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Impact of the COVID19-related economic crisis and mitigation effects of social protection on HIV/AIDS and Tuberculosis: an integrated economic, mathematical and epidemiological modelling study

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1 **The COVID-19 pandemic will have impactful long-term effects on the**
2 **global rise of poverty and social inequalities, potentially compromising the**
3 **achievement of SDGs for poverty-related diseases. We aimed to evaluate the**
4 **impact of poverty increases, and the mitigation effects of social protection**
5 **policies, on HIV/AIDS and Tuberculosis (TB) in Brazil, one of the largest**
6 **and most unequal LMICs. We integrated economic, mathematical and epi-**
7 **demiological models to forecast the trends of HIV/AIDS and TB according**
8 **to different future scenarios, showing that the implementation of social pro-**
9 **tection policies could mitigate long-lasting rises in poverty, avoiding -in the**
10 **most pessimistic economic projections- an increase of 41% in the incidence**
11 **and 50% in the mortality from HIV/AIDS, and of 32% in the incidence and**
12 **53% in the mortality from TB. Overall, more than 250 thousand cases and**
13 **43 thousand deaths from HIV/AIDS and TB could be averted up to 2030.**

14 The COVID-19 pandemic has been one of the most impactful and complex
15 events in recent human history. Its burden will extend far beyond the COVID-
16 19 related diseases, and will encompass a long-term increase in morbidity and
17 mortality due to the global rise in poverty and social inequalities [1]. 120 million
18 people have already been pushed back into extreme poverty leading to an unprece-
19 dented rise in social vulnerability worldwide. The global poverty rate is projected
20 to reach 7% by 2030, and as a consequence, poverty-related diseases, that account
21 for more than 45% of the disease burden in developing countries, will continue to
22 spread among the more than 700 million individuals still living in extreme poverty
23 [2]. This will halt and - in some Low and Middle-Income Countries (LMICs) -
24 reverse all progresses done for most poverty-related infectious diseases, in partic-
25 ular for Tuberculosis (TB) and AIDS [3, 4]. As emphasized in the WHO End TB
26 Strategy, the most immediate and efficient way to reduce tuberculosis in the short
27 and middle-term would be the expansion of social protection and universal health
28 coverage [5]. Recent statistical models estimated that the elimination of extreme
29 poverty would be able to reduce the global incidence of TB by 33% by 2035 [6].
30 Several studies have also shown the significant impact of poverty-reduction poli-
31 cies on HIV prevention [7], and the effects of conditional cash transfers on the
32 reduction of the HIV/AIDS burden [8].

33 Brazil is one of the largest and most populous LMIC, and has also been one of
34 the countries most dramatically affected by the COVID-19 pandemic [9]. Due to
35 the resulting economic recession, poverty rates have suddenly increased all over
36 the country. However, the prompt implementation in April 2020 of the Emergency
37 Benefits Scheme (*Auxilio Emergencial*) (AE) had a strong impact on poverty rate,
38 that reached in a few weeks its historic low of 4.6% [10]. AE was launched to pro-
39 tect the new poor affected by the COVID-19 pandemic, and was initially limited
40 to those not already covered by other social protection policies. By its volume of
41 resources, coverage, timeliness, and impacts on income and poverty, it has been
42 considered one of the soundest social protection responses worldwide. However,
43 its abrupt interruption after a few months caused an increase of 329% of poverty
44 rates, that reached in the first trimester of 2021 an historical high of 16.1%. AE
45 was eventually reshaped with lower benefits and lower coverage, but while so-
46 cial vulnerabilities are still increasing in the country, effective Conditional Cash
47 Transfers (CCTs) such the *Programa Bolsa Familia* (PBF) [11] have been termi-
48 nated and fiscal austerity measures, implemented since the last economic crisis,
49 have been maintained [12], conveying an uncertain future for the social protec-
50 tion in the country. Previous studies have already shown the mitigation effects of
51 poverty-reduction policies on the increase of overall mortality during economic

recessions [13], but their impact on poverty-related infectious diseases has never been evaluated. Due to these sudden changes in poverty rates, to the implementation of large-scale social protection policies such as the AE, and to the uncertainty about future socioeconomic scenarios and policy responses, Brazil represents a natural experiment that could help us to evaluate the importance of mitigating the effects of the current global economic crisis in LMICs, and the consequences of not doing so. Moreover, the high burden of poverty-related infectious diseases in the country allows to assess the impact of such changing socioeconomic conditions on population health. As a matter of fact, Brazil has one of the highest TB burden worldwide, and although there have been improvements in the TB control in the last decades, the achievement of the Sustainable Development Goal (SDG) for TB is unlikely considering the current trends [14]. Regarding HIV/AIDS, while the effectiveness of the Brazilian response, based on the universalization of antiretroviral therapy in the 1990s and the current distribution-free pre-exposure prophylaxis, has been widely recognized, its incidence remains relatively high due to the heterogeneous distribution of socioeconomic conditions and risk factors in the country [15].

In this study, we have created an integrated economic, epidemiological and mathematical model to estimate the future impact of different economic crisis scenarios on the incidence and mortality from AIDS and TB, and the mitigation effect of alternative poverty-reduction policy responses up to 2030 in Brazil.

Results

Modelling poverty trends and poverty projections. Using data from national household surveys we estimated the time series of poverty rate in the country since 2003 (Figure 1): there was a steady reduction trend from the beginning of the period until the economic recession of 2014, when poverty started to increase until 2020, the first year of the pandemic. In this year, we used microdata on the individual income - from nationwide surveys implemented during the pandemic - to estimate the real poverty levels with the introduction of the AE, shown in 2020 by the yellow and blue trajectories in Fig. 1. We also estimated the poverty rates trajectory if the AE would have not been implemented (green and red lines), subtracting the AE benefits from the household income in the individual microdata of the survey. After 2020, poverty rate were projected based on different simulation methods, and four possible economic scenarios up to 2030 were hypothesized: three deterministic scenarios (two pessimistic, one optimistic) developed by ap-

87 plying exponential decay formulas calibrated to the empirical data of 2019-2020,
 88 and one derived by projections of autoregressive models applied to the previous
 89 poverty time series (Figure 1). The two pessimistic scenarios (green and red lines)
 90 illustrate how the lack of state intervention during the pandemic could cause a sig-
 91 nificant increase in the poverty rate for the following years, before an economic
 92 recovery which could occur in the medium term (in 2023 - green line, the less
 93 pessimistic scenario) or in the long term (in 2026, red line, the more pessimistic
 94 scenario). The more optimistic scenario (long term mitigation - blue line) show
 95 how, after the implementation of AE in 2020, hypothetical strong and sustained
 96 social protection interventions will be able to significantly reduce poverty rates,
 97 keeping them close to zero in the long term if maintained. The less optimistic
 98 scenario (mitigation for one year - yellow line) represent an intermediate scenario
 99 with the significant reduction of AE after 2020 (creating the rebound of poverty
 100 already observed in 2021) followed by the implementation of sustained social
 101 protection policies in the following years, able to continue the poverty-reduction
 102 trends of the previous decade.

Fig. 1 Poverty rate scenarios between 2003 and 2030.

103 **Mathematical modelling of HIV/AIDS and TB.** The mathematical models deal-
 104 ing with HIV/AIDS and TB transmission dynamics are described in many papers
 105 [16, 17, 18, 19, 20]. However, the inclusion of social determinants of health, and
 106 in particular poverty, in epidemiological models is still barely addressed. Galanis
 107 and Hanieh (2021) discussed the inclusion of three social determinants of health
 108 into the modelling framework of infectious diseases, but only with as a theoretical

109 approach [21]. In light of this, we developed two compartmental models com-
 110 posed by nonlinear differential equations for HIV/AIDS and for TB transmission
 111 dynamics to forecast the impact of the previously simulated economic scenarios
 112 on the trajectories of incidence and mortality from AIDS and TB in Brazil up to
 113 2030.

114 The HIV/AIDS model was based on the work of Huo et al. (2016), which
 115 considers the population divided into five compartments - susceptible (S), HIV-
 116 positive individuals in the stage of HIV infection (I), individuals with full-blown
 117 AIDS but not receiving ART treatment (A), individuals being treated with unde-
 118 tectable viral load (T), and individuals who have changed their sexual habits such
 119 that they are considerate immune to HIV infection by sexual contact (R) [19].
 120 Although it is a simplified model that contains only the main compartments and
 121 dynamics of the disease, it also considers important aspects such as the possibility
 122 that not everyone is susceptible to the HIV infection. The TB model was based
 123 on the work of Gomes et al. (2019), which presented a mathematical model com-
 124 posed of four nonlinear ordinary differential equations [20]. Here, the population
 125 is divided into Susceptible (S), primary infection (P), latent infection (L), and ac-
 126 tive tuberculosis disease (I). Figure 2 depicts the epidemiological scheme of the
 127 HIV/AIDS and TB models. Epidemiological meaning of each parameter model is
 128 given in the Methods section.

Fig. 2 Epidemiological scheme of the mathematical models. a. HIV/AIDS transmission model (1). **b.** Tuberculosis transmission model (2).

129 The calibration process, developed for both HIV/AIDS and TB up to 2019,
 130 was based on the simultaneous fitting of both the incident cases and the deaths
 131 estimated by the compartmental models with the official data of incidence and

mortality from the Brazilian Ministry of Health. This strategy has been adopted to ensure reliable projections for both indicators of each disease. As a novel approach, during the calibration process, we included the time series of the annual poverty rate into all the parameters of the models (described in Methods), allowing to estimate how poverty was associated with effective contact rate, cure rate, case-fatality rates and all other parameters of HIV/AIDS and TB dynamic compartmental models. Poverty rate was selected for two reasons: first it is the social determinant of health with the strongest influence on TB and HIV/AIDS dynamics, second it is the socioeconomic indicator that had the largest variations over the last decade and during the current COVID-19 related crisis, and could be considered a proxy for other indicators.

Before the model calibration process, a sensitivity analysis of the models was carried out in order to assess which parameter most influenced the variation of the model variables over time. We found that these parameters were β_H (force of the infection) for the HIV/AIDS model and ν (rate of progression from primary infection) for the TB model (Supplementary Information). Model (1) was fitted to the annual new AIDS cases and deaths reported by the Brazilian Ministry of Health between 2007 and 2019 [22]. Similarly, the TB model (2) was fitted to the annual new TB cases and deaths during 2003 and 2019 [23]. The initial year for calibration differs in the models due to the change in notification that occurred in 2007 for HIV/AIDS. We also did not consider the year 2020 due to the beginning of the COVID-19 pandemic and the related under-registration of HIV/AIDS and TB cases. Extended Data Table 1 shows the fitted values of the respective model parameters.

We estimate the HIV/AIDS and TB model parameters applying a multiobjective genetic algorithm [24], which is capable of involve more than one objective function to be optimized simultaneously, in our case, incidence and mortality in each model (see Methods for more details). Following the Brazilian population data [25], the natural birth and mortality rates, which are common parameters in both models, were assumed to take the values $\Lambda = 4,468,962.55$ and $\mu = 0.0132$, respectively, in order to fit the Brazilian total population data between the years 2003 and 2030 (Extended Data Fig. 1). Based on literature, parameter intervals were assumed to each model for the calibration process, (Tables 2 and 3 in Methods section).

Modelling HIV/AIDS and TB incidence and mortality rates. For calculating incidence and mortality rates from HIV/AIDS and TB, we divided the number of cases and deaths for each disease per 100,000 person-years (p-y), respectively. Figure 3 shows that, depending on the economic scenario, the incidence and mor-

170 tality rates of AIDS and TB will follow remarkably different trends: the sudden
 171 increase of poverty rates, due to the economic crisis and the lack of social protec-
 172 tion policies (without mitigation - more pessimistic, red line; and less pessimistic -
 173 green line), will cause a considerable rise in TB incidence (Figure 3c) and mortal-
 174 ity (Figure 3d). While after a certain number of years, depending of the economic
 175 scenarios (red vs green lines), poverty rates will start to steadily decrease, TB in-
 176 cidence and - to a lesser extent - TB mortality will delay their trend reductions. In
 177 the more optimistic scenarios, TB incidence and mortality will tend to have tra-
 178 jectories very similar to poverty rates: in case of the AE mitigation implemented
 179 only for one year (yellow line), followed by sustained social policies, TB inci-
 180 dence and mortality will follow the trends of the previous decade, while in case of
 181 a long-term mitigation with extremely strong AE-like social policies (blue line),
 182 all TB indicators will decrease significantly more. The incidence (Figure 3a) and
 183 mortality rates (Figure 3b) from AIDS will increase less quickly and abruptly than
 184 TB, due to the different compartmental model dynamics and sensitivity to poverty
 185 rates, but the shape of the curves and difference between scenarios will be similar
 186 to TB.

187 Table 1 shows the incidence and mortality rate ratios - in different years of
 188 the study period - using the optimistic scenarios of 1-year AE poverty mitigation
 189 plus sustained social policies in the following years (yellow line) as reference
 190 values. This scenario was considered the most plausible if social protection will
 191 be preserved and strengthened in the country over the next years. While in the
 192 short and medium term the differences between scenarios will be stronger for TB,
 193 both for incidence and mortality (27% and 45% more, respectively, in the most
 194 pessimistic scenario in 2025), in the long term (2030) rate ratios will be slightly
 195 larger for AIDS morbidity and mortality (41% and 50% more, respectively, in the
 196 most pessimistic scenario in 2030). In terms of the overall number of averted new
 197 infections and deaths (last two columns of Table 1) up to 2030, the number of
 198 averted new cases of TB over the period will be more than 3 times higher than
 199 for AIDS in all the scenario, reaching almost 190 thousand (against 64 thousand
 200 for AIDS) averted cases if the effect of the economic crisis would be mitigated
 201 during the acute phase of the recession and afterward. For the same scenarios
 202 comparison, the number of averted deaths will be considerably higher for AIDS
 203 (almost 25 thousand) than for TB (almost 18 thousand). More than 65 thousand
 204 new cases of TB and AIDS and more the 10 thousand of deaths will be averted if
 205 extremely strong AE-like social policies (blue line) will be implemented instead
 206 of the less optimistic scenario (yellow line).

Fig. 3 AIDS and TB morbimortality. **a.** AIDS incidence rate under different scenarios of poverty rate between 2007 and 2030. **b.** AIDS mortality rate under different scenarios of poverty rate between 2007 and 2030. **c.** TB incidence rate under different scenarios of poverty rate between 2003 and 2030. **d.** TB mortality rate under different scenarios of poverty rate between 2003 and 2030.

Table 1 Incidence and mortality rate ratios in specific years, and avoided cases and death over the all period, between the economic scenarios and the mitigation policy for one year as reference category.

Economic crisis scenario		Rate ratio by year						Cases and deaths averted over the period (n.)	
		2021		2025		2030			
		AIDS	TB	AIDS	TB	AIDS	TB	AIDS	TB
Scenario 1 (higher)	Incidence	1.02	1.17	1.19	1.27	1.41	1.32	64,083	189,381
	Mortality	1.06	1.15	1.25	1.45	1.50	1.53	24,811	17,877
Scenario 2 (medium)	Incidence	1.02	1.17	1.18	1.24	1.33	1.25	55,905	162,996
	Mortality	1.05	1.15	1.23	1.41	1.40	1.40	21,820	15,257
Scenario 3 (lower)	Incidence	1.00	1.00	0.97	0.93	0.93	0.92	10,760	55,203
	Mortality	1.00	1.00	0.94	0.87	0.90	0.88	5,711	4,691

Discussion

In our study we have integrate economic, mathematical and epidemiological models to show for the first time, in one of the largest LMICs, the strong impact that the COVID19-related global economic crisis will have on the increase of HIV/AIDS and TB morbidity and mortality, and the important mitigation effects of a prompt and long-lasting implementation of social protection policies to counteract the rise in poverty rates. While during the COVID-19 pandemic all efforts have been focused on the control and elimination of its infectious agent, a large economic recession have hit the majority of LMICs, and its length and magnitude will profoundly affect the trends of all poverty-related diseases, in particular HIV/AIDS and TB. Relieving poverty should be the core of economic development since it directly reflects the well-being of the population. High poverty rates are for instance commonly indicative of high levels of unemployment, inequality, crime, food insecurity and malnutrition [26]. Brazil witnessed a persistently high rate of poverty the last century, before the economic and structural reform successfully implemented in the last two decades allowed the creation of a progressively larger welfare state [27]. Since then, Brazil has been one of the international references on poverty reduction until 2015, when a large economic crisis hit the country. Social welfare programs such as CCTs targeted at the poor population and minimum wage valorization were mostly responsible for the reduction of poverty in Brazil from early 2000s [27, 28], whereas its increase from the year 2015 is attributed to the political and economic crisis that caused an expressive rise in un-

229 employment [29]. This economic recession caused the increase of the number of
230 Brazilians below the poverty line from about 17.0 to 23.3 million, meaning about
231 6.3 million “new poor” Brazilians [29]. The Covid-19 pandemic aggravated the
232 already growing poverty rate trends as the employment of the poor and middle-
233 class was mostly affected by the crisis [30]. While the AE was an important
234 mitigating factor in the first phase of the crisis, this has been temporary since the
235 value and coverage of the financial aid reduced steadily, whereas unemployment
236 continued increasing – 11.8% to 13.8% from the year 2019 to 2020 [31]. Achiev-
237 ing the Sustainable Development Goal of zero poverty by the year 2030 appears
238 to be remote if Brazil continues on the trend observed since the year 2015. Given
239 the past experience, conditional cash transfer programs and financial aid for the
240 poorest have been a successful interventions for reducing poverty rates and have
241 also shown to be effective in mitigating the effect of the COVID-19 pandemic.
242 Given the projections of this study, eradicating poverty by 2030 would be feasible
243 only through the implementation of a broad and consistent welfare state focused
244 on the most vulnerable populations.

245 While poverty has consistently been recognized as one of the most impor-
246 tant risk factors for Tuberculosis [6], and poverty-reduction programs such as
247 cash transfers have repeatedly shown a significant reduction in TB morbidity and
248 mortality [29, 32, 33], for HIV/AIDS the evidence is weaker [8]. Poverty could
249 affect housing conditions, overcrowding common spaces and decreasing ventila-
250 tion in the rooms of the house, consequently increasing the possibility to con-
251 tract TB through aerosol from infected individuals [34]. Regarding HIV/AIDS,
252 poverty could force transactional sex and/or prostitution among the most vulnera-
253 ble women, besides acting negatively on other mechanisms related to self-esteem
254 and sexual behaviours [35, 36]. Moreover, poverty could threat household food
255 security and worsen the nutritional status of the members of the family, which
256 has a direct effect on the risk to pass from the latent stage of TB and HIV to the
257 infectious status [37, 38]. Furthermore, poverty can negatively affect the access
258 to diagnostic and treatment, both because the lack of money for transportation
259 fares and the impossibility to take days-off at work due to the extreme economic
260 vulnerability [39]. Moreover, poverty tend to reduce the time of schooling, that is
261 an important protection factor for both HIV/AIDS and TB in several steps of the
262 causal pathway [40, 41].

263 Mathematical models of infectious diseases or biological systems are extremely
264 useful tools for performing in silico experiments and predicting how diseases or
265 biological processes evolve over time under different scenarios [42]. However,
266 a single mathematical model approach is unable to provide exact answers since

267 these models need to have a restricted number of factors to analyze and obtain
268 an understanding of the transmission dynamics. Therefore, the integration of dif-
269 ferent areas becomes crucial for the investigation of complex process or diseases
270 since the introduction of methods or mechanisms from different areas can con-
271 tribute significantly to an overview of the overall phenomenon.

272 Our models have limitations. First, only poverty was included as a social
273 determinant of health because, for an integrative approach, it was necessary a re-
274 duced number of parameters and factors to calibrate the mathematical models.
275 However it has to be considered that, during the current COVID19-related global
276 economic recession and for the future years, the vulnerability indicator that will
277 change the most will undoubtedly be the poverty rate. The influence of other so-
278 cial determinants of health less sensitive to economic shocks, together with the ef-
279 fects of the introduction of new diagnostic and therapeutic technologies, have not
280 been included in the models because we focused on comparing scenarios based
281 on changes in poverty and in poverty-mitigation policies, and not on projecting
282 the future trends of HIV/AIDS and TB. We assume that all factors not included
283 in our models, and that could have influenced such trends, would have affected
284 all the scenarios in a similar way, and would not have significantly changed our
285 HIV/AIDS and TB morbidity and mortality comparisons. Another limitation is
286 the simplicity of our compartmental models for HIV/AIDS and TB that, although
287 they have already been used in similar studies [19, 20], do not consider more
288 complex disease status, differences in treatment compliance, TB resistance and
289 multi-morbidity of HIV/AIDS and TB. However, such models can be considered
290 reliable for modelling these infectious diseases in the Brazilian context, where
291 treatment compliance is overall high, TB resistance is below 1% and HIV/AIDS-
292 TB-multi-morbidity below 10% [43]. The last limitation is related to the poverty
293 projections: while the exponential decay curves have been calibrated on real data,
294 and have been used in similar studies [12], they model a behaviour of the eco-
295 nomical crisis, and the year of its ending, that is just assumed based on theoretical
296 considerations, while the unpredictability of the pandemic could still affect future
297 economic scenarios.

298 In conclusion, understanding and measuring complex phenomena - such as
299 the COVID19-pandemic effects on socioeconomic and health outcomes - requires
300 the integration of multidisciplinary models, combining methods from different
301 fields such as economics, mathematics, and epidemiology. Using this compre-
302 hensive approach, we were able to show the importance of implementing strong
303 social protection policies to avert a large increase in morbidity and mortality from
304 HIV/AIDS and TB during the post-pandemic period in LMICs. Further efforts

305 should be made to understand and estimate the impact of the current global reces-
 306 sion on other poverty-related diseases.

307 Methods

308 **HIV/AIDS transmission model.** Our mathematical model for HIV/AIDS transmission dynamics
 309 is based on the work of Huo et al. (2016), which is composed of five dynamical variables, which
 310 are susceptible (S), HIV-positive individuals in the stage of HIV infection (I), individuals with
 311 full-blown AIDS but not receiving ART treatment (A), individuals being treated with undetectable
 312 viral load (T), and individuals who have changed their sexual habits such that they are considerate
 313 immune to HIV infection by sexual contact (R) [19].

314 Susceptible individuals have a constant per-capita birth rate Λ and a per-capita death rate μ .
 315 These individuals can be infected in contact with HIV-positive individuals through the effective
 316 contact rate β_H . Besides, some susceptible individuals change their sexual habits at a per-capita
 317 rate ε_1 , which we considered that they now have safe sexual habits and because of that they do
 318 not contribute to the HIV transmission. However, some individuals in the R class can neglect
 319 their safe sexual habits and return to the susceptible compartment at a per-capita rate ε_2 . HIV-
 320 positive individuals after a period ρ^{-1} become individuals with full-blown AIDS but not receiving
 321 treatment. On the other hand, HIV-positive individuals receiving treatment after a period η^{-1}
 322 reach a undetectable viral load. In addition, if the treatment is stopped, the individuals in the T
 323 class can increase their viral load and becoming infectious (I) or even full-blown AIDS (A) at
 324 a per-capita rate α_1 and α_2 , respectively. We also considered that full-blown individuals at per-
 325 capita rate γ receiving treatment going to the compartment T ; and individuals in T or A classes
 326 have a diseased-related death rate δ_1 and δ_2 , respectively. The mathematical model is given by the
 327 following nonlinear system of ordinary differential equations

$$\begin{cases} \frac{dS}{dt} &= \Lambda - \frac{\beta_H}{N} IS - (\varepsilon_1 + \mu)S + \varepsilon_2 R \\ \frac{dI}{dt} &= \frac{\beta_H}{N} IS + \alpha_1 T - (\mu + \rho + \eta)I \\ \frac{dA}{dt} &= \rho I + \alpha_2 T - (\mu + \delta_1 + \gamma)A \\ \frac{dT}{dt} &= \eta I + \gamma A - (\alpha_1 + \mu + \delta_2 + \alpha_2)T \\ \frac{dR}{dt} &= \varepsilon_1 S - (\varepsilon_2 + \mu)R \end{cases} \quad (1)$$

328 with $S(0) > 0$, $I(0) \geq 0$, $A(0) \geq 0$, $T(0) \geq 0$, $R(0) \geq 0$, and N represents the total population,
329 which is given by $N = S + I + A + T + R$. Table 2 describes the nonnegative parameters of the
330 system (1).

Table 2 Parameter description of the HIV/AIDS model (1).

Parameter	Description	Value	Reference
Λ	Birth rate	4, 468, 962.55	[25]
μ	Natural mortality rate	1/75.50	[25]
ε_1	Rate of susceptible individuals who changed their habits	(0.029, 0.031)	[19]
ε_2	Rate of individuals who changed their habits and return to the susceptible compartment	(0, 0.0031)	[19]
β_H	HIV transmission rate	(0, 10)	Assumed
ρ	Progression rate to A from I	(0.066, 0.1)	[44]
η	Progression rate to T from I	(2, 4)	[45]
α_1	Treatment failure rate (T to I compartmental)	(0, 0.4)	[46, 47, 48, 49]
α_2	Treatment failure rate (T to A compartmental)	(0, 0.4)	[46, 47, 48, 49]
δ_1	AIDS-related death rate (individuals with full-blown Aids)	(0, 0.1)	[50]
δ_2	AIDS-related death rate for individuals being treated	(0, 0.05)	[50]
γ	Progression rate to T from A	(0.2, 2)	[51, 45]

331 **Tuberculosis transmission model.** We based on the work of Gomes et al. (2019), which pre-
332 sented a mathematical model composed of four nonlinear ordinary differential equations [20]. The
333 population is divided into Susceptible (S), primary infection (P), latent infection (L), and active
334 tuberculosis disease (I). We assumed that only susceptible individuals have a birth rate Λ but all
335 compartments have a natural death rate μ . In contact with an infectious individual (I), represent-
336 ing by the parameter β_T the susceptible individual comes into a primary infection. After a period
337 ν^{-1} individuals in the compartment P , a fraction ϕ acquires active tuberculosis, while a fraction
338 $(1 - \phi)$ moves to the latent compartment. Active tuberculosis individuals have an additional mor-
339 tality rate μ_T due to the tuberculosis disease. We considered that through treatment representing
340 by the per-capita rate τ , a fraction θ completely eliminate the bacteria, which makes this individual
341 return to the susceptible compartment. On the other hand, a fraction $(1 - \theta)$ cannot eliminate the
342 bacteria and becomes latent. These individuals in the latent compartment can become infectious
343 in contact with infectious individuals I or through reactivation return to the compartment I at a
344 per-capita rate ω . We also assume that latent individuals can return to the susceptible compartment
345 at a per-capita rate σ .

$$\begin{cases} \frac{dS}{dt} = \Lambda - \mu S - \frac{\beta_T}{N} IS + \theta \tau I + \sigma L \\ \frac{dP}{dt} = \frac{\beta_T}{N} (IS + LI) - (\nu + \mu) P \\ \frac{dI}{dt} = \phi \nu P + \omega L - (\mu_T + \mu + \tau) I \\ \frac{dL}{dt} = (1 - \theta) \tau I + (1 - \phi) \nu P - \frac{\beta_T}{N} LI - (\omega + \mu + \sigma) L \end{cases} \quad (2)$$

346 with nonnegative initial conditions and N is the total population defined by $N = S + P + I + L$.
 347 The nonnegative parameters of the system (2) are described in Table 3.

Table 3 Parameter description of the TB model (2).

Parameter	Description	Value	Reference
Λ	Birth rate	4,468,962.55	[25]
μ	Natural mortality rate	1/75.50	[25]
β_T	TB transmission rate	(0, 50)	Assumed
θ	Proportion clearing infection upon treatment	(0.75, 0.85)	[52, 53]
ν	Rate of progression from primary infection	(2, 4)	[20]
ϕ	Proportion progressing from primary infection to active disease	(0.01, 0.1)	[20, 54, 55, 56]
τ	Rate of successful treatment	(0.66, 2)	[20, 52, 53]
ω	Rate of reactivation of latent infection	(0.001, 0.1)	[20, 54, 55, 56]
μ_T	TB-related death rate	(0.03, 0.08)	[43]
σ	Progression rate to S from L	(0.001, 0.05)	Assumed

348 **Incorporating poverty in the mathematical modelling.** Models (1) and (2) capture the dynamics
 349 of HIV and Tuberculosis transmission in a simplified way. However, social determinants signifi-
 350 cantly impact incidence and mortality rates of these diseases. Accordingly to the work of Galanis
 351 and Hanieh (2021), here we assumed a linear form to include the effect of economical aspects
 352 in some model parameters through the annual poverty rate [21], that is, a biological component
 353 characterized by the constant term and a linear term characterized by the influence of the annual
 354 poverty rate. For the HIV/AIDS model (1), the parameters influenced by the poverty rate are

$$\beta_H(t) = \beta_{H1} + \beta_{H2}p(t) \quad (3)$$

$$\delta_1(t) = \delta_{11} + \delta_{12}p(t) \quad (4)$$

$$\delta_2(t) = \delta_{12} + \delta_{22}p(t) \quad (5)$$

$$\alpha_1(t) = \alpha_{11} + \alpha_{12}p(t) \quad (6)$$

$$\alpha_2(t) = \alpha_{12} + \alpha_{22}p(t) \quad (7)$$

$$\rho(t) = \rho_1 + \rho_2p(t) \quad (8)$$

$$\eta(t) = \eta_1 - \eta_2p(t) \quad (9)$$

$$\gamma(t) = \gamma_1 - \gamma_2p(t) \quad (10)$$

$$\varepsilon_1(t) = \varepsilon_{11} - \varepsilon_{12}p(t) \quad (11)$$

$$\varepsilon_2(t) = \varepsilon_{21} + \varepsilon_{22}p(t) \quad (12)$$

where $0 < p(t) < 1$ represents the proportion of poor individuals in year t . Based on the literature, we assumed a positive relationship of the poverty rate with all parameters except η , ε_1 , and γ .

For the TB model (2), we assume that the following parameters are influenced by the poverty rate, and are defined as

$$\beta_T(t) = \beta_{T1} + \beta_{T2}p(t) \quad (13)$$

$$\nu(t) = \nu_1 + \nu_2p(t) \quad (14)$$

$$\tau(t) = \tau_1 - \tau_2p(t) \quad (15)$$

$$\omega(t) = \omega_1 + \omega_2p(t) \quad (16)$$

$$\mu_T(t) = \mu_{T1} + \mu_{T2}p(t) \quad (17)$$

Therefore, in order to incorporate the poverty rate influence, we include the parameter formulation given by (3) to (17) in the models (1) and (2).

Forecast and scenarios of poverty rate. *Data.* We calculate poverty rates using three National Household Surveys (PNAD) – the regular PNAD, Continuous-PNAD, and PNAD-COVID are used for 2001-2011, 2012-2019, and 2020, respectively. These surveys are representative of the entire Brazilian population and are similar in structure, although they differ in terms of sample size and collection strategy. The benefit values and eligibility criteria of the *Bolsa Família* cash transfer program (PBF) are obtained from official documents published by the Ministry of Social Development (MDS).

Poverty Measurement Method. Poverty lines are monetary values used to determine the percentage of a population below specific levels of economic wellbeing, measured using income levels. In this study, poverty rate in year t is measured as the proportion of individuals that earn per capita income below the poverty line stipulated as the eligibility condition for participation in the PBF, $Poor_t$, compared to the total Brazilian population, Pop_t , i.e. $Poor_t/Pop_t$. The poverty rate is obtained for the year 2010 by linear interpolation due to the lack of household surveys since the national Census was conducted in the same year.

Autoregressive approach. The poverty rates calculated from the year 2001 to 2020 are used to forecast values from 2021 to 2030 using Vector Autoregression (VAR) models represented as

$$Y_t = \beta_0 + \beta_1 Y_{t-k} + trend + \varepsilon_t \quad (18)$$

where the dependent variable, Y_t , is the poverty rate for the year t , and the regressors are the k lagged values of poverty rate, Y_{t-k} , and a trend, $trend$; ε_t is the error term that is assumed to be a ‘white noise’ [57].

Deterministic approach. Besides the autoregressive approach, we perform the forecast of poverty rate using an exponential growth function. This deterministic approach permits the flexible creation of a wide range of poverty scenarios and growth tendencies using specified parameters. The scenarios created in this study are grouped into two major categories – optimistic (where the poverty rate reduces) and pessimistic (where the poverty rate increases). Optimistic scenarios are calculated using the following equation

$$Pov_t = Pov_{t0} - C_i Pov_{t0} (1 - e^{-K_i t}) \quad (19)$$

whereas the pessimistic scenario is expressed as

$$Pov_t = Pov_{t0} + C_i Pov_{t0} (1 - e^{-K_i t}) \quad (20)$$

Although the optimistic and pessimistic scenarios are simply mirrored equations, the behaviors of the projected trends depend on the values of the parameters detailed below

- t – time variable, whereby $t = \{2001, 2002, \dots, 2030\}$ and $t0$ is the baseline or reference year;
- i – identifies the moments of growth. In this study, we formulate two moments, i.e $t = \{1; 2\}$ – the first moment of high growth and a second moment of low and steady growth. The time duration of these moments t is specified randomly and can be adjusted;
- Pov_t – is the calculated poverty rate at time or year t ;
- Pov_{t0} – is the Poverty rate at the baseline or reference year;
- C_i – represents the intensity of impact the baseline poverty rate on future rates for each growth moment, and;
- K_i – represents the growth rate of poverty rate for each growth moment.

Using the exponential growth function, the parameters are specified to create two optimistic and one optimistic projections (Extended Data Table 2), i.e. three deterministic time series. In the first pessimistic projection, we assume that the poverty rate grows expressively for five years and then stabilizes in subsequent years. In the second, the poverty rate grows significantly for three years and then stabilizes in subsequent years. As for the optimistic projection, poverty rate reduces expressively for five years and stabilizes in subsequent years.

Parameter estimation. All data sets used in this article are publicly available. We collect Brazilian data on the HIV/AIDS Epidemiological Bulletin of 2020 [22]. We consider in the model calibration, the annual new cases of AIDS and the annual AIDS deaths between the years 2007 and 2019. Due to the COVID-19 pandemic, we do not consider data of the year 2020.

411 The demographic terms in the models (1) and (2) were estimated. The parameter μ was
 412 assumed as the inverse of the mean value of the Brazilian life expectancy between 2003 and 2030.
 413 The recruitment rate Λ was found in order to the value of the total population from the model N
 414 approximates the Brazilian population size between 2003 and 2030.

415 We calibrate the model (1) to the reported data of new AIDS cases and annual deaths from
 416 2007 to 2019 (Extended Data Fig. 2), represented by $\hat{C}$ and $\hat{D}$, respectively.

417 We include the equations in the system (1)

$$\frac{dF_1}{dt} = \rho I + \alpha_2 T \quad (21)$$

$$\frac{dF_2}{dt} = \delta_1 A \quad (22)$$

418 where F_1 represents cumulative new cases and F_2 represents cumulative annual AIDS deaths. To
 419 compare annual data, we consider

$$C(i) = F_1(i) - F_1(i-1) \quad (23)$$

$$D(i) = F_2(i) - F_2(i-1) \quad (24)$$

420 representing the new AIDS cases and annual deaths from the model (1).

421 Parameters presented in Table 2 were estimated by fitting the new AIDS cases and annual
 422 AIDS deaths. We used a genetic algorithm (GA) in order to fit the model to the data. A genetic al-
 423 gorithm is an optimization technique in which an initial population of “chromosomes” is generated
 424 and a proportion of them may survive to the next generation or be replaced by a new individual,
 425 depending on its fitness score [58]. The fitness score is given by the mean squared errors (RMSE)

$$E_C = \sqrt{\frac{1}{n} \sum_{i=1}^n [C(i) - \hat{C}(i)]^2} \quad (25)$$

$$E_D = \sqrt{\frac{1}{n} \sum_{i=1}^n [D(i) - \hat{D}(i)]^2} \quad (26)$$

426 In order to obtain the values of $C(i)$ and $D(i)$, we used the fourth-order Runge-Kutta method
 427 and the initial population $I(0) = 2.6 \times 10^5$, $A(0) = 1.5 \times 10^5$, $C(0) = 38,302$, $R(0) = 0$,
 428 $T(0) = 0.4I(0)$, $D(0) = 11,372$ and $S(0) = 1.91 \times 10^8 - I(0) - A(0) - T(0) - R(0)$. To perform
 429 the GA, we considered the package NSGA-II, which is a multiobjective genetic algorithm [24] for
 430 the Python programming language, with 1,500 generations and initial population of 1.0×10^5
 431 chromosomes in order to calibrate the model with the two data sets. To define the set of values for
 432 the parameters, the one that gave the smallest joint error for the fitness score, that is, the smallest
 433 value of $E_C + E_D$, was the parameter values chosen.

434 For the TB model, the same methodology was applied altering the equations (21) and (22) for
 435 the following equations

$$\frac{dF_1}{dt} = \phi\nu P + \omega L \quad (27)$$

$$\frac{dF_2}{dt} = \mu_T I \quad (28)$$

Here, parameters presented in Table 3 were estimated by fitting the TB incidence and annual deaths between 2003 and 2019 [23] (Extended Data Fig. 3). We applied the fourth-order Runge-Kutta method to solve the system (2), and the equations (27) and (28) assuming the initial population $I(0) = 78,615$, $L(0) = 5 \times 10^6$, $P(0) = 5 \times 10^4$, $C(0) = 78,615$, $D(0) = 4,987$ and $S(0) = 1.7687 \times 10^8 - I(0) - L(0) - P(0)$ in order to define the TB parameter values fitted to the data.

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Competing interests

The authors declare no competing interests.

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Extended Data Table 1 Fitted parameters of the HIV/AIDS and TB models.
Parameter values obtained by the multiobjective genetic algorithm in order to fit to the TB and AIDS incidence and deaths.

HIV/AIDS model			
Parameter	Fitted Value	Parameter	Fitted Value
β_{H1}	0.0487	β_{H2}	4.5235
δ_{11}	0.0738	δ_{12}	0.0279
δ_{12}	0.0176	δ_{22}	0.0465
α_{11}	0.3452	α_{12}	0.1245
α_{22}	0.0941	α_{22}	0.0011
ρ_1	0.0885	ρ_2	0.0697
η_1	3.3376	η_2	3.7288
γ_1	0.2116	γ_2	0.3766
ε_{11}	0.0294	ε_{12}	0.0296
ε_{12}	0.0007	ε_{22}	0.0031

TB model			
Parameter	Fitted Value	Parameter	Fitted Value
β_{T1}	3.0939	β_{T2}	2.9195
ν_1	2.9316	ν_2	2.6039
τ_1	0.9624	τ_2	0.8349
ω_1	0.0093	ω_2	0.0161
μ_{T1}	0.0557	μ_{T2}	0.0315
ϕ	0.0203	θ	0.7633
σ	0.0059		

Extended Data Table 2 Parameter specification for the exponential growth function.

		Scenarios	
		Optimistic	Pessimistic
Growth moment 1	K_1	1.2	1.9
	C_1	0.9	0.8
Growth moment 2	K_2	0.02	0.02
	C_2	1.5	2.0

Note: The parameters are chosen such that the the predicted values for Pov_{2020} are closest to the real values.

Extended Data Fig. 1 Function representing the Brazilian total population fitting to the data and population projection until 2030 reported by Health Minister, in which the birth rate of the HIV/AIDS and TB models was estimated.

Extended Data Fig. 2 Annual AIDS new cases and deaths between 2007 and 2019.

Extended Data Fig. 3 Annual TB new cases and deaths between 2003 and 2019.

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