Projecting the public health, economic and educational benefits of CEPI's 100 day mission with the DAEDALUS model

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Contents

1 Aim

The objective of the proposed work is to use scenario modelling to help ascertain the value of current CEPI investments into the development and distribution of a vaccine 100 days after identification of a new SARS virus (SARS-X) with pandemic potential. In addition, we will estimate the value of a broadly protective sarbecovirus vaccine (BPSV) that would be available prior to the development of the SARS-X–specific vaccine. The analysis scope is to run three new SARS-X health, economic and education impacts scenarios (both for SARS-X 100-day mission and BPSV+SARS-X 100-day mission options) allowing for variations in preparedness and epidemiological parameters (to be discussed). We will will estimate the value of investments for different country types in monetary terms across three dimensions of societal welfare, combining economic losses due to business closures and lost education, and lives lost:

- Health: Live-years saved, monetised using the value of a statistical life (VSL);
- GDP: Gain to short-term economic output from reduced economic closures and disruptions to demand and labour supply;
- Education: long-term economic gains of reduced length and severity of closures of educational institutions.

We will simulate hypothetical pandemics caused by a SARS virus with a disease profile informed by past epidemics. We will use the integrated epi-econ model DAEDALUS developed in our group for estimating the benefit of pandemic preparedness (P2) (Haw et al. 2022). We will construct three representative hypothetical countries (low- and lower-middle income, upper-middle income, and high income) using real-world demographic, societal and economic data from 197 countries. Within those, we will construct two types of epidemic: those that emerge within the country (which we label "origin"), and those imported from outside (which we label "secondary"). The nature and stringency of non-pharmaceutical mitigation interventions (NPIs) implemented by policy makers once the emergency strikes is an important unknown that will determine benefits of vaccinations. We will therefore evaluate outcomes for four alternative mitigation strategies ("unmitigated," "adaptive economic closures," "school closures," and "elimination") for each vaccination scenario. The faster vaccines control infections, the earlier NPIs can be relaxed. The reduced need for stringent NPIs constitutes the benefit of the 100 day-mission. However, the types of benefit that countries enjoy depend on the chosen NPI. For example, for an unmitigated strategy, significant benefits accrue in terms of deaths averted; for adaptive economic closures, significant benefits accrue in terms of economic gains. It is unknown what NPIs countries will choose for future emergencies. We select the cost-minimising strategy for each country type and income level, assuming that the policy makers' aim is to maximize societal welfare.

We will estimate the value of the programme to each country group as the difference in total societal costs between scenarios with and without accelerated availability of both a SARS-X–specific vaccine and a BPSV.

2 Modelling framework

We will use an extensive modelling framework for COVID-19 that has been developed by our team over the last 3 years, the integrated economic–epidemiological model DAEDALUS (Haw et al. 2022). It is described briefly below and in more detail in the cited publications. The model has been developed in an open-access framework with all code available on Github. The model has been continuously updated throughout the pandemic as our understanding of SARS-CoV-2 transmission and the impact of vaccination has evolved, and is being further updated currently to model other hypothetical respiratory pandemics to answer questions on pandemic preparedness.

2.1 The integrated economic-epidemiological model

The epidemiological component of the DAEDALUS model consists of seven disease states (susceptible, exposed, asymptomatic infectious, symptomatic infectious, hospitalised, recovered, and died), in triplicate to represent vaccination states. The population is stratified by age (into four age groups: infants, adolescents, working-age adults, and retirement-age adults). The working-age adults are further stratified by sector of work (into 46 groups: 45 sectors according to the OECD classification, and one non-working group). We will use epidemiological parameters expected of a future SARS pandemic, where we use past respiratory pandemics to inform our expectations. Epidemiologically relevant demographic parameters, such as mixing matrices, will be drawn from published estimates [Béraud et al. (2015); Prem2021; Walker2020]. As far as this is possible, parameters, assumptions and modelling approaches will be closely aligned with Imperial's SARS-X model that is being developed by Prof Azra Ghani and team for Stage 2 of the technical work for CEPI.

The economic model takes as input the pre-pandemic Gross Value Added (GVA) per sector of countries, which uses the OECD classification of 45 economic sectors. Both models further take as input the observed economic configurations over 2020. These are the observed combinations of sector closures, i.e. the extent to which each sector was open in each period (month or quarter). This depends on the chosen mitigation strategy. All economic configuration profiles will be based on sectoral GVA profiles

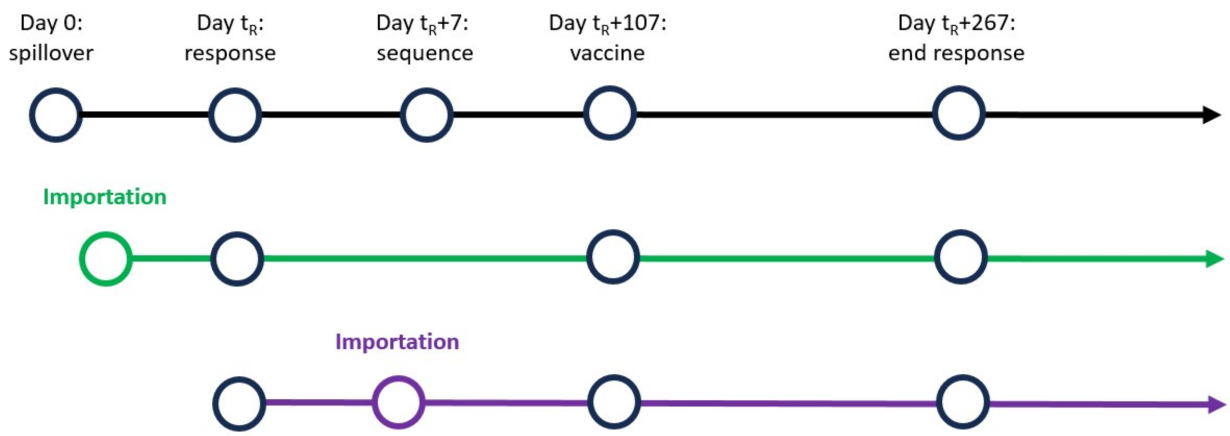

Figure 1: Schematic view of the timeline of a pandemic. At time 0 a new SARS pathogen emerges. At time t_R the pathogen is identified following a number of hospitalisations. A pandemic is declared. Genomic sequencing begins. Governments may implement non-pharmaceutical interventions. A broadly protective Sarbecovirus vaccine (BPSV) is rolled out in all places to people aged 65 and over. At time $t_R + 7$ the pathogen is sequenced. Vaccine R&D begins. At time $t_R + 107$ a vaccine specific to the new pathogen is rolled out in all places to people aged 15 and over. At time $t_R + 267$ vaccine rollout completes. All non-pharmaceutical interventions cease. At time t_i the pathogen is imported into country i.

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.

A sector is open to a maximum amount of 100%, when its full monthly pre-pandemic GVA value is realised. If a sector is open to 50%, it contributes 50% of its maximum GVA for that period. Sector closures describe the extent of reduction of contacts (and disease transmission) among and between workers and consumers. In the epidemic model, contacts associated with a partially closed sector are scaled down. Observed economic configurations, i.e. sector closures, capture also changes in demand and supply due to infection avoidance of individuals and interruptions in supply chains; we do not attempt to disentangle these from mandated closures.

2.2 Mitigation strategies

We will model four mitigation strategies that decision maker may adopt once the novel pathogen has been identified. These are "unmitigated," "adaptive economic closures," "school closures," and "elimination." The strategy defines government-mandated actions. In addition, we model behaviour changes in response to case numbers that impact on transmission. - Unmitigated: no aversive actions are taken. - Economic closures: sectors close to a pre-specified economic configuration when hospital occupancy approaches its capacity, and open again once infections have reduced sufficiently. - School closures: schools remain closed at 10% and other economic sectors open and close reactively, as in Economic closures. - Elimination: stringent economic closures are maintained until case numbers can be contained by a testing programme. We will designate the strategy that minimises costs across health, GDP and education to be the mitigation choice for each country type and income level and vaccination scenario.

2.3 Countries

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

- LLMIC, using inputs from LICs and LMICs
- UMIC, using inputs UMICs

- HIC, using inputs from HICs

We will generate a distribution over outcomes through sampling inputs. This distribution represents a catalogue of synthetic countries whose characteristics are randomly taken from candidate countries. We will include uncertainty in as many parameters as possible. We will 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. We will weigh parameter values according to population sizes of all countries, giving those parameter values greater importance that originate from larger countries.

2.4 Vaccination scenarios

Vaccination scenarios will be encoded via the parameters for vaccine effects, the time that vaccination begins, the rate of vaccine administration, and uptake among the population. The baseline scenario will mimic vaccination as observed in the COVID-19 pandemic, with all parameters taken from observations in 2020 and 2021. The 100-day vaccine scenario will assume a vaccine-effect profile similar to those of mRNA COVID-19 vaccines, and that vaccination begins 100 days after SARS-X is sequenced, with alternative administration rate and uptake explored in sensitivity analyses. The BPSV scenario will assume that the 100-day vaccine events will occur, and that, prior to that, the BPSV will be available, with effect parameters more similar to those of an influenza vaccine, with vaccination beginning at the time of identification of the SARS-X virus, and with alternative administration rate and uptake explored in sensitivity analyses.

2.5 Valuations

The outcomes of the DAEDALUS model are:

1. Health: Live-years lost globally and by country income groups;
2. GDP: Short-term economic loss from economic closures and disruptions to demand and labour supply, globally, by country income groups, and by economic sectors;
3. Education: long-term economic loss from closures of educational institutions, globally and by country income groups.

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 remote learning. Education loss is valued by taking into consideration life-long earning losses, following (Psacharopoulos, Collis, and Patrinos 2021).

Taken together, these form the societal cost (SC) of the epidemic in the country, expressed as a percentage of GDP (for the year prior to the pandemic). For each scenario and each country type and income level, we will assume that the social planner chooses the mitigation strategy that minimises the expected SC – call it the minimum expected SC, or MESC. The value of the 100-day vaccine in each country type and income level will be the MESC of the 100-day vaccine scenario minus the MESC of the baseline scenario. Similarly, the value of the BPSV in each country type and income level will be the MESC of the BPSV scenario minus the MESC of the 100-day vaccine scenario.

2.6 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)

2.7 Value of information

We use value-of-information methods to quantify relationships between inputs and outputs. 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.

2.8 Scenario levels

Variable	Levels	Description
Income level	HIC	High-income countries
	UMIC	Upper-middle–income countries
	LLMIC	Low- and lower-middle–income countries
Mitigation strategy	No closures	Unmitigated pandemic
	School closures	Schools close reactively
	Economic closures	Sectors close reactively
	Elimination	Contain by testing
Country type	Origin	Where the outbreak begins
	Secondary	To where cases are exported
Vaccination	BAU	Business as usual
	100 day	SARS-X vaccine available after 100 days
	BPSV	Broadly protective sarbecovirus vaccine

2.9 Fixed parameters

Parameter	Value
Maximum R_0	4
Vaccines given per day	0.5% of population
Final vaccine coverage	80% of people aged 15+

3 Results

We first present results on the outcomes or costs of pandemics for the analysed scenarios, in total and separately by the three types of outcomes. We then present the estimated values of the vaccine scenarios that arise by computing the reduction in costs associated with vaccination.

3.1 Distributions over outcomes

In this section we present the costs of pandemics, by country category, mitigation strategy, vaccination scenario, and for the three costs separately and summed up. For illustration, results for the BAU Origin countries are shown in Figure 2; the figures for the other scenarios are in the Appendix (Figures 3 to 5). Because we are varying key characteristics across countries within a category (LLMIC, MIC, or HIC), there is a distribution over costs, which we present with violin plots (e.g. Figure 2). They show the outcomes of 2,048 modelling runs of the same scenario where each run has a different set of randomly drawn parameters. The top row shows projections for total costs across three outcomes, while the 2nd, 3rd and 4th rows show the different types of costs (YLLS, education and GDP losses). Each shape represents a probability distribution: the most likely value to take is where the figure is widest. The tip of the tail indicates the highest value projected by any modelling run, after which point the density is 0. The base of the violin is given by the lowest value projected. Plots for all virus profiles are shown in Figures 2 to 5, and mean values and 95% prediction intervals are given in Table **??**.

There is high variation in projected costs across modelling runs, for all country types. For some favourable combinations of the randomly drawn parameters (bottom of the violin), costs are just above zero. On the other hand, for a few unfavourable parameter combinations (top of the violin), costs approach 500% of annual pre-pandemic GDP in Figure 2. This area represents extreme adverse outcomes. Our aim in Section 2.7 is to identify which parameters lead to these high-cost outcomes.

Table 3: Results for the BAU scenario in a Origin country. Mean values and 95% prediction intervals.

Strategy	Income group	Total costs	YLLs	Education	GDP
No Closures	LLMIC	42.9 (0, 192.7)	40.5 (0, 185.6)	0.4 (0, 1.3)	1.9 (0, 6.3)
School Closures	LLMIC	62.5 (0, 201.3)	21.6 (0, 125.4)	32.9 (0, 111.7)	8.1 (0, 28.3)
Economic Closures	LLMIC	60.2 (0, 194.4)	13.7 (0, 88.7)	23 (0, 94)	23.6 (0, 49.9)
Elimination	LLMIC	81.9 (3, 196.4)	8.1 (0, 70.1)	38.4 (0.2, 119.2)	35.4 (2.7, 55.9)

Strategy	Income group	Total costs	YLLs	Education	GDP
No Closures	UMIC	35.9 (0, 160.2)	34.4 (0, 157.1)	0.2 (0, 0.7)	1.2 (0, 4.1)
School Closures	UMIC	38.7 (0, 143.9)	20 (0, 107.7)	13.2 (0, 49.5)	5.6 (0, 15.5)
Economic Closures	UMIC	38.1 (0, 143.7)	14.6 (0, 79.9)	7.8 (0, 40.5)	15.7 (0, 40.9)
Elimination	UMIC	53.3 (3.2, 127.1)	6.4 (0, 62)	17.2 (0.1, 56.4)	29.7 (3, 46.7)
No Closures	HIC	33 (0, 146.7)	31.8 (0, 143.1)	0.2 (0, 0.5)	1.1 (0, 3.8)
School Closures	HIC	31.8 (0, 129.1)	19.5 (0, 100.5)	7.9 (0, 34.5)	4.4 (0, 13.6)
Economic Closures	HIC	30.3 (0, 116.2)	15 (0, 73.1)	4.2 (0, 23.4)	11.2 (0, 36.4)
Elimination	HIC	40.8 (3.2, 108.4)	5.4 (0, 52.9)	11.2 (0, 39.9)	24.3 (3, 42.3)

Table 4: Results for the BAU scenario in a Secondary country.
Mean values and 95% prediction intervals.

Strategy	Income group	Total costs	YLLs	Education	GDP
No Closures	LLMIC	41.6 (0, 186.9)	39.3 (0, 180.5)	0.4 (0, 1.3)	1.8 (0, 6.2)
School Closures	LLMIC	59.3 (0, 195.6)	21.1 (0, 122.7)	30.6 (0, 108.8)	7.6 (0, 26.2)
Economic Closures	LLMIC	57.4 (0, 191.3)	13.4 (0, 87.9)	21.7 (0, 91.7)	22.2 (0, 48.8)
Elimination	LLMIC	81.7 (3.1, 192.8)	7.2 (0, 65.6)	38.8 (0.2, 120.6)	35.7 (2.7, 57)
No Closures	UMIC	34.3 (0, 153.4)	32.9 (0, 150.7)	0.2 (0, 0.7)	1.2 (0, 3.9)
School Closures	UMIC	36.5 (0, 138.6)	19.4 (0, 103.9)	11.9 (0, 46.2)	5.2 (0, 14.8)
Economic Closures	UMIC	35.9 (0, 139.8)	14.2 (0, 78.4)	7.3 (0, 38.7)	14.5 (0, 39.2)
Elimination	UMIC	52.6 (3.2, 122.4)	5.7 (0, 57.7)	17.2 (0.1, 56.4)	29.6 (3, 46.7)
No Closures	HIC	30.9 (0, 141.1)	29.7 (0, 137.1)	0.1 (0, 0.5)	1.1 (0, 3.7)
School Closures	HIC	29.3 (0, 124.1)	18.4 (0, 98.3)	7 (0, 31.7)	4 (0, 12.8)
Economic Closures	HIC	28 (0, 111.3)	14.1 (0, 70.3)	3.8 (0, 22.2)	10.1 (0, 34.8)
Elimination	HIC	40.2 (3.2, 101.9)	4.7 (0, 46.3)	11.2 (0, 39.9)	24.3 (3, 42.3)

Table 5: Results for the 100 days scenario in a Origin country.
Mean values and 95% prediction intervals.

Strategy	Income group	Total costs	YLLs	Education	GDP
No Closures	LLMIC	28.7 (0.2, 126.3)	26.9 (0, 122.3)	0.4 (0, 1.2)	1.3 (0.1, 4.8)
School Closures	LLMIC	30.5 (0.1, 120)	16.9 (0, 77.9)	10.3 (0, 44.2)	3.3 (0.1, 13.3)
Economic Closures	LLMIC	29.5 (0.1, 116.7)	14 (0, 69.5)	7.7 (0, 32.1)	7.9 (0.1, 21.5)
Elimination	LLMIC	36.2 (1.9, 96.4)	12.3 (0, 67)	12.2 (0.2, 35.9)	11.7 (1.2, 18.2)
No Closures	UMIC	24.9 (0.2, 109.5)	23.8 (0, 105.7)	0.2 (0, 0.7)	0.9 (0.1, 3)
School Closures	UMIC	22.6 (0.1, 93.8)	15.6 (0, 75.8)	4.4 (0, 18.2)	2.5 (0.1, 7.9)
Economic Closures	UMIC	22.2 (0.1, 91.1)	12.9 (0, 64.7)	3.2 (0, 16.1)	6.1 (0.1, 16.7)
Elimination	UMIC	28.4 (2.1, 76.6)	9.8 (0, 55.3)	6.8 (0.1, 22.5)	11.8 (1.5, 17.7)
No Closures	HIC	23.4 (0, 101.8)	22.5 (0, 99.2)	0.2 (0, 0.5)	0.8 (0, 2.5)
School Closures	HIC	20.3 (0, 85.2)	15.4 (0, 72.1)	2.8 (0, 12.9)	2 (0, 6.7)
Economic Closures	HIC	19.5 (0, 79.8)	13.1 (0, 60.5)	1.9 (0, 10.3)	4.6 (0, 15)
Elimination	HIC	24.8 (1.9, 70.9)	9.3 (0, 51.6)	4.9 (0.1, 16.7)	10.7 (1.6, 17.8)

Table 6: Results for the 100 days scenario in a Secondary country.
Mean values and 95% prediction intervals.

Strategy	Income group	Total costs	YLLs	Education	GDP
No Closures	LLMIC	25.9 (0.1, 118.8)	24.3 (0, 114.2)	0.4 (0, 1.2)	1.2 (0.1, 4.5)
School Closures	LLMIC	27 (0.1, 116.3)	15.3 (0, 72.9)	8.8 (0, 42.4)	2.9 (0.1, 12.9)
Economic Closures	LLMIC	26.5 (0.1, 111.4)	13 (0, 63.5)	6.7 (0, 32.1)	6.8 (0.1, 21.8)
Elimination	LLMIC	35.5 (1.9, 93.9)	11.6 (0, 63.1)	12.2 (0.2, 35.8)	11.6 (1.2, 18.1)
No Closures	UMIC	22.4 (0.1, 103.1)	21.3 (0, 99.8)	0.2 (0, 0.7)	0.8 (0.1, 2.9)
School Closures	UMIC	19.8 (0.1, 86)	14 (0, 68.3)	3.7 (0, 16.4)	2.2 (0.1, 7.4)
Economic Closures	UMIC	19.7 (0.1, 83.3)	11.9 (0, 61.5)	2.7 (0, 14.8)	5.1 (0.1, 15.7)

Strategy	Income group	Total costs	YLLs	Education	GDP
Elimination	UMIC	27.9 (2.1, 74)	9.3 (0, 50.3)	6.8 (0.1, 22.5)	11.8 (1.5, 17.6)
No Closures	HIC	20.7 (0, 92.4)	19.8 (0, 89.6)	0.2 (0, 0.5)	0.7 (0, 2.4)
School Closures	HIC	17.9 (0, 79.3)	13.9 (0, 68.5)	2.2 (0, 11.6)	1.7 (0, 6.2)
Economic Closures	HIC	17.3 (0, 73.5)	12.1 (0, 57.5)	1.5 (0, 9.3)	3.7 (0, 13.4)
Elimination	HIC	24.3 (1.9, 69)	8.8 (0, 45.7)	4.9 (0.1, 16.6)	10.7 (1.6, 17.9)

Table 7: Results for the BPSV scenario in a Origin country. Mean values and 95% prediction intervals.

Strategy	Income group	Total costs	YLLs	Education	GDP
No Closures	LLMIC	27.7 (0.2, 125.6)	25.9 (0, 120.8)	0.4 (0, 1.2)	1.4 (0.1, 5)
School Closures	LLMIC	28.9 (0.1, 117.5)	15.7 (0, 77.7)	10 (0, 43.4)	3.2 (0.1, 13)
Economic Closures	LLMIC	27.9 (0.1, 118)	12.9 (0, 71.1)	7.4 (0, 31.3)	7.6 (0.1, 20.8)
Elimination	LLMIC	35.3 (1.9, 95)	11.6 (0, 65.1)	12.1 (0.2, 35.8)	11.6 (1.2, 18.2)
No Closures	UMIC	23.2 (0.1, 108.4)	22 (0, 104.6)	0.2 (0, 0.7)	0.9 (0.1, 3.2)
School Closures	UMIC	20.4 (0.1, 89.6)	13.7 (0, 73.7)	4.3 (0, 17.6)	2.4 (0.1, 7.5)
Economic Closures	UMIC	20 (0.1, 86.1)	11 (0, 61.7)	3.1 (0, 15.7)	5.9 (0.1, 16.3)
Elimination	UMIC	27.5 (2, 74)	8.9 (0, 53.2)	6.8 (0.1, 22.4)	11.8 (1.5, 17.7)
No Closures	HIC	20.9 (0, 96)	20 (0, 93.4)	0.2 (0, 0.5)	0.8 (0, 2.7)
School Closures	HIC	17.8 (0, 79.3)	13 (0, 67.2)	2.7 (0, 12.4)	2 (0, 6.6)
Economic Closures	HIC	16.9 (0, 71.5)	10.7 (0, 51.1)	1.8 (0, 9.9)	4.4 (0, 14.8)
Elimination	HIC	23.7 (1.9, 66.1)	8.2 (0, 45.6)	4.9 (0.1, 16.6)	10.6 (1.6, 17.8)

Table 8: Results for the BPSV scenario in a Secondary country. Mean values and 95% prediction intervals.

Strategy	Income group	Total costs	YLLs	Education	GDP
No Closures	LLMIC	25.1 (0.1, 116.6)	23.5 (0, 112.5)	0.4 (0, 1.2)	1.3 (0.1, 4.7)
School Closures	LLMIC	25.8 (0.1, 116.9)	14.4 (0, 71.7)	8.6 (0, 42.1)	2.9 (0.1, 12.8)
Economic Closures	LLMIC	25.3 (0.1, 107.6)	12.1 (0, 61.9)	6.6 (0, 31.4)	6.6 (0.1, 21.6)
Elimination	LLMIC	34.8 (1.8, 93.6)	11.1 (0, 61.8)	12.1 (0.2, 35.8)	11.6 (1.2, 18.1)
No Closures	UMIC	21 (0.1, 101.1)	19.9 (0, 97.9)	0.2 (0, 0.7)	0.9 (0.1, 3.1)
School Closures	UMIC	18.1 (0.1, 83.5)	12.5 (0, 65.4)	3.5 (0, 16.2)	2.1 (0.1, 7.2)
Economic Closures	UMIC	18 (0.1, 80)	10.4 (0, 57)	2.6 (0, 14.2)	5 (0.1, 15.3)
Elimination	UMIC	27 (2, 70.2)	8.4 (0, 47.4)	6.8 (0.1, 22.5)	11.8 (1.5, 17.6)
No Closures	HIC	18.8 (0, 87.6)	17.9 (0, 84.3)	0.2 (0, 0.5)	0.8 (0, 2.6)
School Closures	HIC	15.8 (0, 73.2)	11.9 (0, 61.6)	2.2 (0, 11.1)	1.7 (0, 6.1)
Economic Closures	HIC	15.2 (0, 66.2)	10.1 (0, 50.1)	1.5 (0, 8.8)	3.6 (0, 13.3)
Elimination	HIC	23 (1.9, 62.7)	7.6 (0, 41.4)	4.9 (0.1, 16.6)	10.6 (1.6, 17.8)

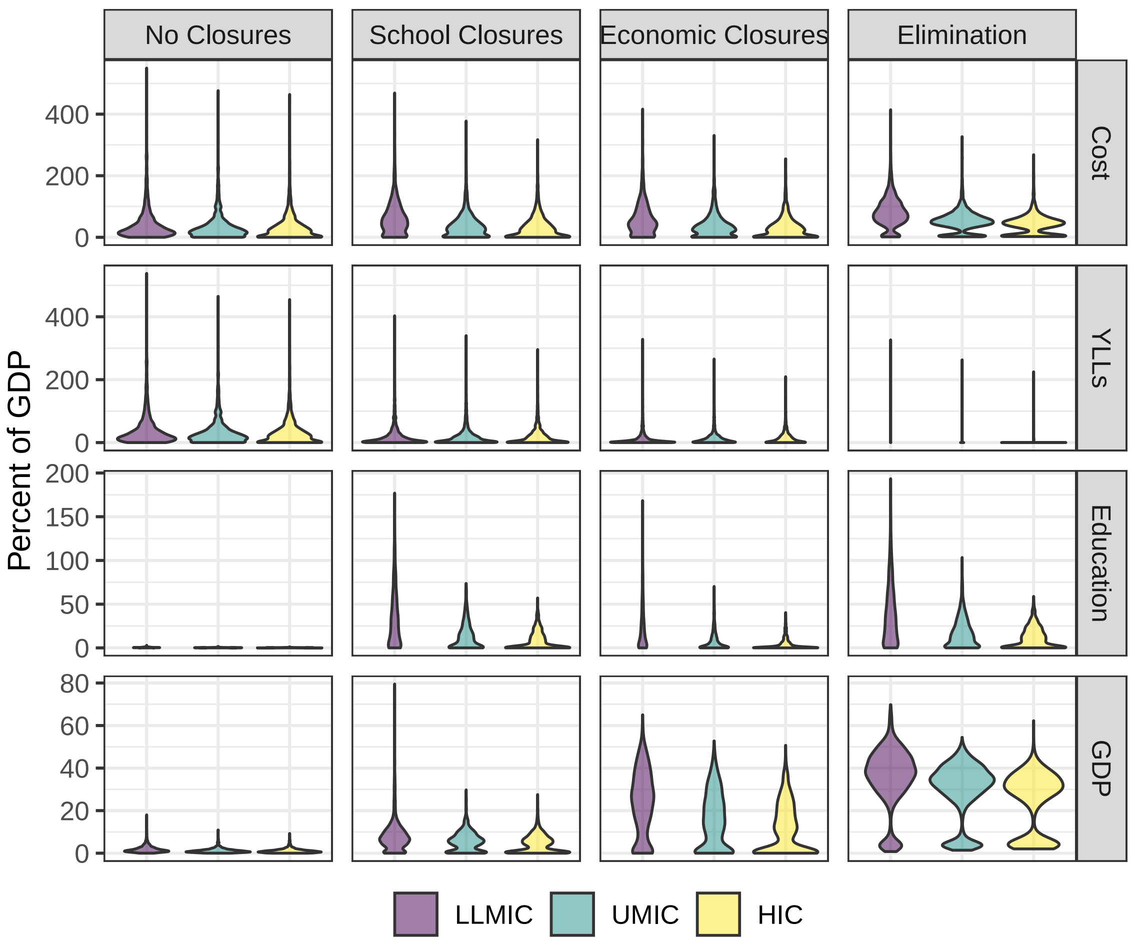

Figure 2: Model results for the BAU scenario in Origin countries.

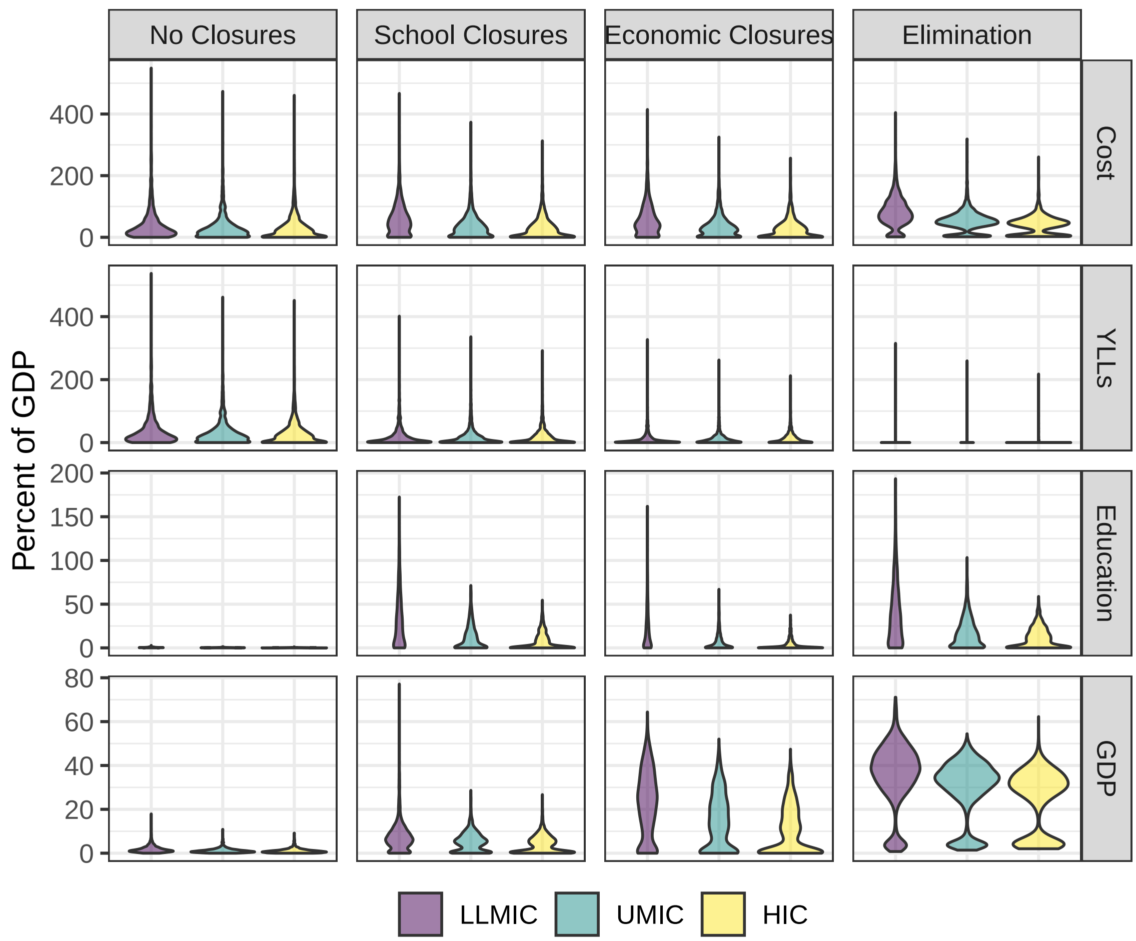

Figure 3: Model results for the BAU scenario in secondary countries.

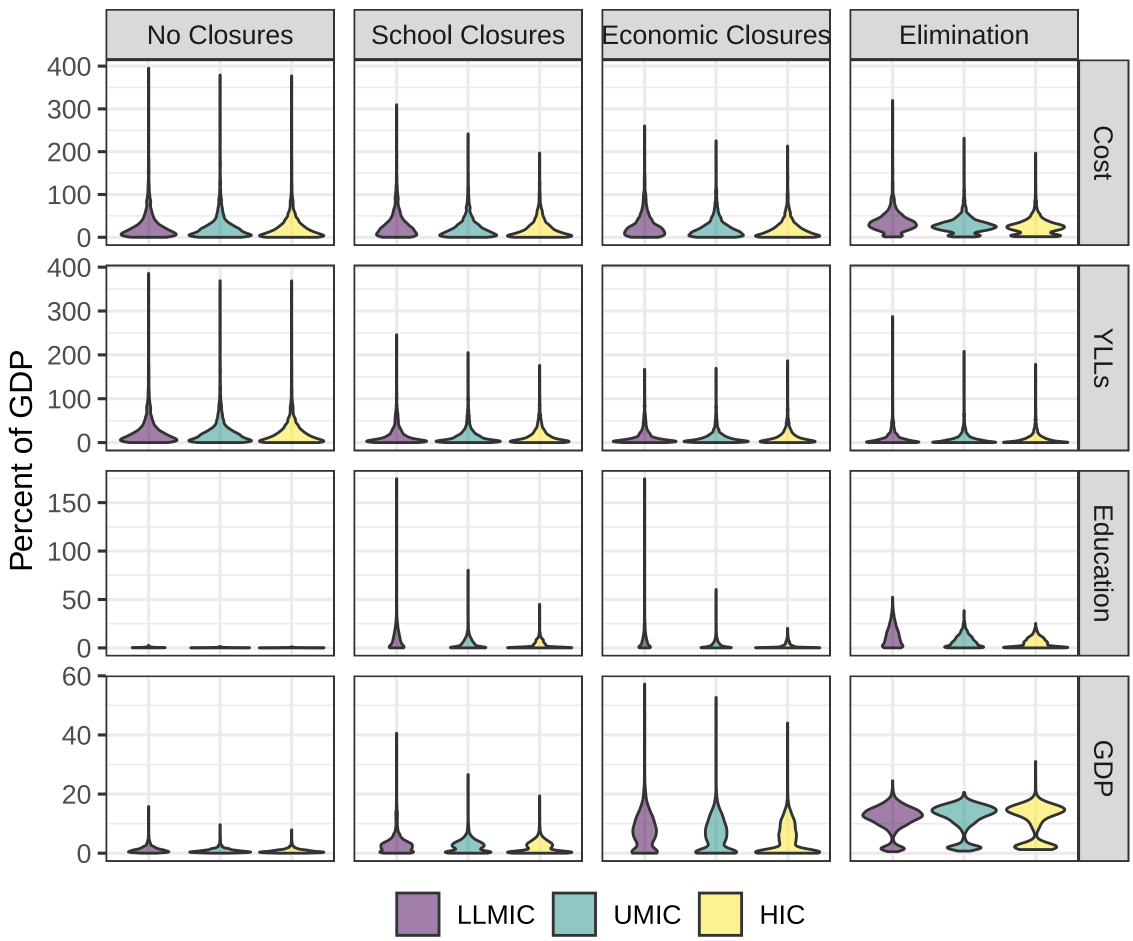

Figure 4: Model results for the 100-day scenario in Origin countries.

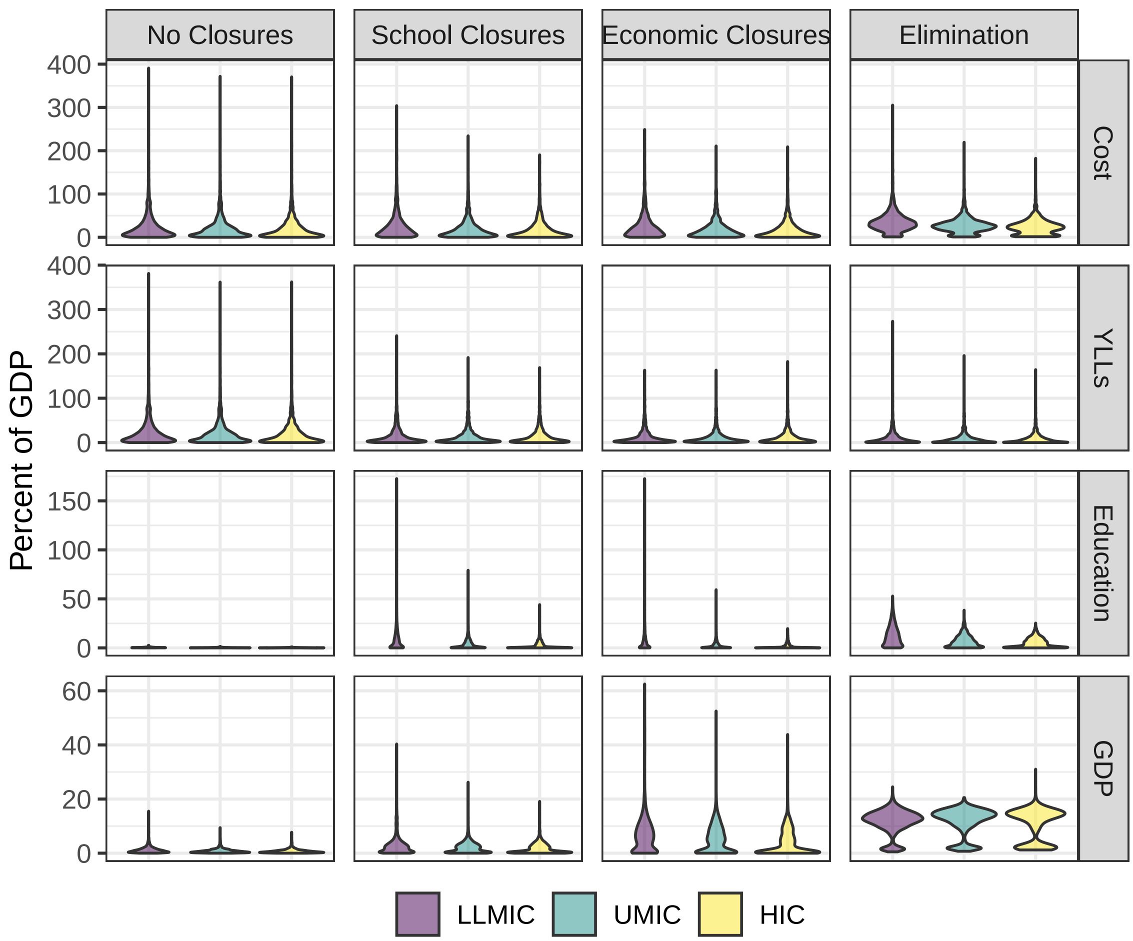

Figure 5: Model results for the 100-day scenario in secondary countries.

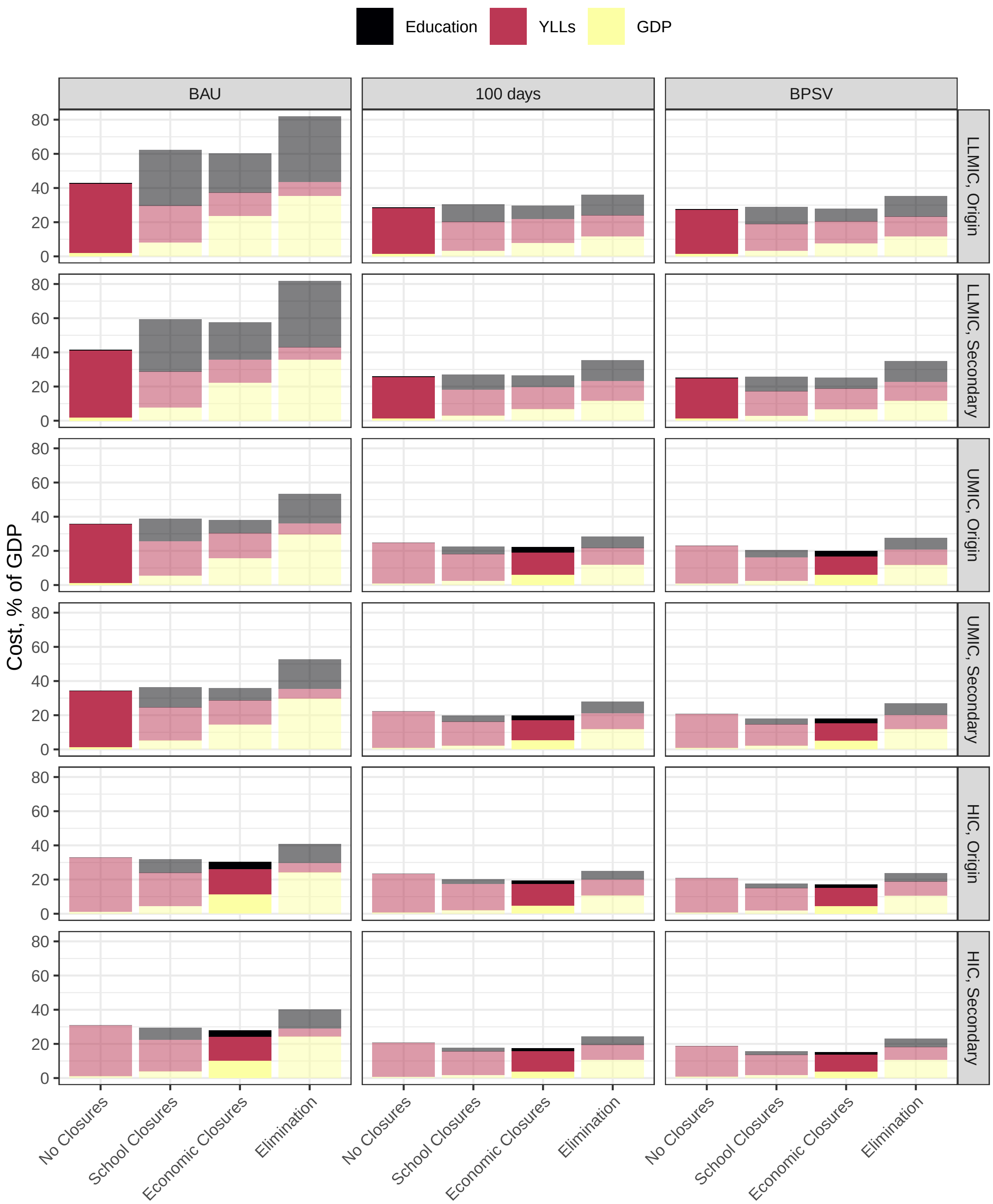

Figure 6: Expected values of model results.

3.2 Value of vaccination scenarios

Selecting the mitigation strategy that minimises the expected cost for each country type and income level and vaccination scenario, we estimate the value of the vaccines as the difference in costs. These are shown graphically in Figure 7 and tabulated in Table 9. The expected value of the 100-day vaccine ranges from in countries to in countries. The expected value of the BPSV ranges from in countries to in countries.

In some cases, the same mitigation strategy is chosen across scenarios, e.g. Economic Closures are chosen by the HIC for all scenarioss (see Figure 6). Where the choice is the same in the two vaccination scenarios compared, there are expected benefits across all costs. In other cases, the chosen mitigation strategy changes, e.g. an Origin UmIC chooses Economic Closures with the 100-day vaccine and Unmitigated with BAU. Here, there is a greater gain in expected deaths averted offset by expected losses in education and GDP.

Finally, note that there are samples with a negative value. These come from unlikely large exit waves that arise when all NPIs are suspended following completion of the vaccine rollout.

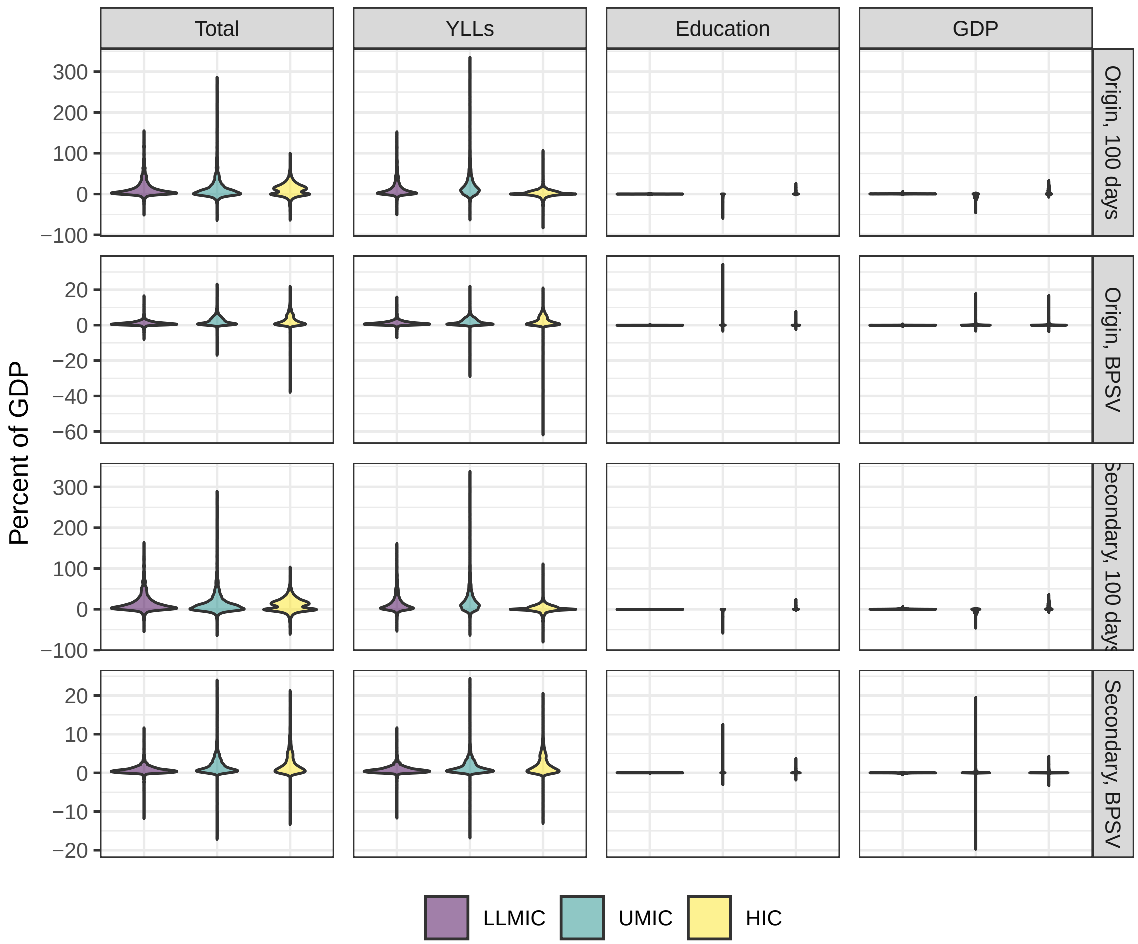

Figure 7: Model results for costs saved by 100-day and BPS vaccines.

Table 9: Value of vaccines as a percent of GDP: expected difference between BAU and 100 days, and between 100 days and BPSV. Mean values and 95% prediction intervals.

Country	Vaccination	Income group	Total value	YLLs	Education	GDP
Origin	100 days	LLMIC	14.2 (-6.3, 77.5)	13.6 (-6.2, 75.9)	0 (-0.2, 0.2)	0.6 (-0.1, 2.2)
Secondary	100 days	LLMIC	15.7 (-8.7, 80.1)	15 (-8.5, 78.3)	0 (-0.2, 0.2)	0.6 (-0.2, 2.4)
Origin	100 days	UMIC	13.7 (-10.4, 81.6)	21.6 (-8.1, 96.7)	-3 (-15.5, 0.1)	-4.9 (-13.5, 0.7)
Secondary	100 days	UMIC	14.5 (-9.9, 81.3)	21 (-8.9, 97.4)	-2.5 (-14.1, 0.1)	-3.9 (-12.6, 0.8)
Origin	100 days	HIC	10.8 (-13.4, 42.6)	1.9 (-15.8, 17.4)	2.3 (-0.2, 14.6)	6.6 (-0.2, 21.7)
Secondary	100 days	HIC	10.6 (-15.2, 45)	2 (-16.1, 20.4)	2.3 (-0.2, 14.4)	6.3 (-0.2, 21.6)
Origin	BPSV	LLMIC	1 (-0.9, 3.8)	1.1 (-0.6, 4)	0 (0, 0)	-0.1 (-0.3, 0)

Country	Vaccination	Income group	Total value	YLLs	Education	GDP
Secondary	BPSV	LLMIC	0.8 (-0.6, 3.1)	0.8 (-0.4, 3.1)	0 (0, 0)	0 (-0.2, 0)
Origin	BPSV	UMIC	2.2 (0, 7.8)	1.9 (0, 6.4)	0.1 (-0.1, 1)	0.2 (-0.8, 1.3)
Secondary	BPSV	UMIC	1.8 (0, 6.9)	1.5 (0, 5.7)	0.1 (0, 0.8)	0.1 (-0.1, 1.1)
Origin	BPSV	HIC	2.6 (0, 9.8)	2.3 (0, 9)	0.1 (-0.2, 0.8)	0.1 (-1.2, 1.3)
Secondary	BPSV	HIC	2.1 (0, 8.7)	2 (0, 7.9)	0.1 (-0.1, 0.7)	0.1 (-0.4, 1.1)

3.3 Other visualisations

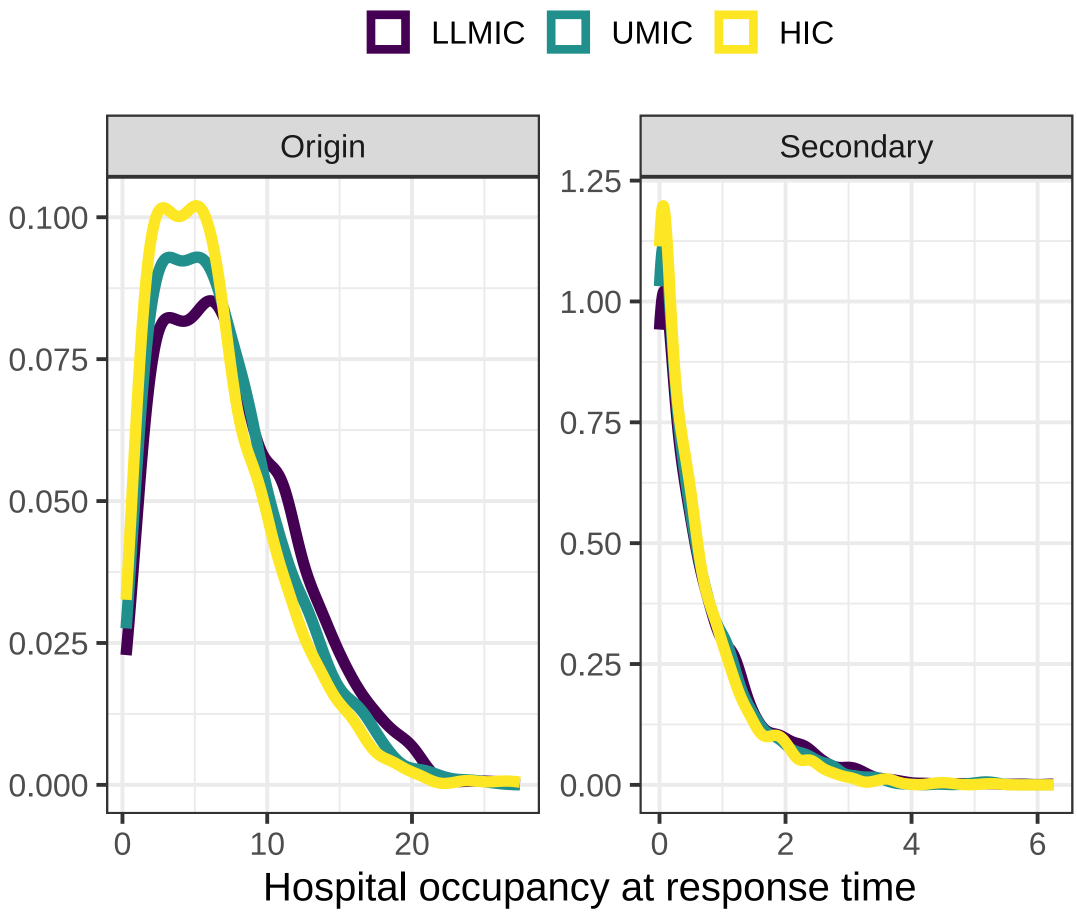

Figure 8: Hospital occupancy at time of response.

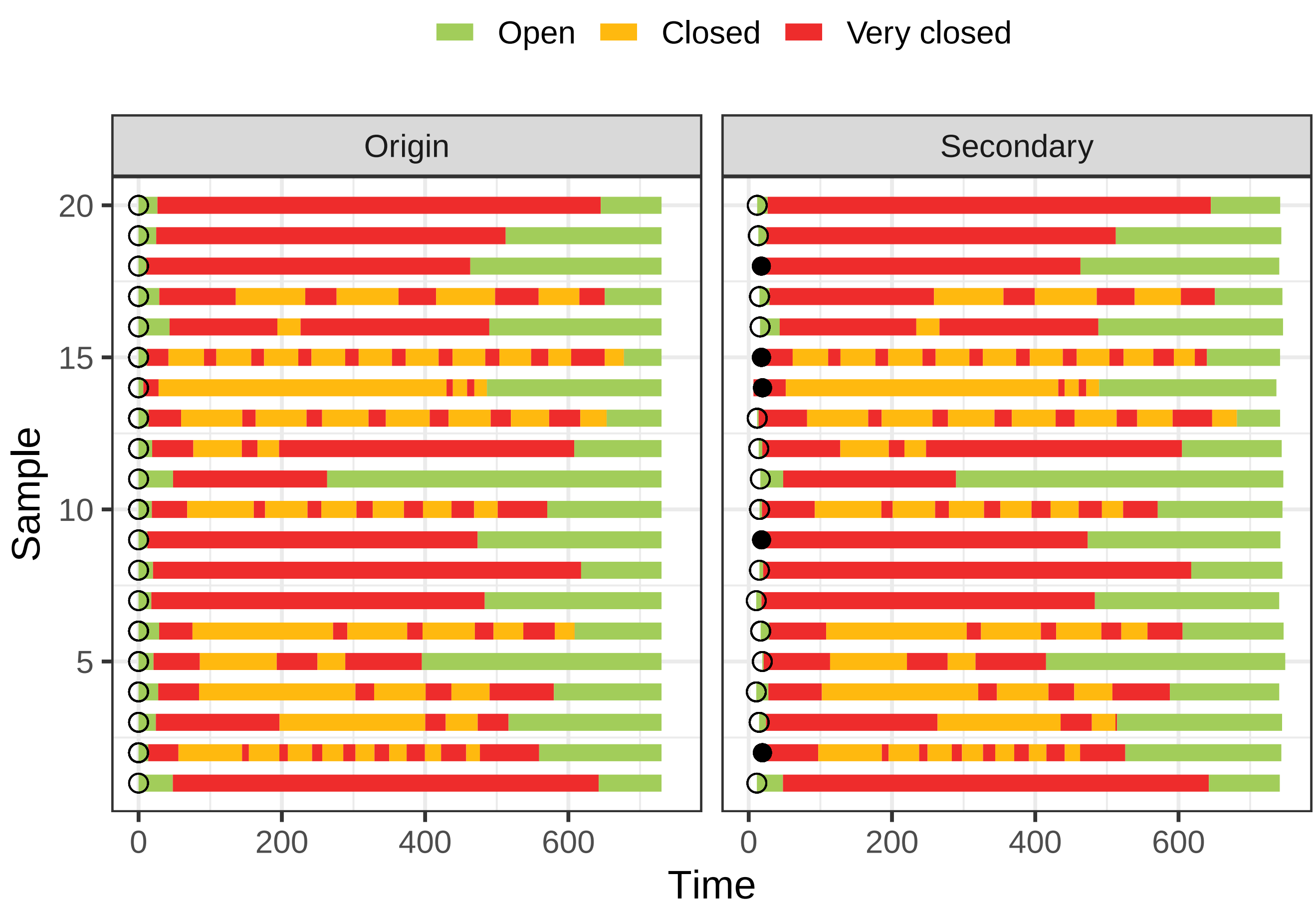

Figure 9: Closures for HICs under the Economic Closures strategy.

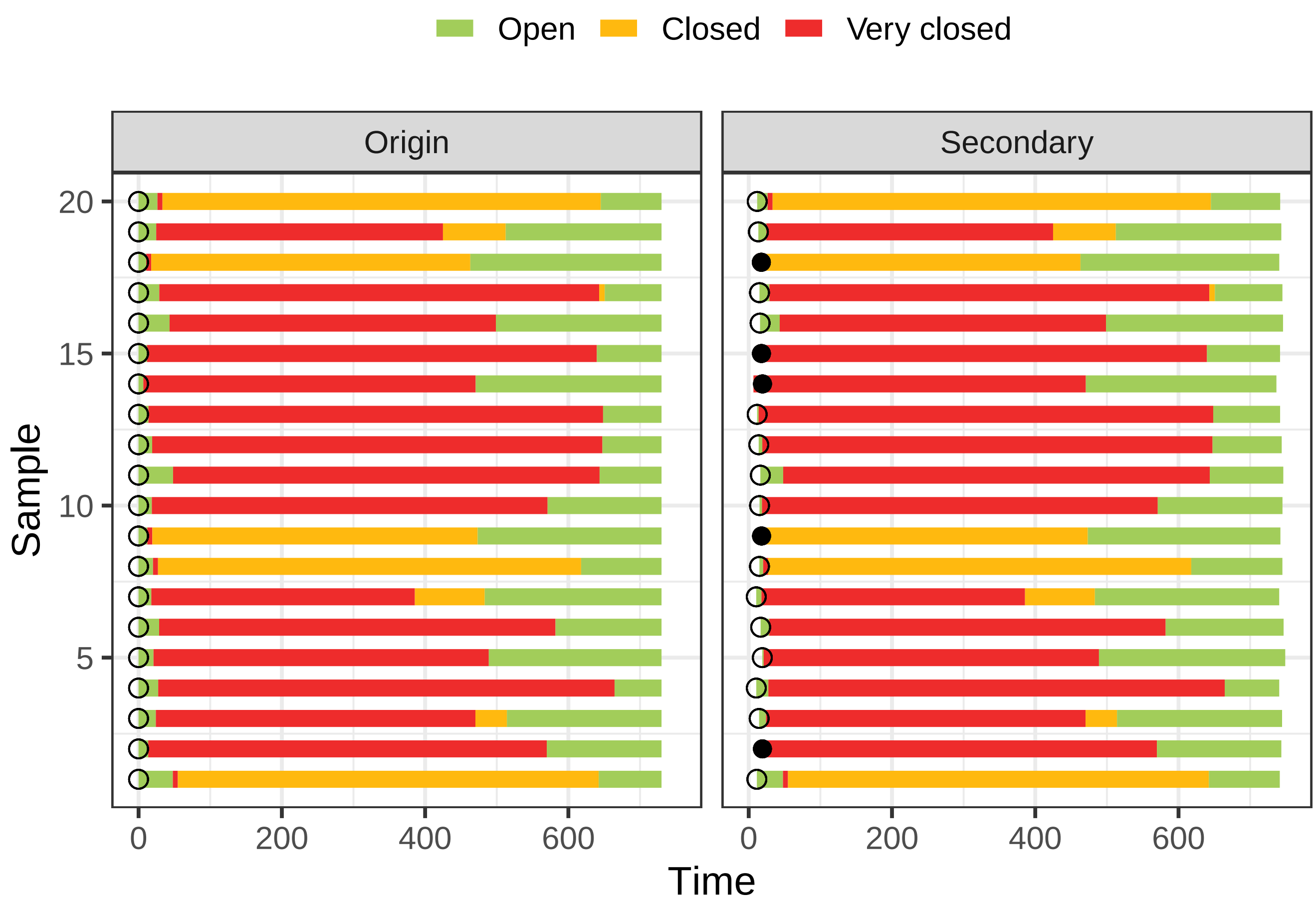

Figure 10: Closures for HICs under the Elimination strategy. *Future development: find the most open configuration for "Closed" that will allow Rt to remain below 1.*

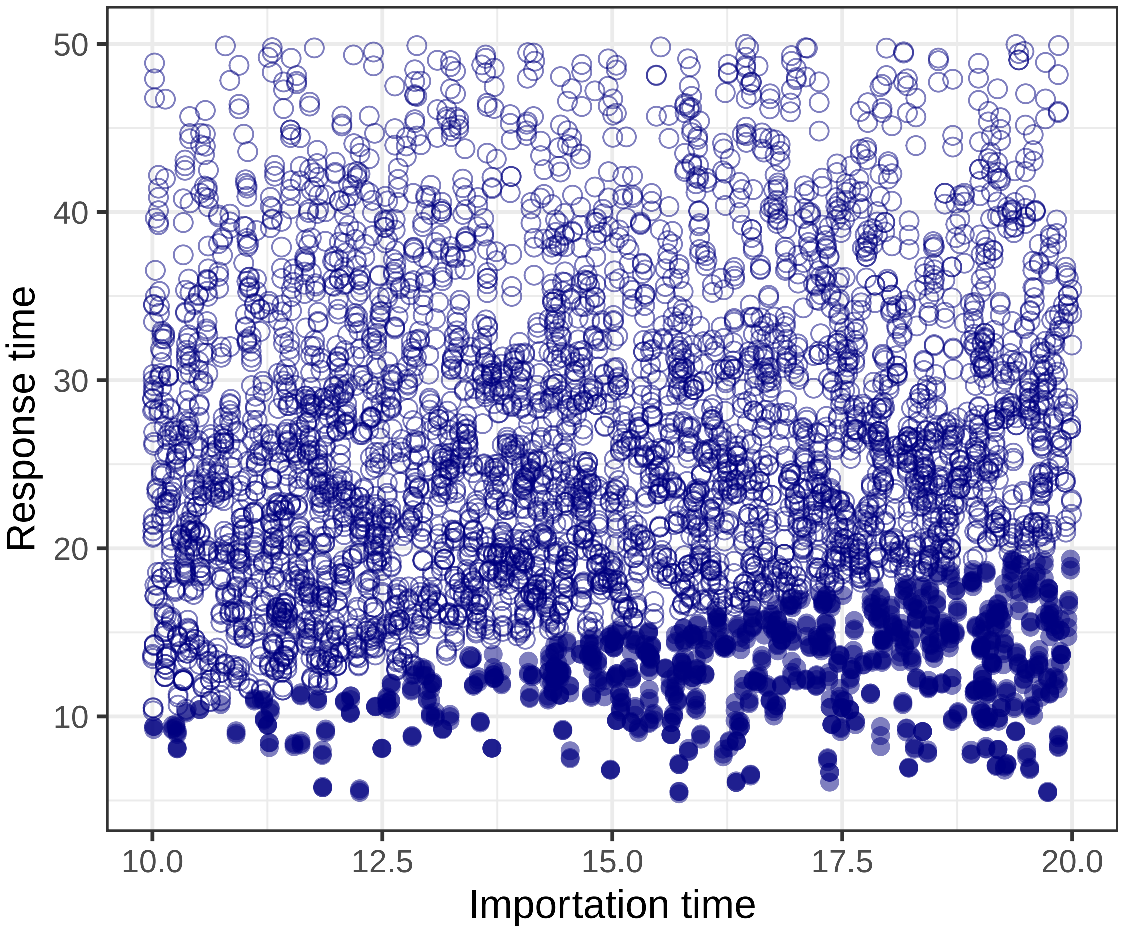

Figure 11: Secondary countries: importation time vs. response time. Where importation time is before response time, the epidemic unfolds as in the Origin country, but with an earlier response time. *Future development: there is not a qualitative difference between Origin and Secondary countries. We could therefore remove this label and vary the importation time from 0 to 20, to include the Origin feature. This would also allow for the possibility that a Secondary country with early importation detects, reports and responds earlier than the Origin country.*

3.4 Value of information

The value of information associated with a number of parameters for all costs considered is shown in Figure 13. 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 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.

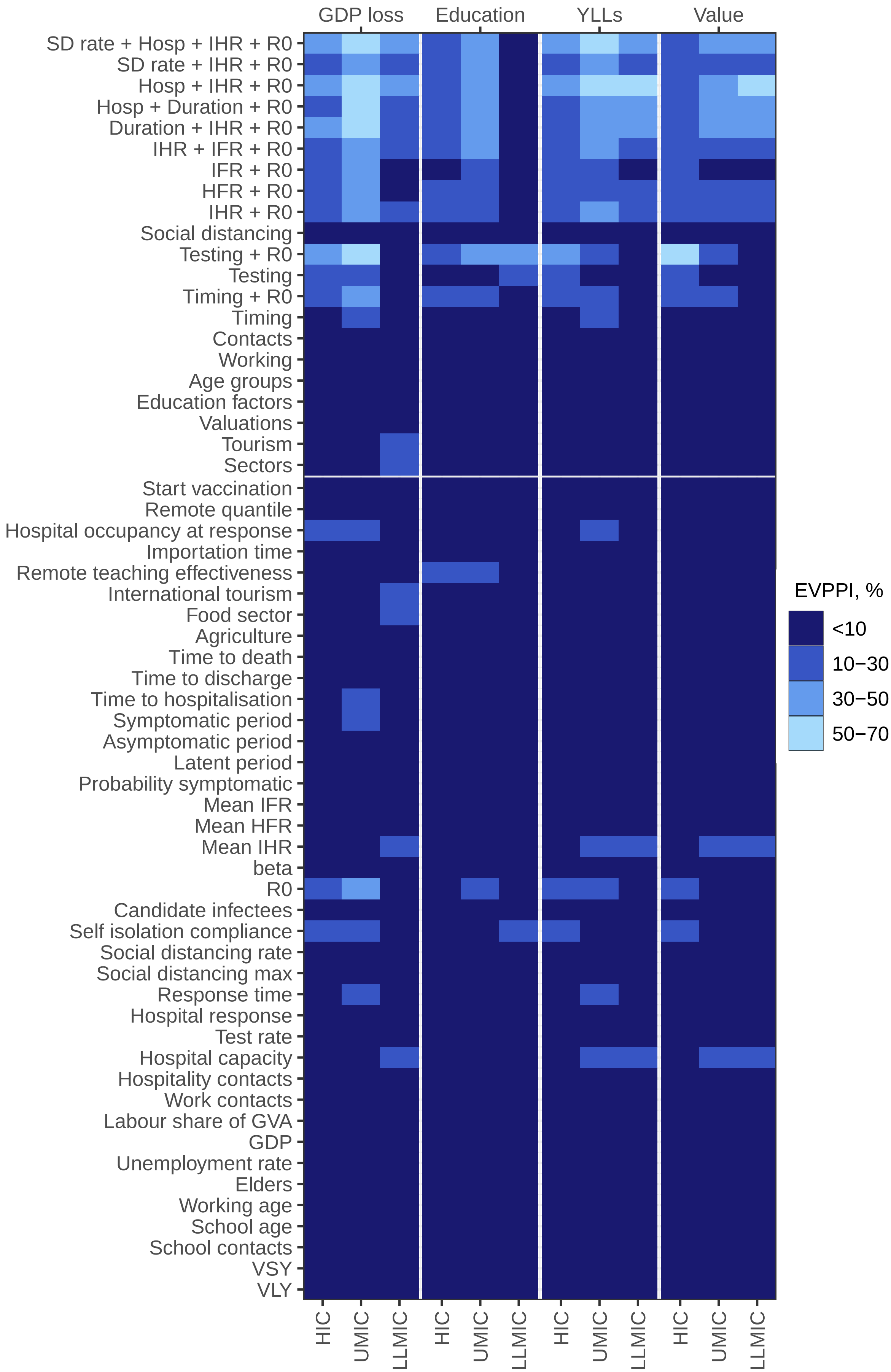

Figure 12: Value of information for 100-day vaccine value, Origin country.

Figure 13: Value of information for BAU, Origin country.

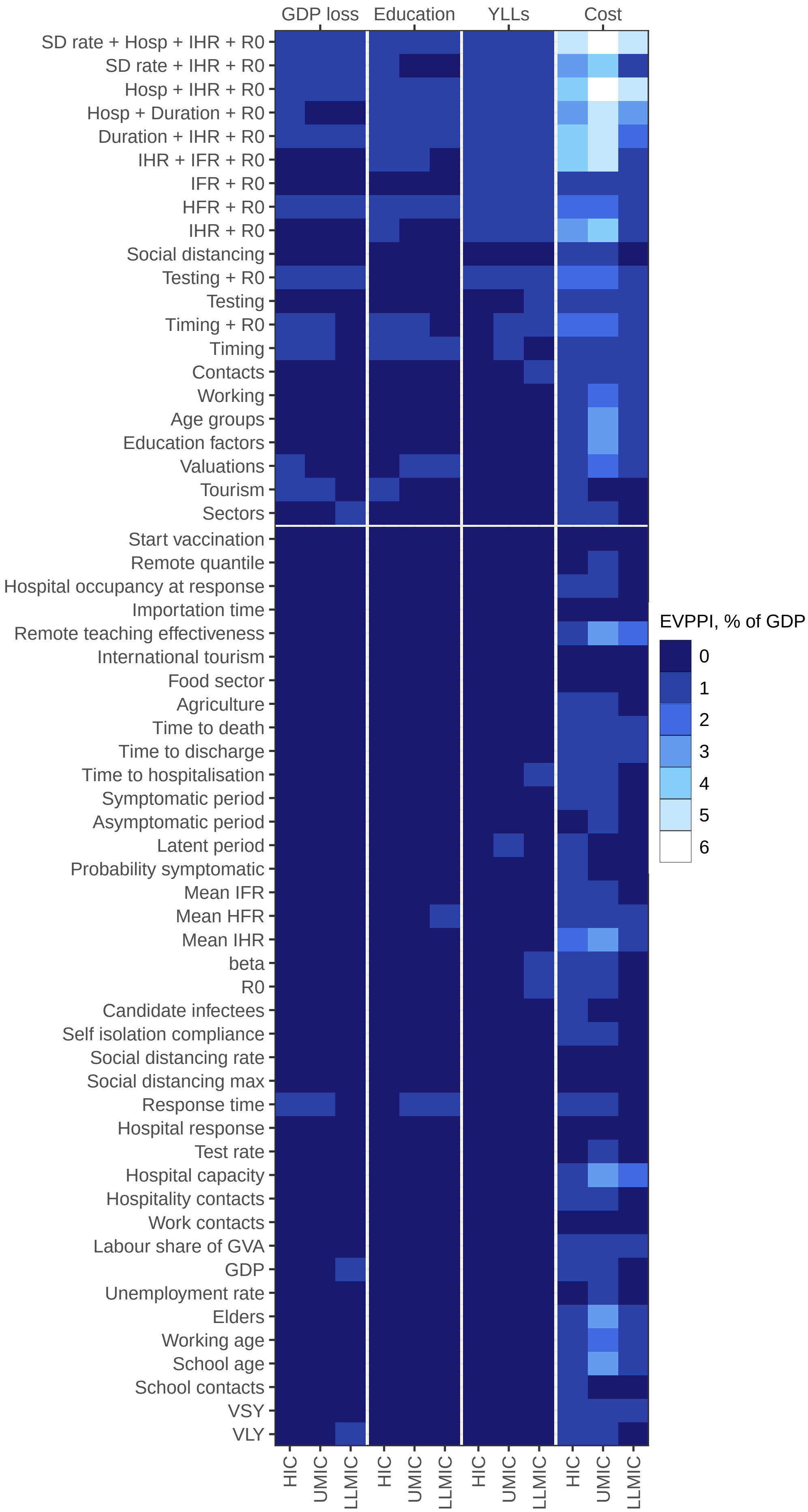

Figure 14: Decision VOI for BAU. Which parameters would enable the decision maker to choose a strategy that minimises

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 17: 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.

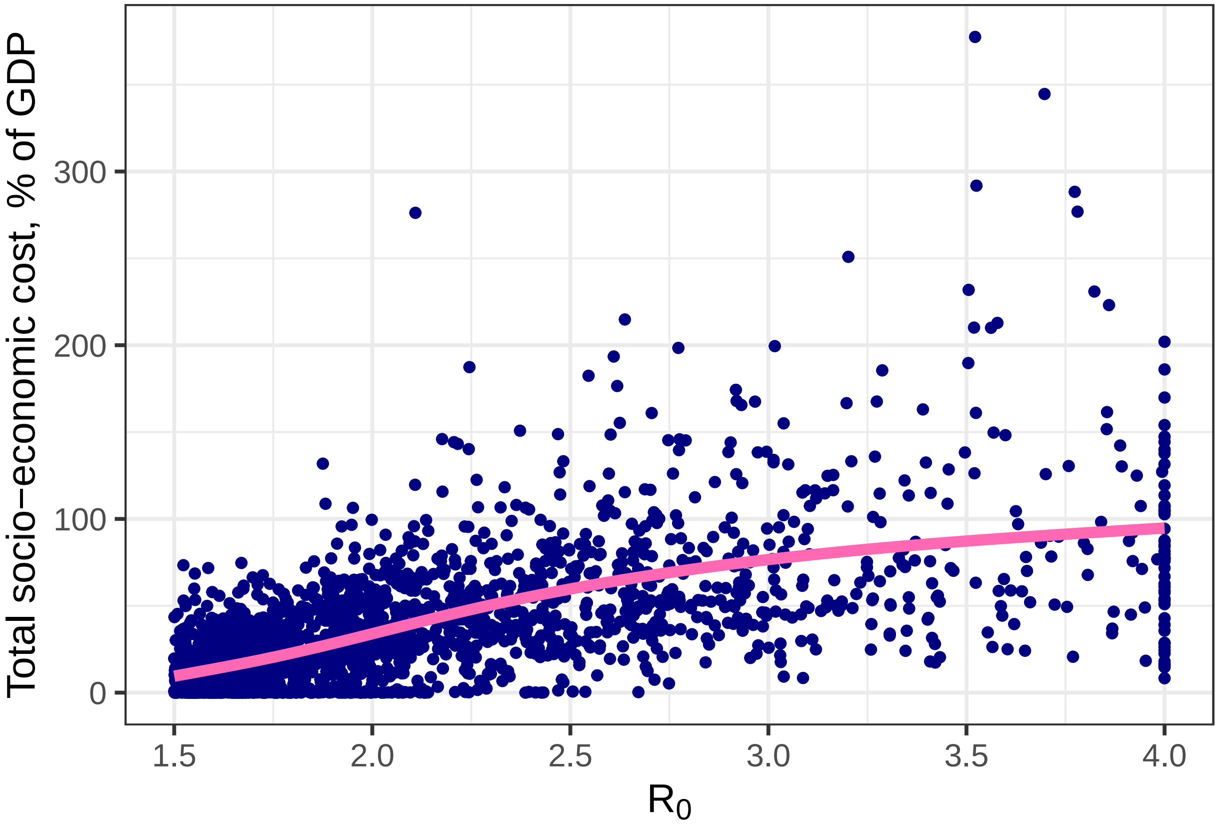

Figure 15: Relationship between R_0 and total costs for Origin UMICs with the "School Closures" strategy.

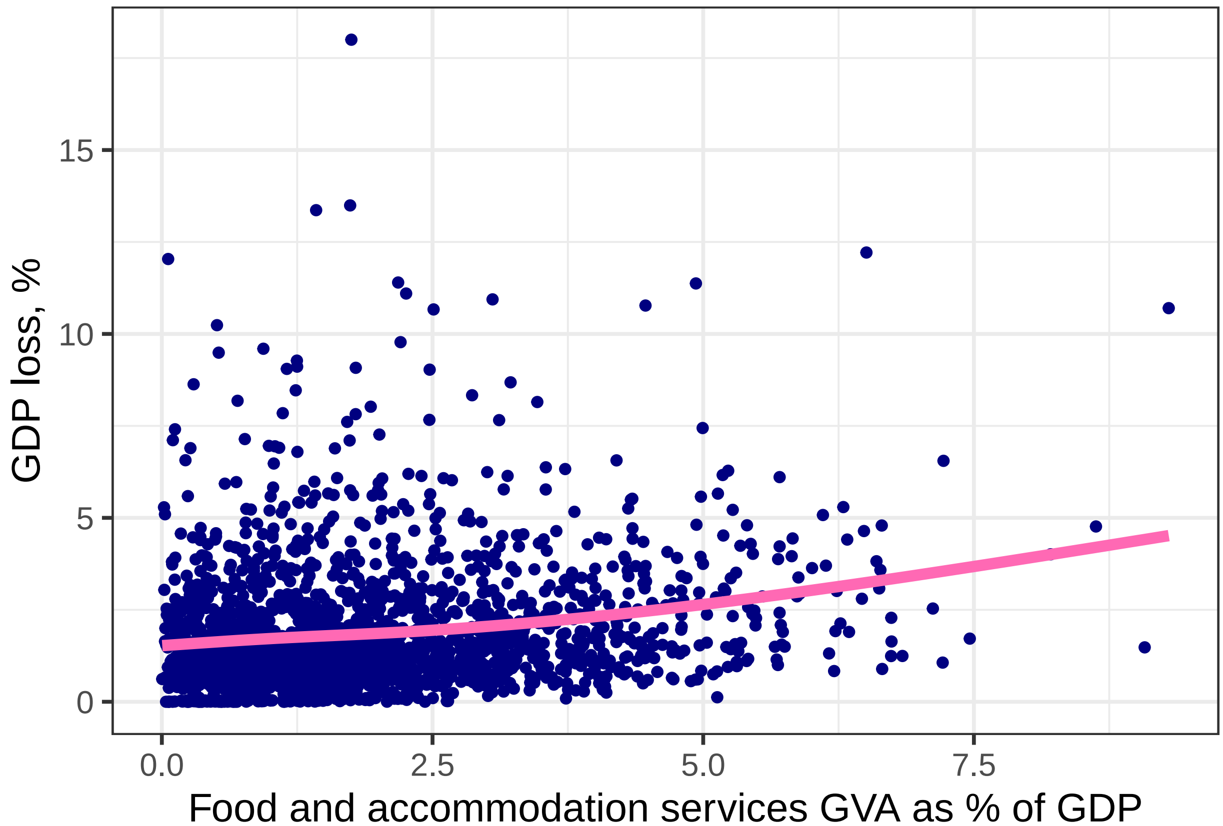

Figure 16: Relationship between the "tourism sector" size and GDP loss for Origin LLMICs with the "No Closures" strategy.

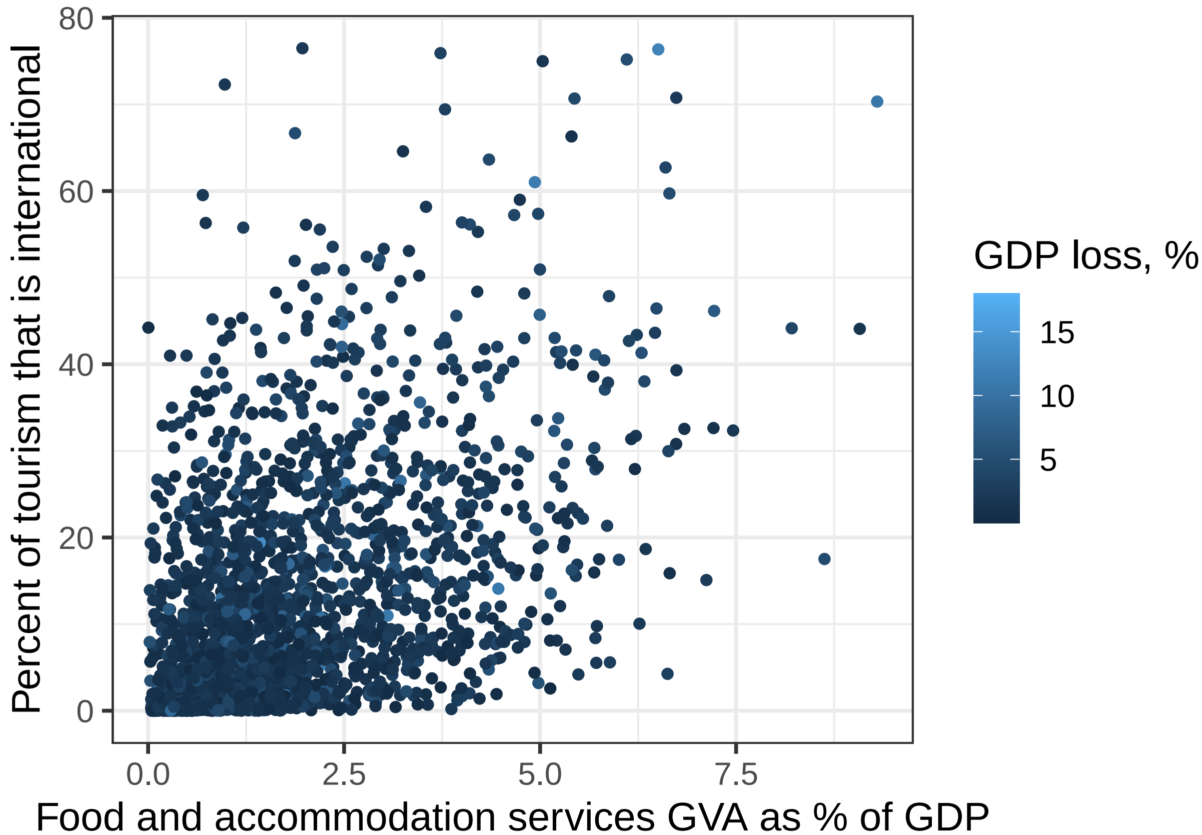

Figure 17: Relationship between tourism parameters and GDP loss for LLMICs with the "No Closures" strategy.

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 18 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).

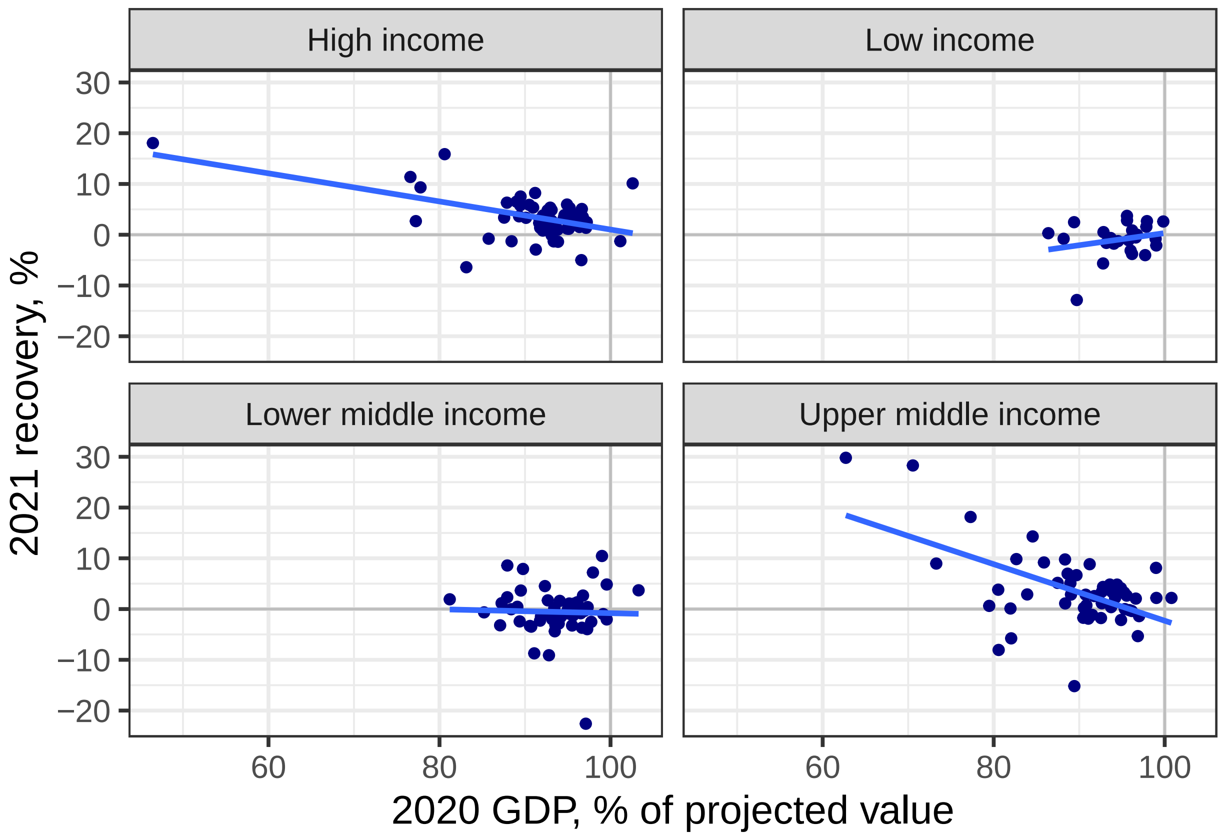

Figure 18: GDP loss and recovery. On the x axis is the GDP of 2020 relative to its 2019 projected value (IMF). On the y axis is 2021 GDP relative to its 2019 projected value relative to the same value for 2020 (ratio of ratios). x values below 100 represent a loss in the year 2020. y values above 0 represent 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 Economic configurations

Table 10: 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

Sector	Elimination	Lockdown	Economic Closures	Lockdown (School Closures)	School Closures
Air transport	18	63	82	16	42
Warehousing and support activities for transportation	91	63	82	64	91
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

7 Methodological developments specific to this application

7.1 Impact of tourism

7.1.1 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 19.)

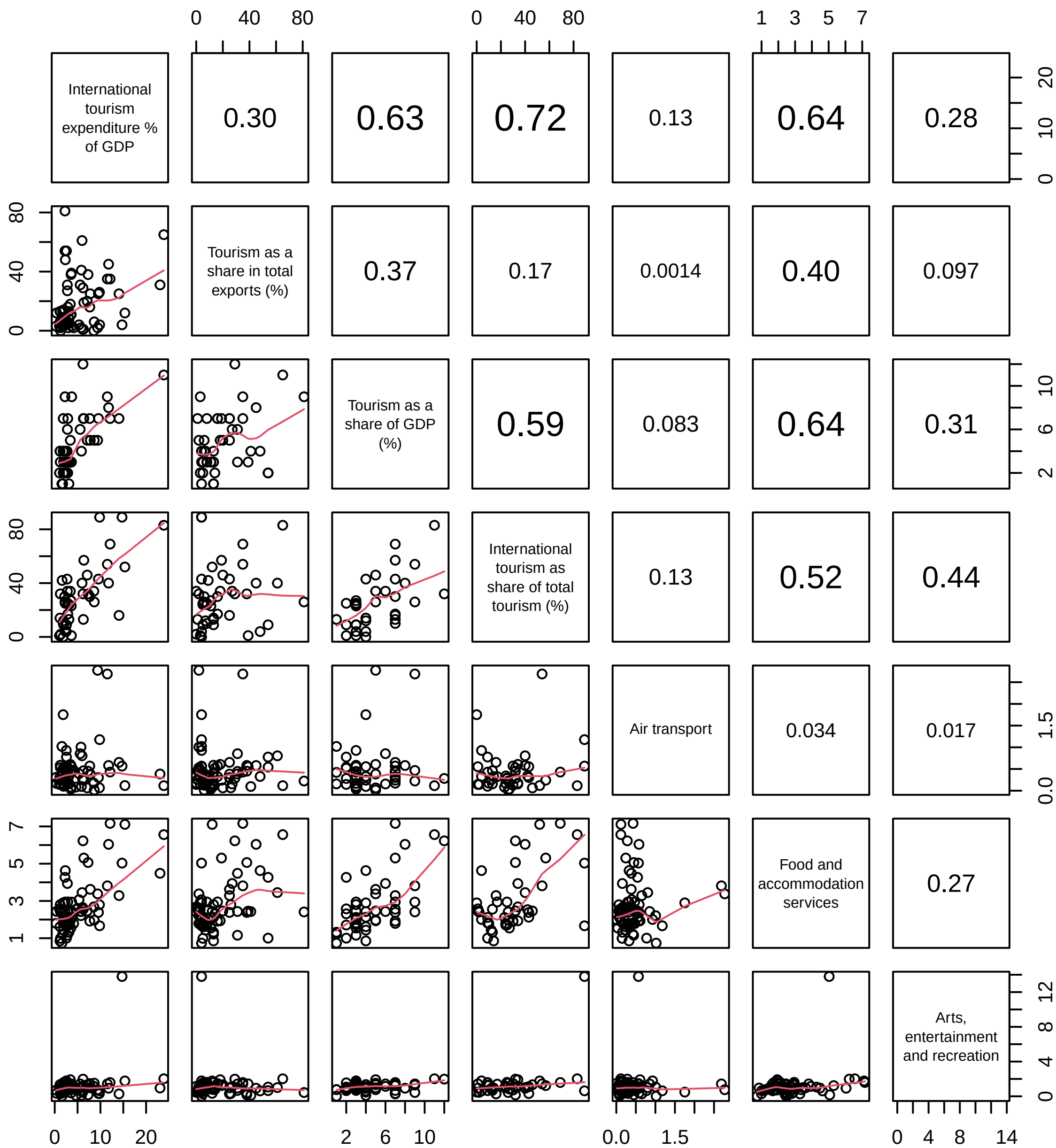

Figure 19: Correlations between tourism-related data. First: https://www.unwto.org/tourism-statistics/key-tourism-statistics. Second to fourth: https://www.unwto.org/tourism-data/international-tourism-and-covid-19. Fifth to seventh: OECD.

7.1.2 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.

7.1.3 Loss of international tourists

We model the distribution of z using data from 2020 (Figure 20, bottom-right plot). We fit to it a log-normal distribution, and find mean value -1.39 and standard deviation 0.39 (Figure 21). We use these values as inputs for all country models.

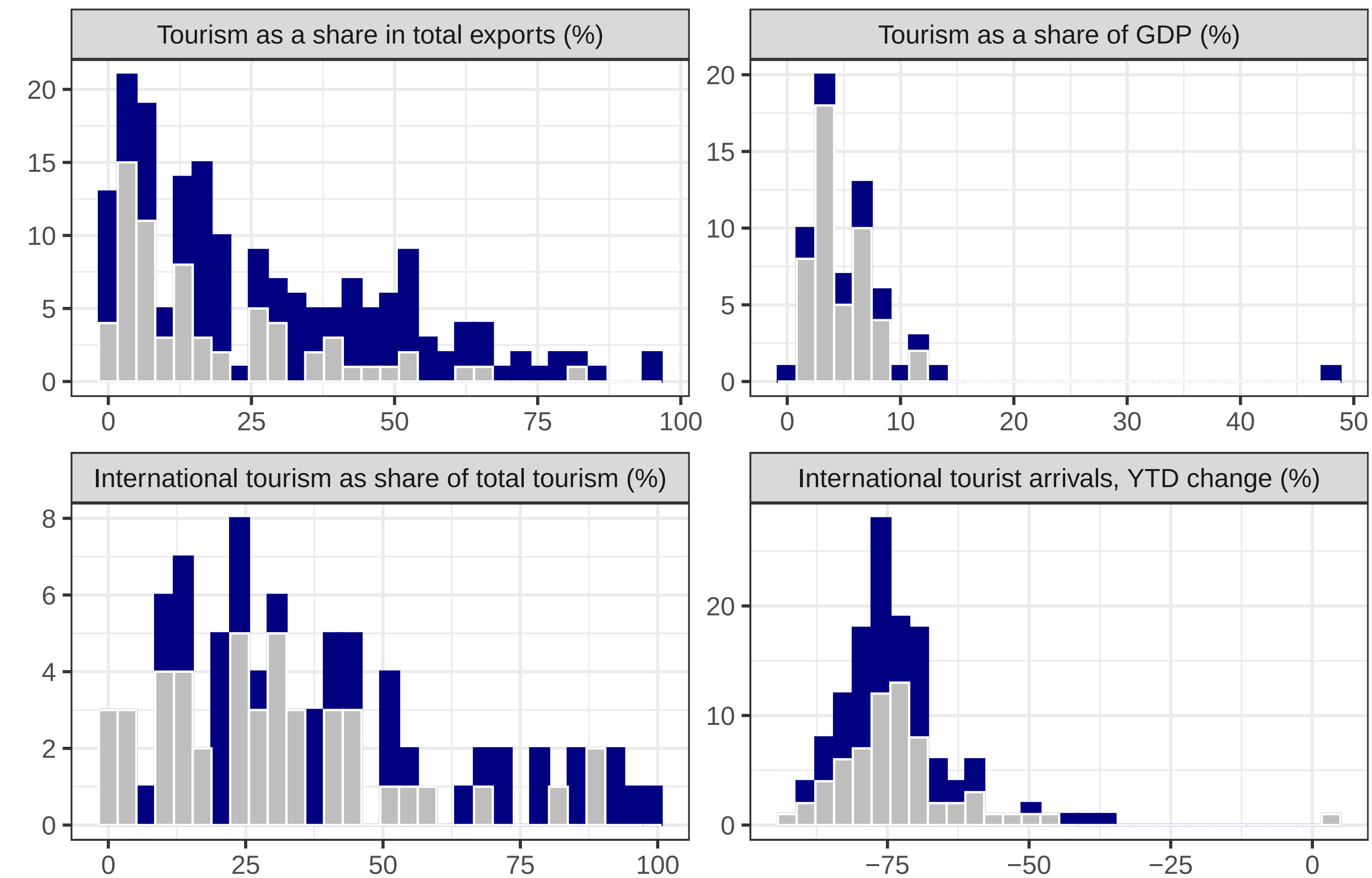

Figure 20: Distributions of tourism-related data from https://www.unwto.org/tourism-data/international-tourism-and-covid-19. In grey are the subset of countries for which we have GVA data by sector.

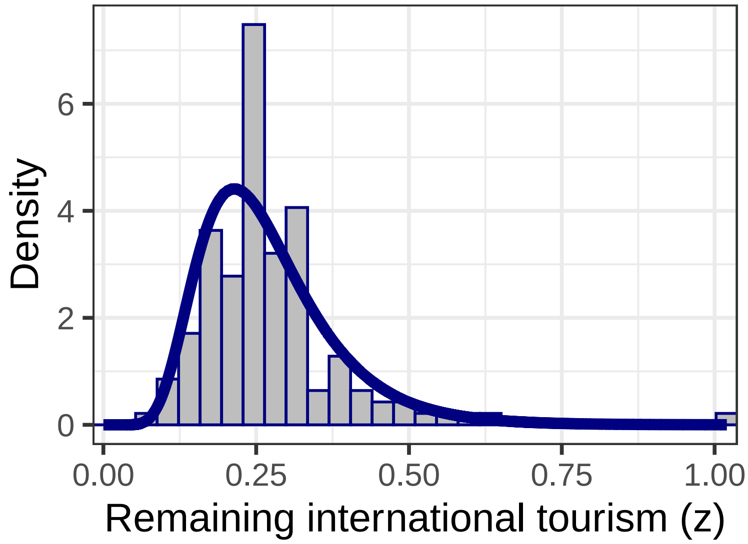

Figure 21: Fit of log-normal distribution to loss-of-tourism data.

7.1.4 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 **??**. We use these values as inputs for all country models.

7.2 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.

7.3 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 β values from the generating model using the average number of candidate infectees (CI, where CI $= R_0/\beta$). We regress β against R_0 to get a one-to-one mapping from the R_0 we sample to the β used in simulations. This means that a single disease sample has a fixed β, and its R_0 will depend on the country characteristics.

7.4 Remote working

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 / UMIC / 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

7.5 Remote learning

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

$$L = \mathrm{PV} \cdot Y \cdot \alpha \cdot r \cdot \left(S \cdot \beta + (1-\beta) \cdot \int_t I_S(t)dt \right)$$

where PV is the present value of lost earnings:

$$\mathrm{PV} = \frac{1}{S} \sum_a N_a \left(\frac{1-(1+v)^{-(n+20-a)}}{v} - \frac{1-(1+v)^{-(20-a)}}{v} \right)$$

for discount rate $v = 0.03$, number N_a students currently age a, and expected number of years of work $n = 45$. Y is mean annual earnings, α is the extent and amount of time (in years) schools are closed:

$$\alpha = \int_{\tau=1}^{T} (1 - x_{ed,\tau}) d\tau,$$

$r = 0.08$ is the rate of return for one year, S is the total number of students, β is the proportion of students affected, and $\int_t I_S(t)dt$ represents education lost due to student sickness with COVID-19. The value β represents the ineffectiveness of remote teaching, which we sample as a standard uniform random variable. We note that no strong predictors of effectiveness of remote teaching have been identified (Patrinos 2023). We assume that losses are linear in duration of school closure, although there is not consensus even on this (Betthäuser, Bach-mortensen, and Engzell 2023). Important factors to include in future work might be those relating to parental circumstances including education level, engagement and socio-economic status (Moscoviz and Evans 2022). However, these factors might be more pertinent to intra- rather than international modelling.

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 22).

We model these values with Beta distributions. For LLMICs, we have parameters 5.09 and 4.51. For UMICs, we have parameters 7.06 and 8.18. For HICs, we have parameters 7.97 and 6.87.

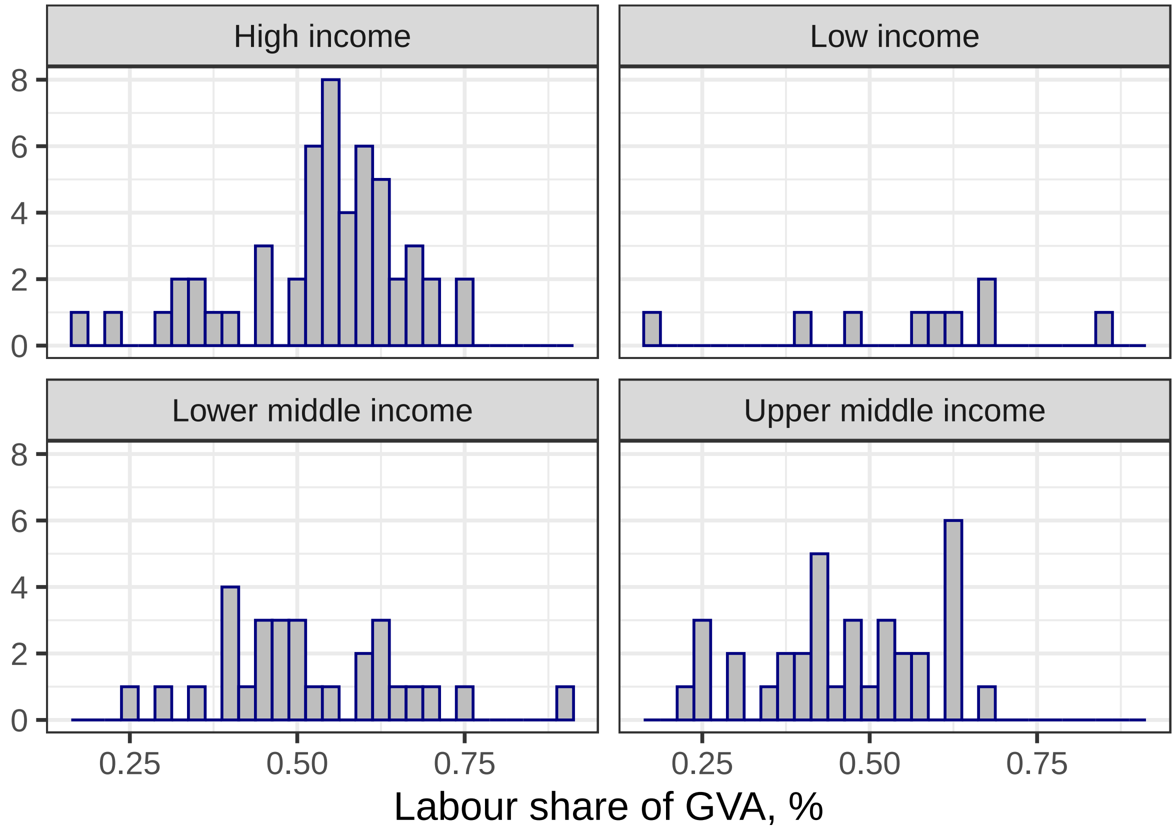

Figure 22: Fraction of GVA that goes to labour (PWT, 2011).

7.6 Hospital capacity

We model these values with gamma distributions. For LLMICs, we have parameters 1.3 and 0.05. For UMICs, we have parameters 1.73 and 0.02. For HICs, we have parameters 2.05 and 0.02. (Data sources: World Bank (beds); OECD, WHO euro (bed occupancy rates).)

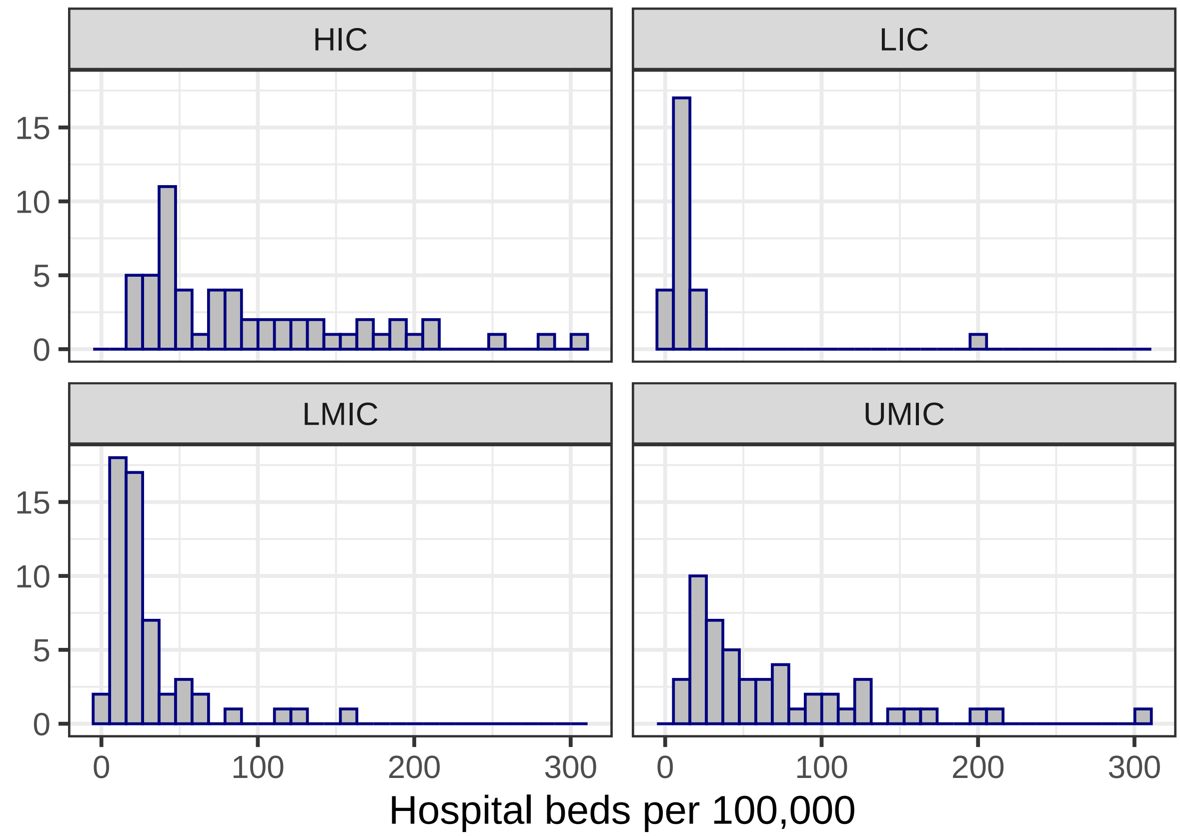

Figure 23: Fraction of GVA that goes to labour (PWT, 2011).