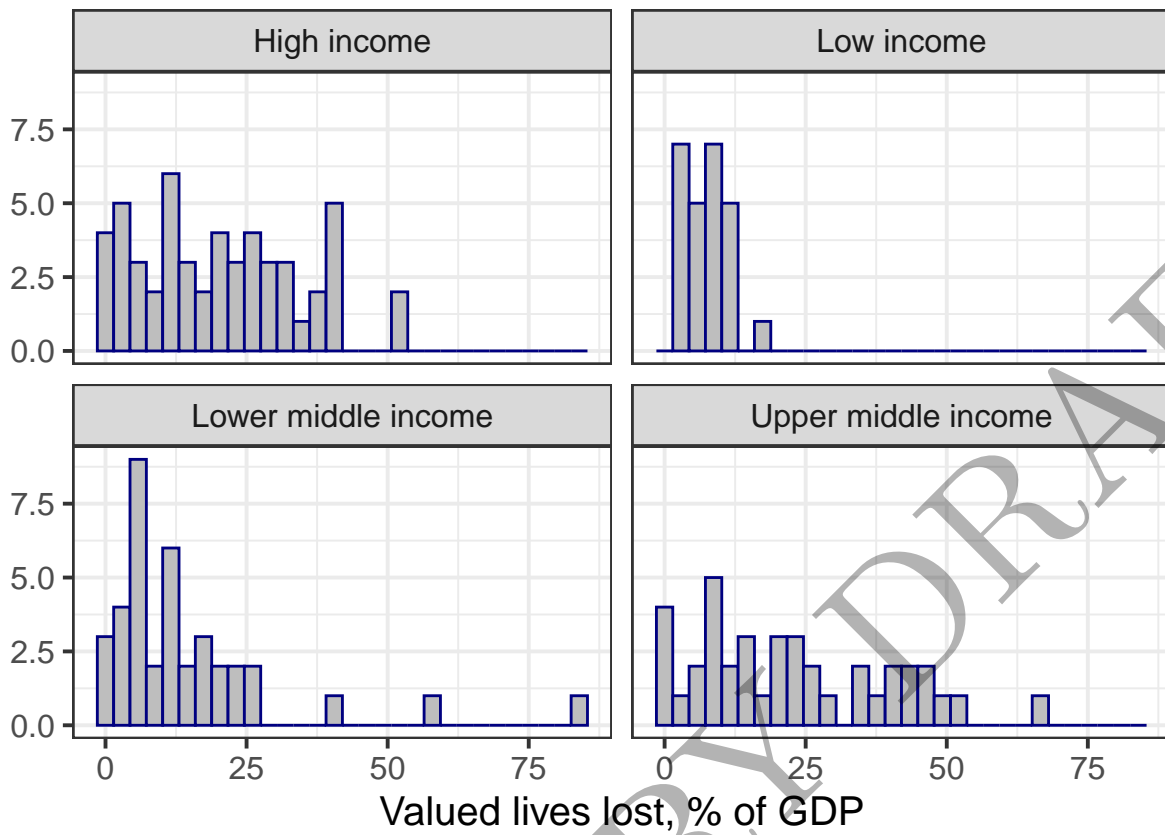
Figure 25: Valued loss of life, using IHME estimates ("cumulative deaths") for the first year of accumulated deaths. The value of a statistical life used is 160 times GDP per capita. (This means that a 0.625% mortality rate is worth 100% of GDP.)

12   Pathogen profiles

12.1   Parameters from Pandemic Potential, plus seven P2 profiles
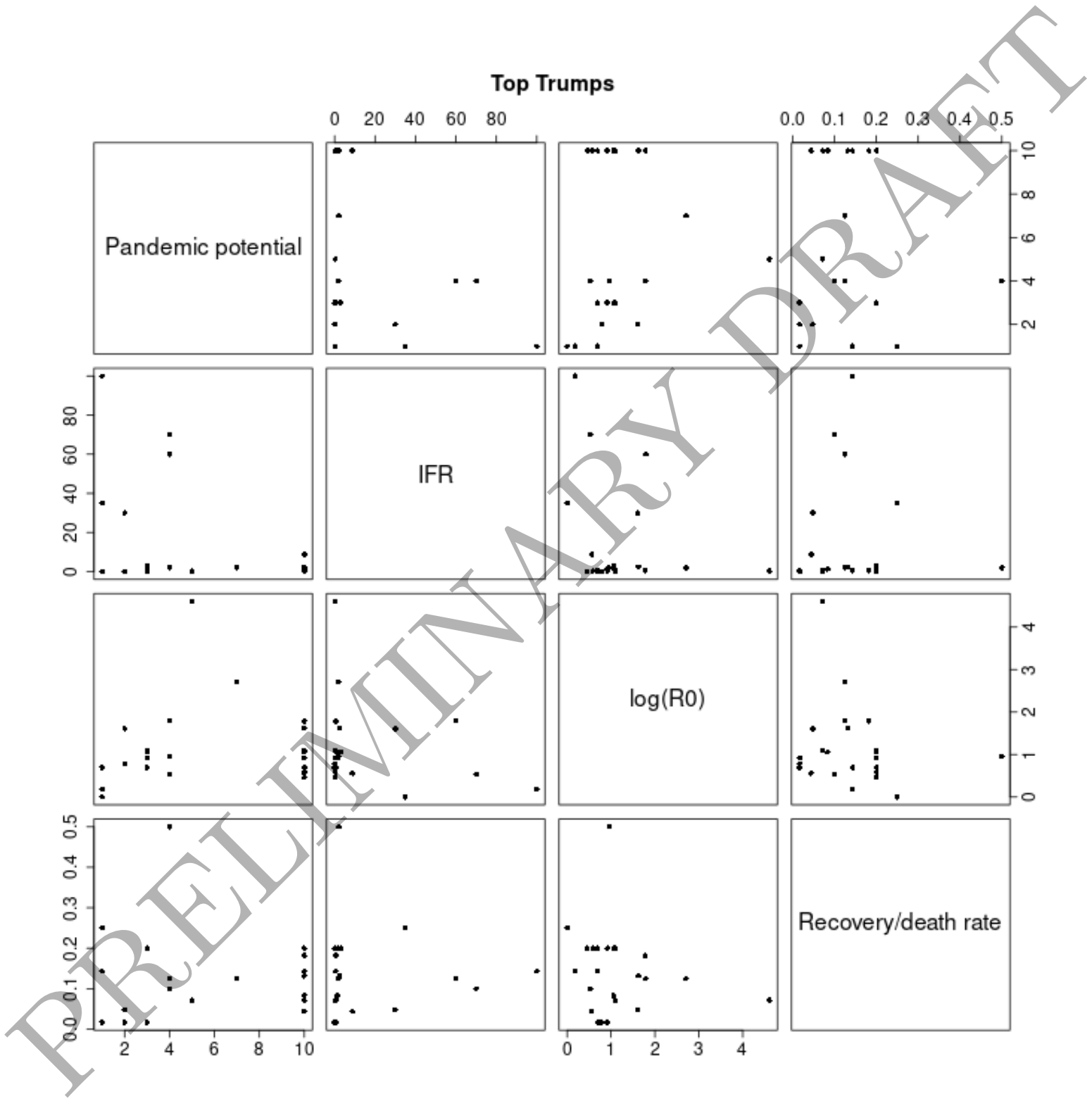
Figure 26: Profiles from the game Pandemic Potential
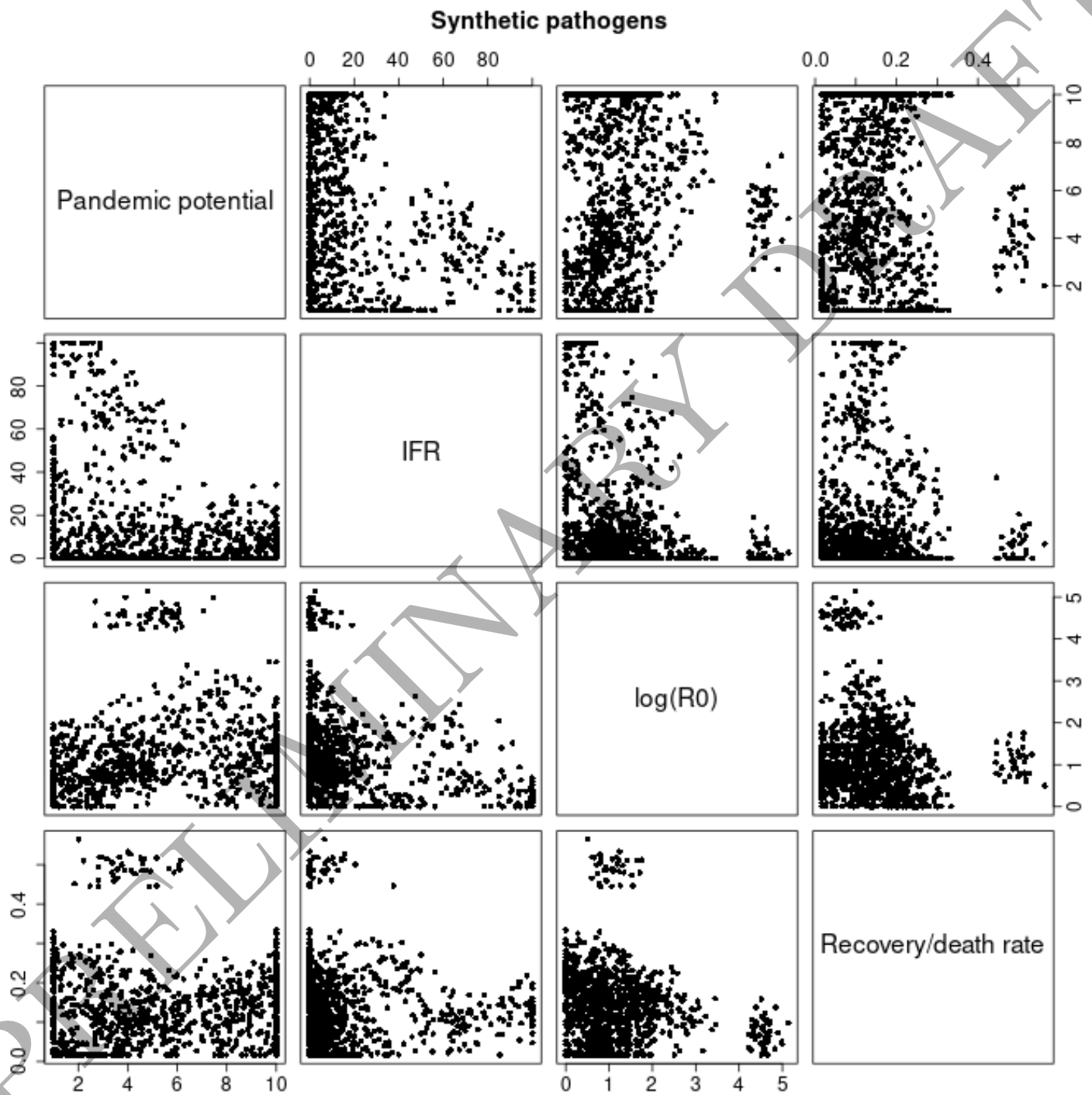
Figure 27: Profiles made using distribution from game
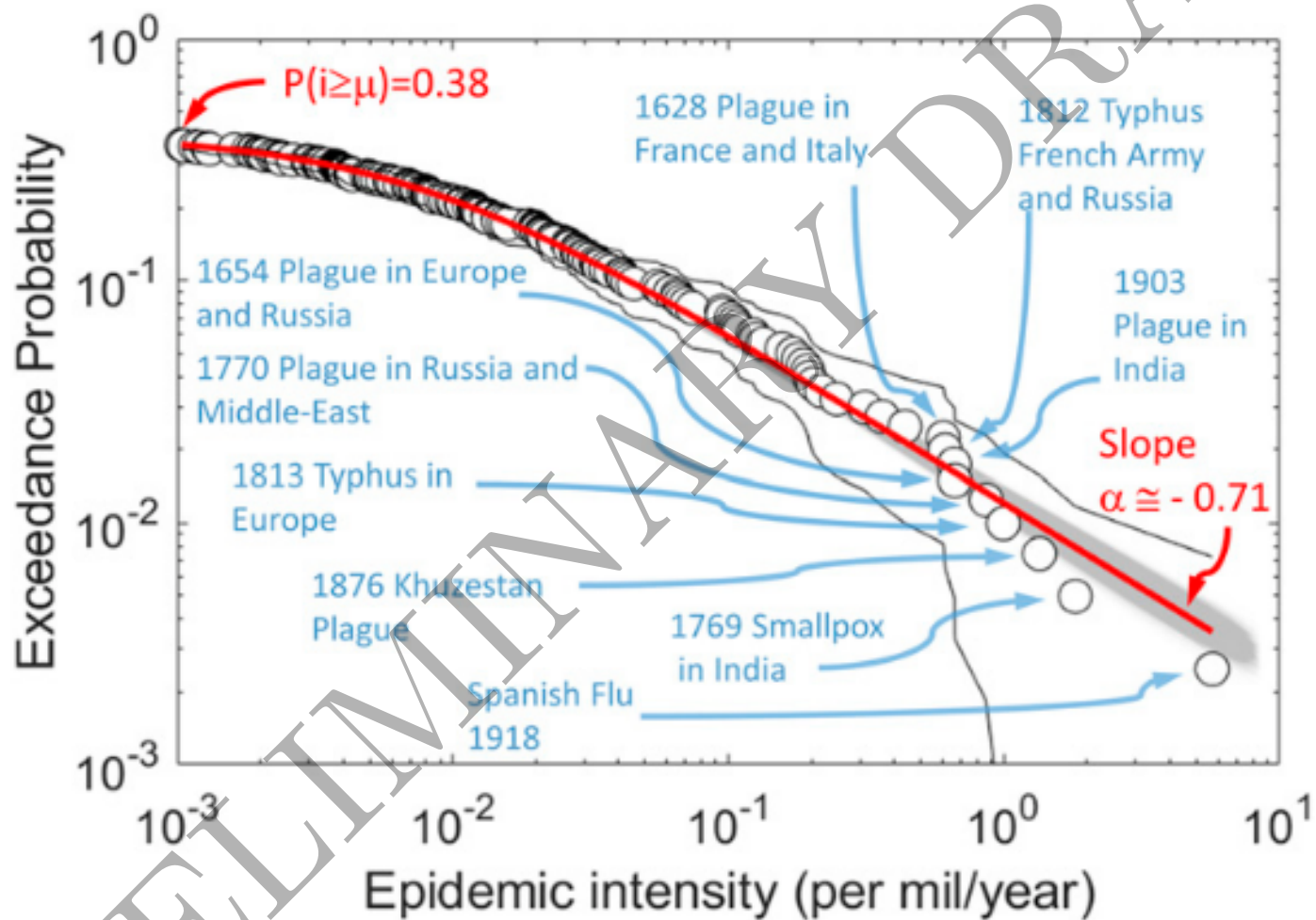
Figure 28: Intensity and frequency of extreme novel epidemics, Marani et al., PNAS, 2021

12.2 Infection-hospitalisation rate (IHR)
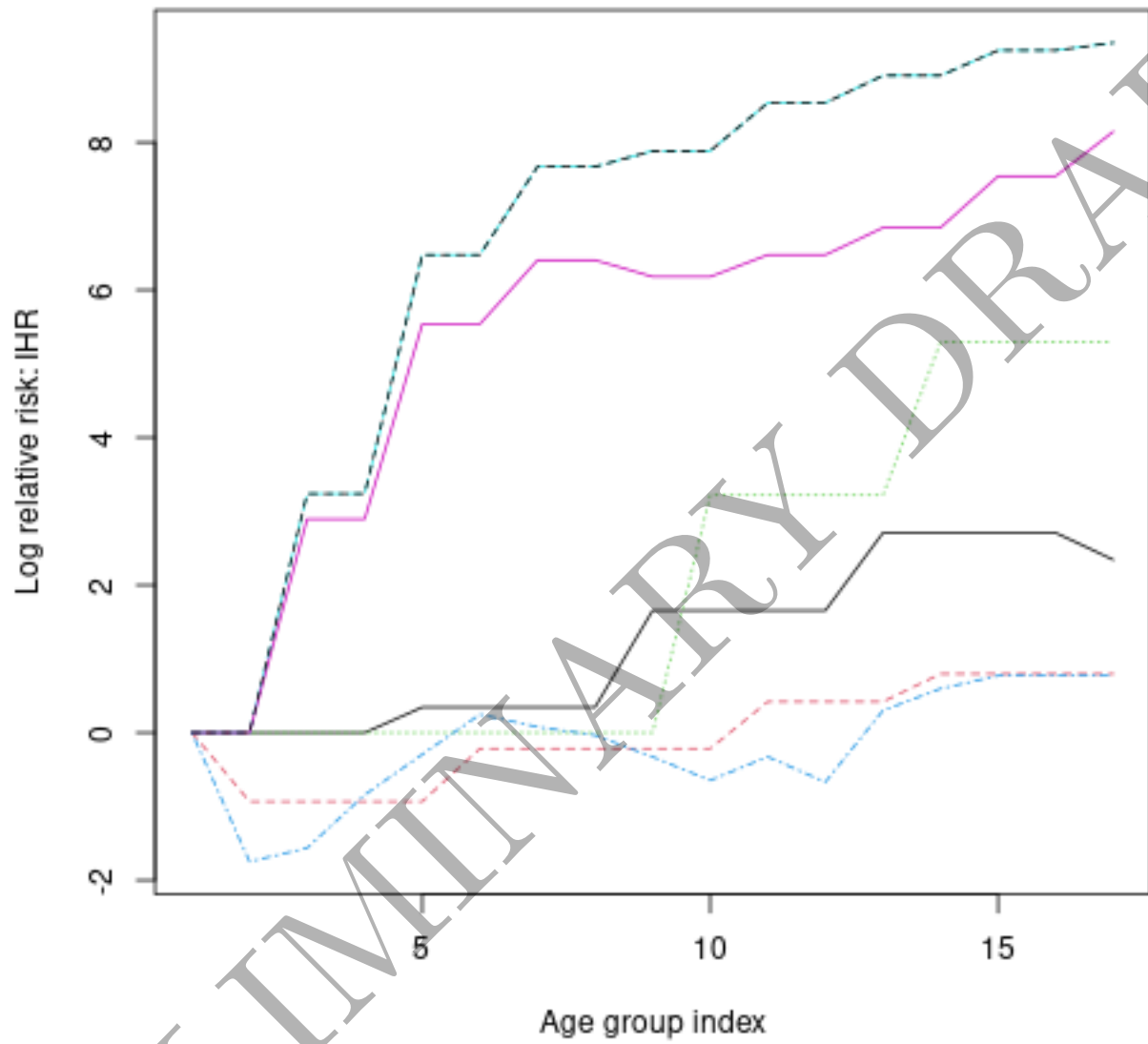
Figure 29: IHR by age for seven P2 pathogen profiles
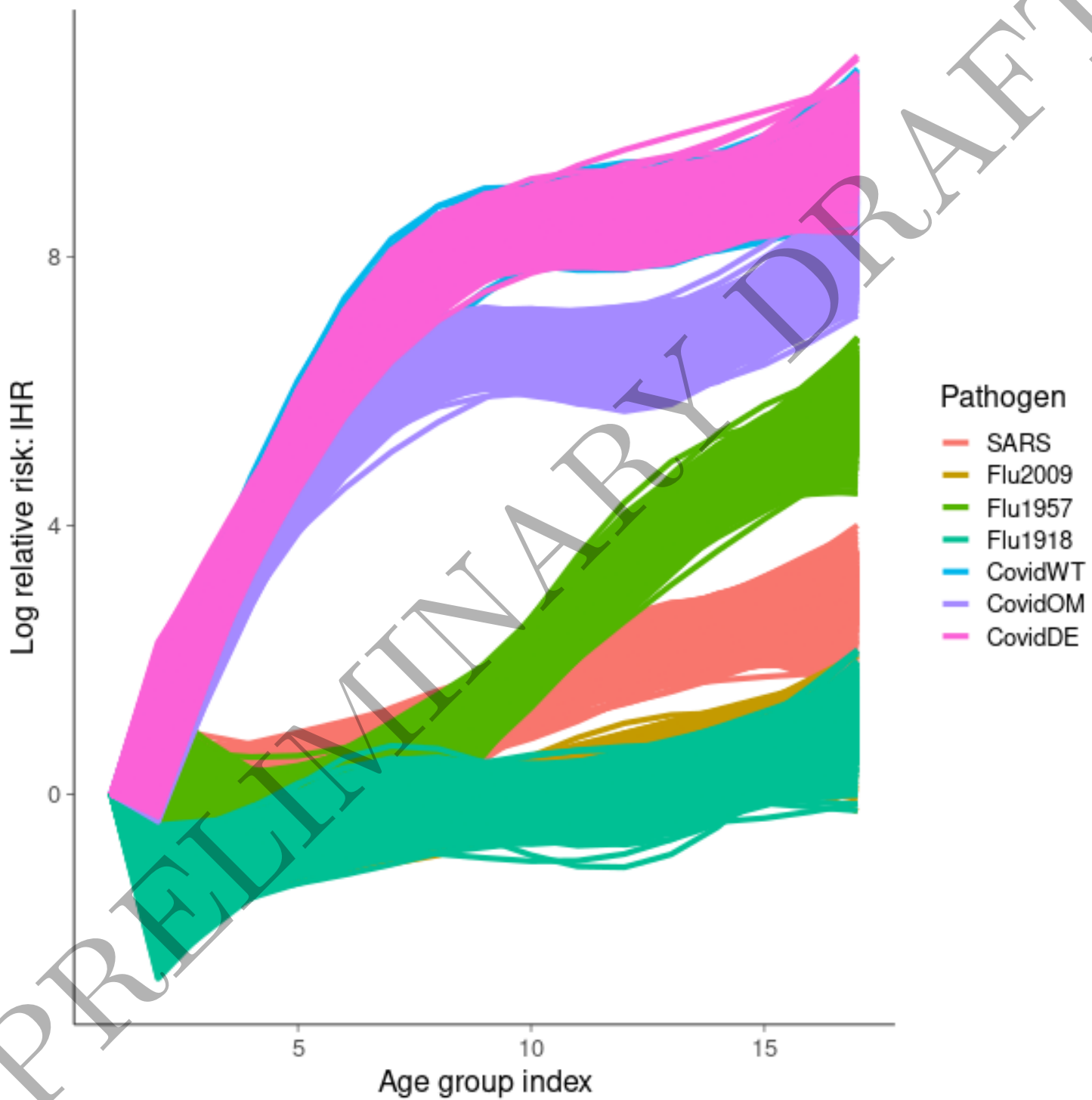
Figure 30: Posterior samples for seven P2 pathogen IHR profiles
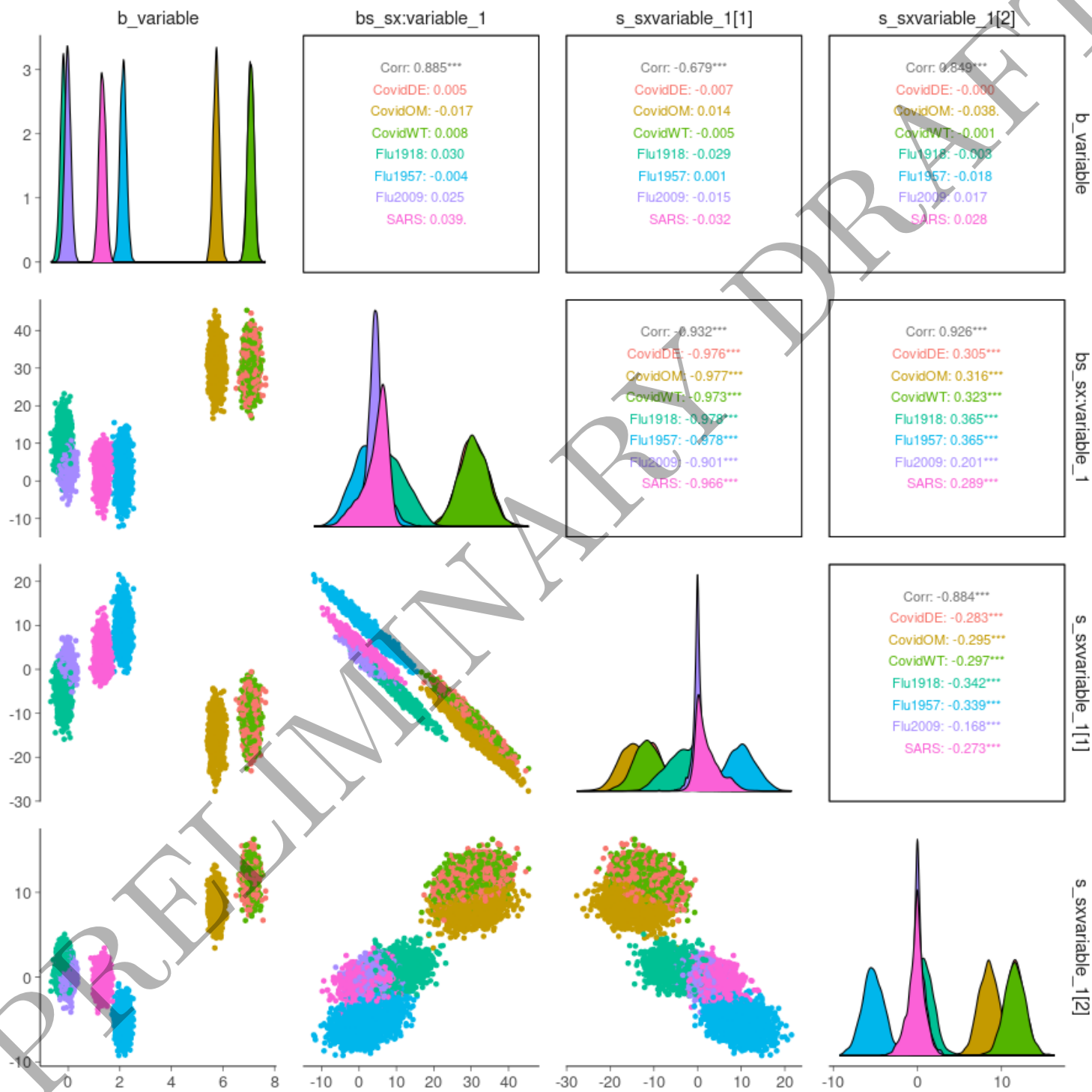
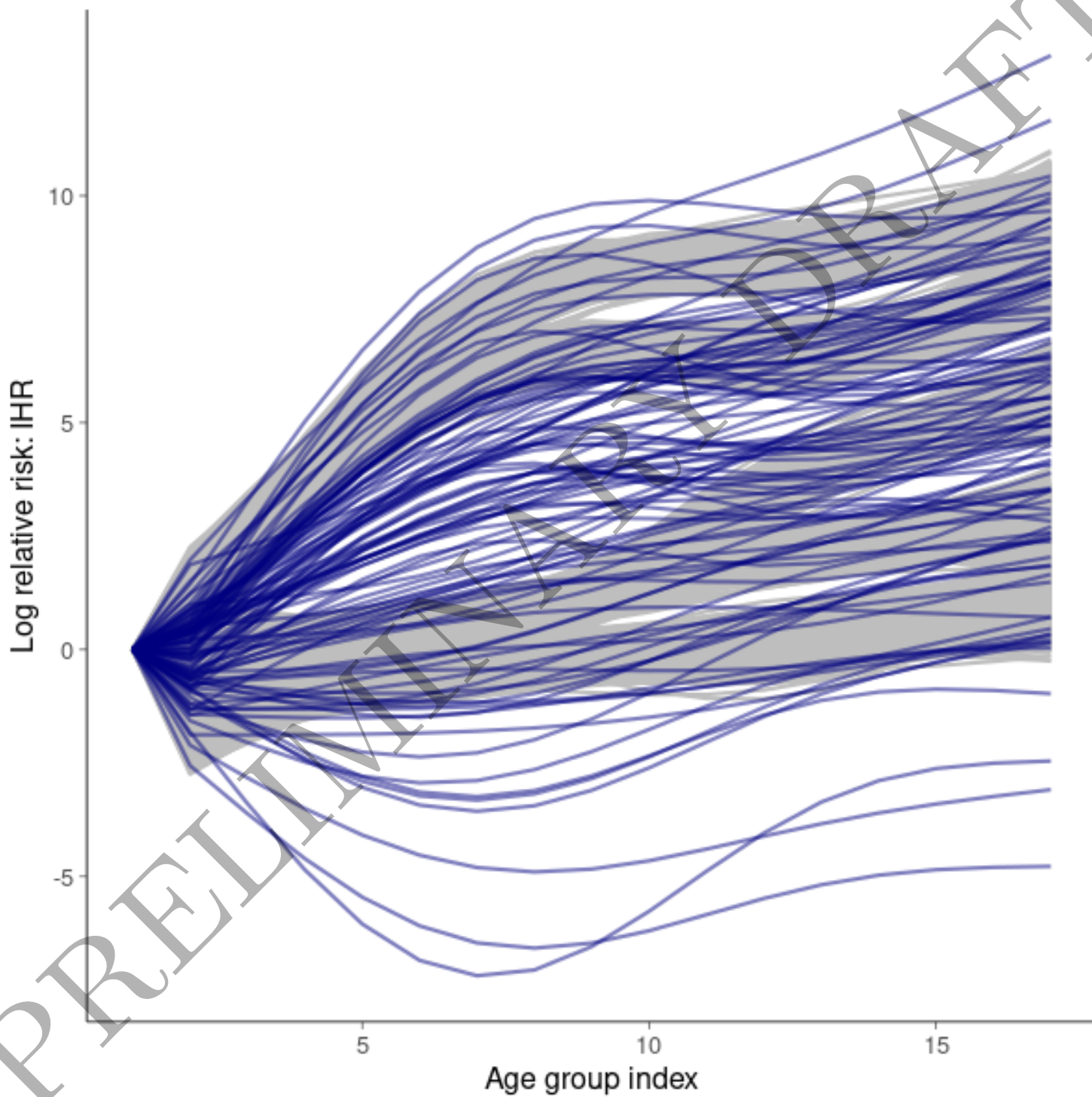Figure 31: Posterior distributions for IHR smooths

Figure 32: New IHR samples for synthetic pathogens
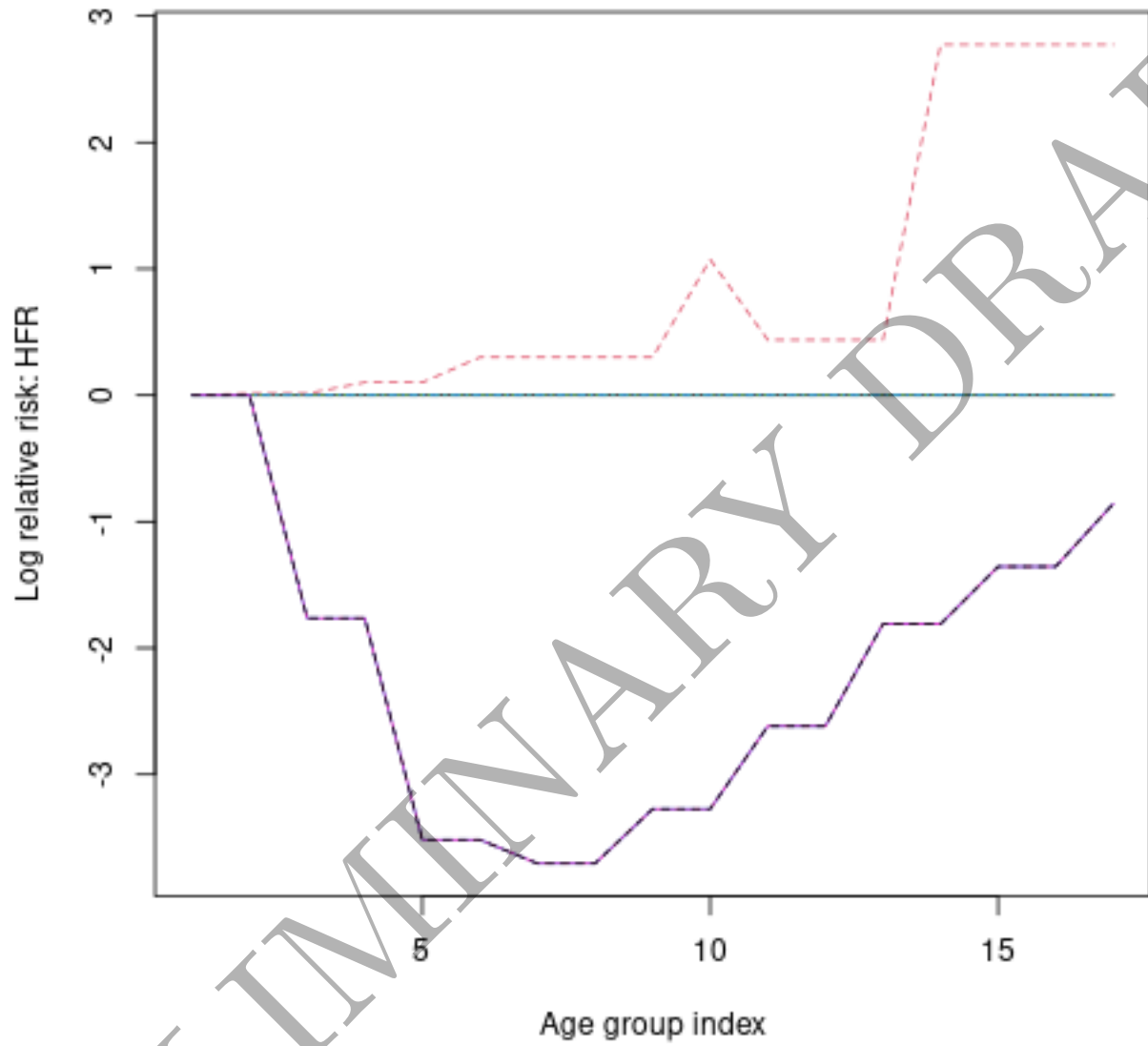
12.3 Hospital-fatality rate (HFR)

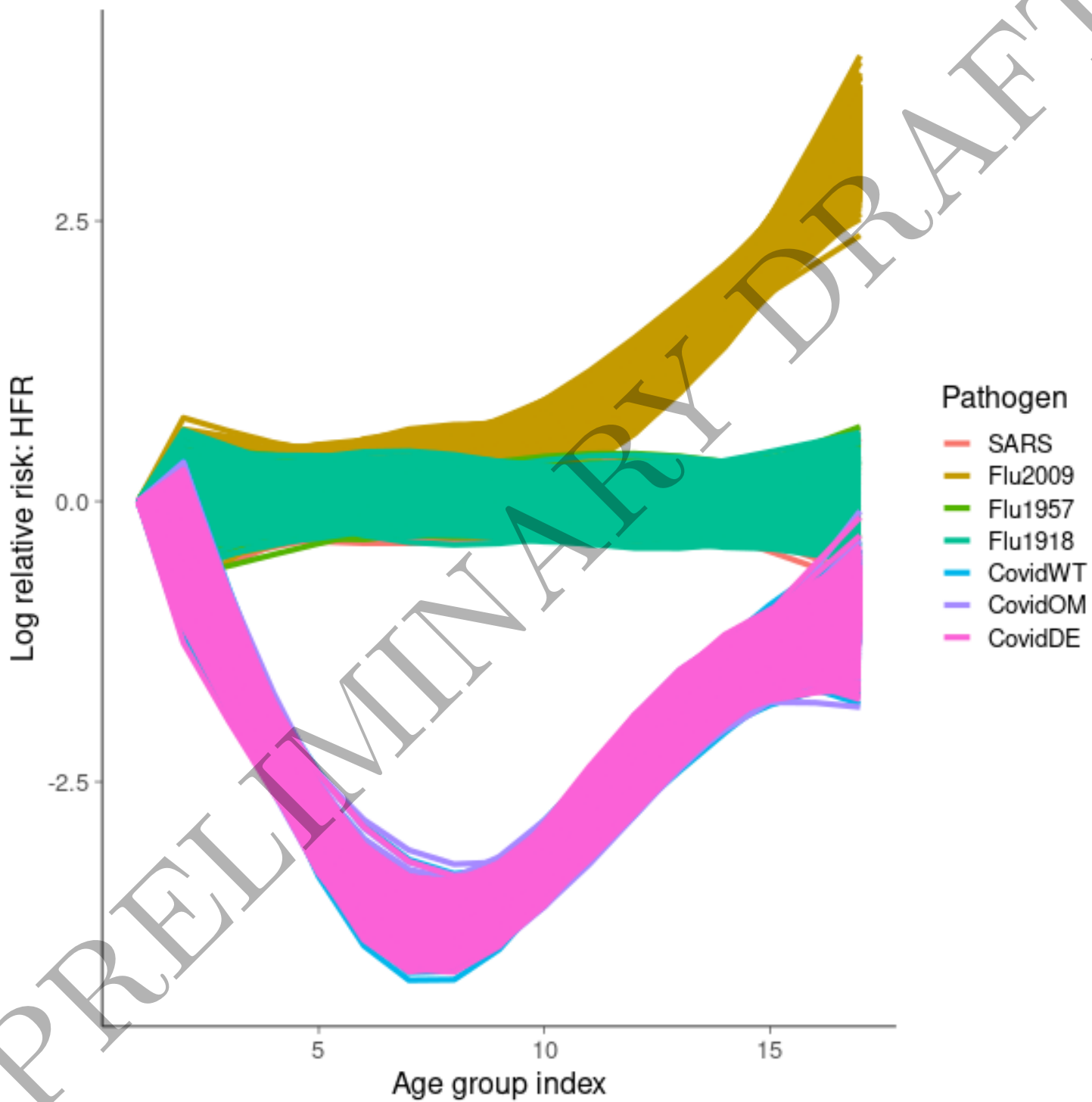Figure 33: HFR by age for seven P2 pathogen profiles

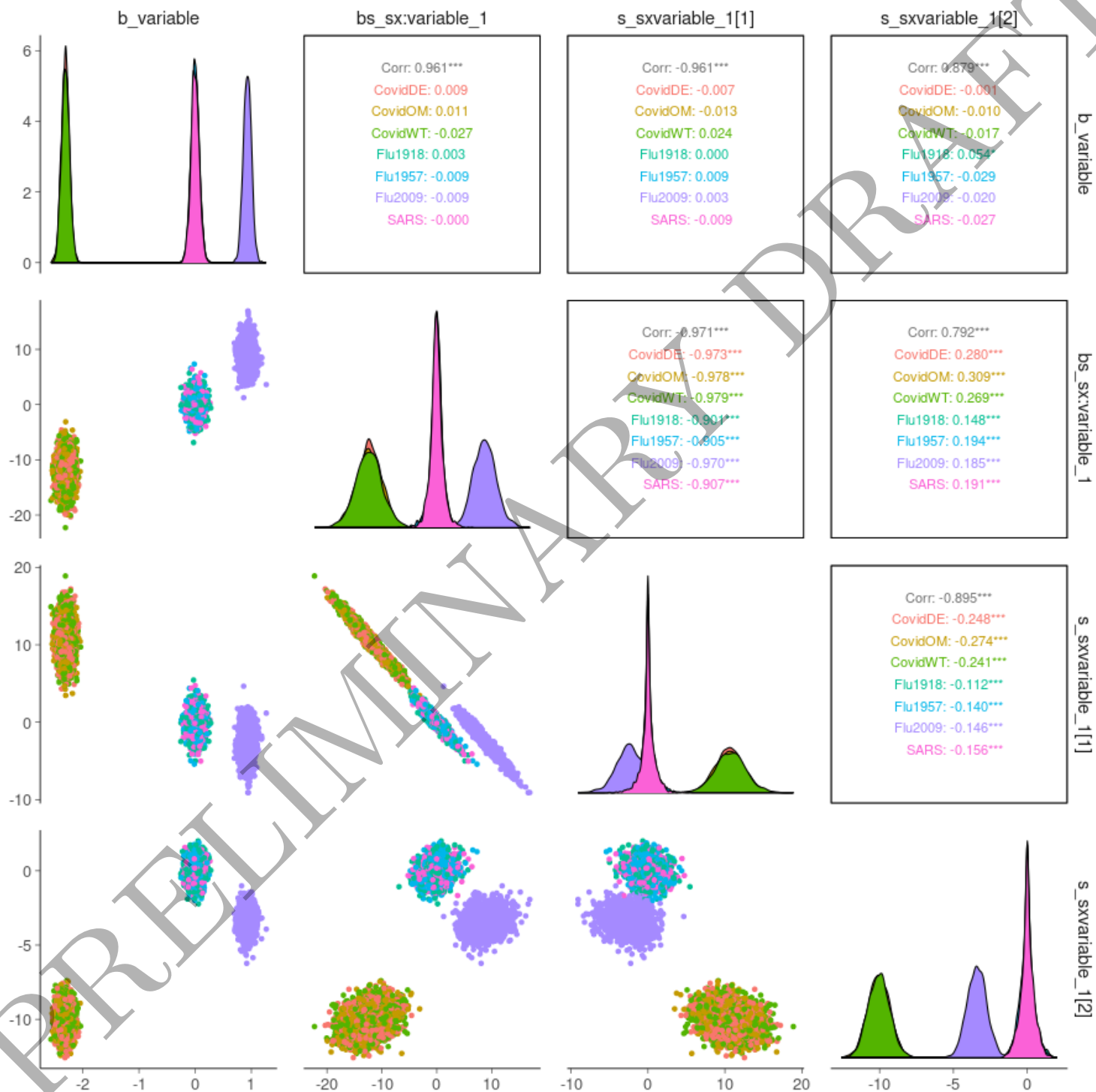Figure 34: Posterior samples for seven P2 pathogen HFR profiles

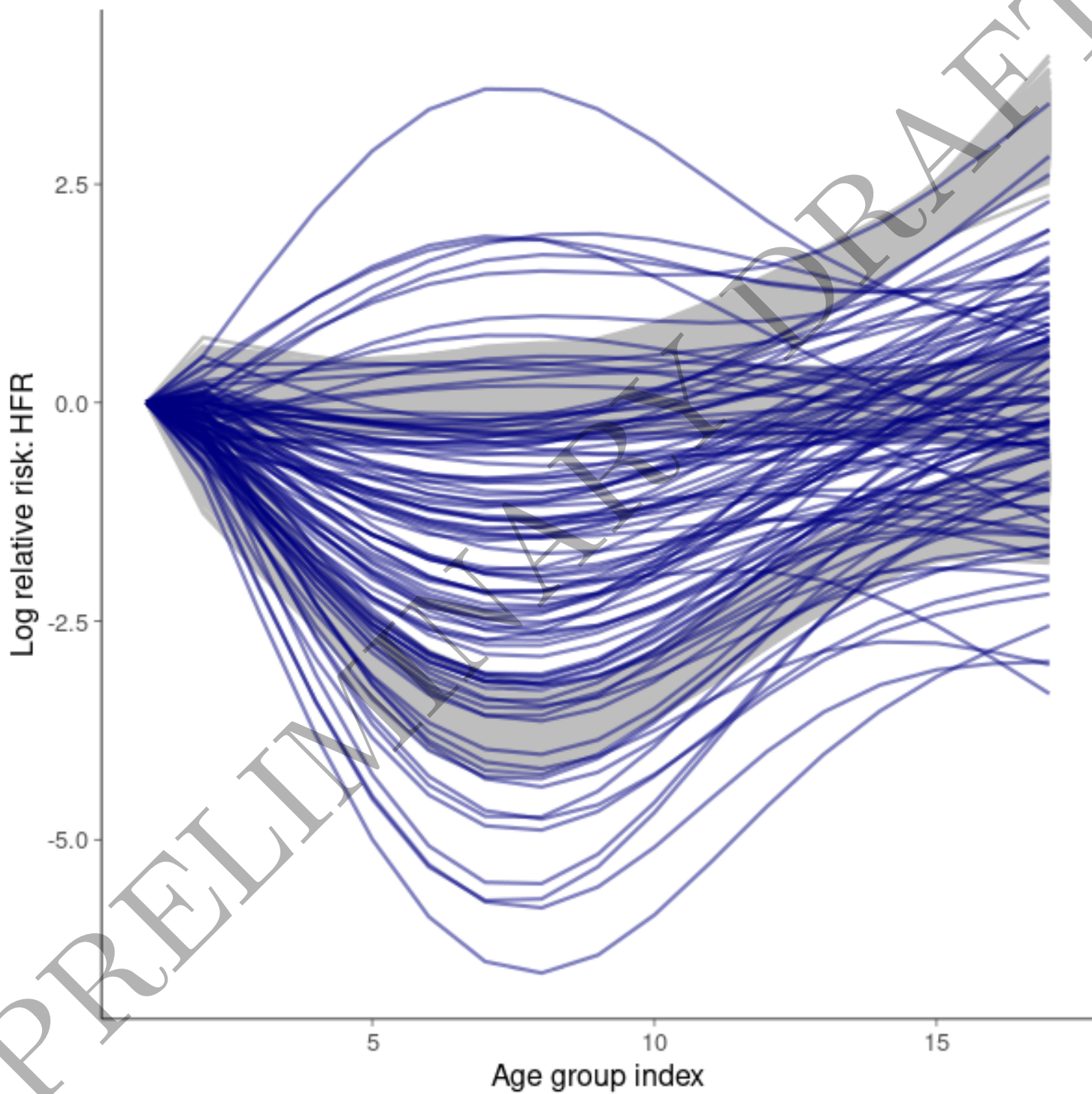Figure 35: Posterior distributions for HFR smooths

Figure 36: New HFR samples for synthetic pathogens

13 Population health

From the Mexico BMI work, we can model disease transition rates as depending on population mean BMI. There are data available for many countries (though some are very old).

We could use a linear model with boundaries beyond which there is no further change. The range in population mean BMI in the Mexico scenarios (excluding the no-obesity scenario) was 26.9 to 28.9. Therefore we could extrapolate to 25.9 and 29.9, and assume fixed after that?

Writing relative risk $RR_{a,t} \sim \mathcal{N}(m_{a,t} \cdot \text{BMI} + c_{a,t}, \sigma_{a,t}^2)$ for age groups a and transitions t:

Age group	Transition	m	c	σ
20-64	Infection	0.040	-0.030	0.0016
20-64	Hospitalisation	0.13	-0.092	0.0054
20-64	Death	0.133	-0.096	0.018
65 plus	Infection	0.011	-0.0070	0.0019
65 plus	Hospitalisation	0.063	-0.048	0.0060
65 plus	Death	0.027	-0.022	0.012