Supplement for The Potential Effect of Ending CDC Funding for HIV Tests: A Modeling Study in 18 States

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Contents

1 Calibration Methods

The full calibration process for the Johns Hopkins Epidemiologic and Economic Model (JHEEM) is described elsewhere (1), but here, we perform an abridged calibration process that extends the parameters for the 1000 simulations produced for each state using the following reasoning.

Let θ_1 be the vector of all parameters calibrated previously and θ_2 be the two CDC-funded HIV testing related parameters to calibrate now. D_1 and D_2 correspond to the calibration targets for θ_1 and θ_2 respectively. To construct our likelihoods we assume:

$$p(\theta_1, \theta_2 | D_1, D_2) = p(\theta_2 | \theta_1, D_1, D_2) p(\theta_1 | D_1, D_2)$$

according to the law of total probability. We simplify this to:

$$p(\theta_2 | \theta_1, D_2) p(\theta_1 | D_1)$$

assuming

$$\theta_1 \perp D_2 | D_1$$

$$\theta_2 \perp D_1 | D_2, \theta_1$$

1.1 Calibration Targets

We calibrate our CDC HIV Testing related parameters to two calibration targets 1) Number of CDC-Funded HIV Tests from 2011-2019 for each state (2-10) and 2) The positivity rate among CDC-Funded HIV Tests from 2011-2019 for each state. For the state of Mississippi, CDC Funded HIV Testing positivity is not included for the years 2011 and 2013 as a calibration target and the year 2020 is not included in the calibration because of the abnormal trends of the COVID-19 pandemic.

1.2 Parameters Governing CDC-Funded Testing

We posit two model components that govern CDC-funded tests in each state: 1) the proportion of all tests done in a state that are funded by the CDC and 2) the proportion of all new diagnoses in a state that are made with CDC-funded tests. Multiplying the first component by the model-estimated total number of tests in a state allows us to simulate our first calibration target (the number of CDC-funded tests) and multiplying the second component by the model-estimated new diagnoses, then dividing that by the simulated number of CDC-funded tests allows us to simulate our second calibration target (the positivity of CDC-funded tests). Decreasing the second component (proportion of diagnoses made by CDC-funded tests) is how we simulate the impact of ending CDC funding for HIV tests.

1.2.1 The Proportion of Tests Funded by the CDC

We formulated this component as a logistic-linear function of time, with differing fixed intercepts and slopes (β_{0s} and β_{1s}) for each stratum s of age, race, sex, and HIV risk factor, as well as random effects for intercept and slope (α_{0s} and α_{1s}):

$\text{logit}(\text{p}_s) = \beta_{0s} + \beta_{1s} \times year + \alpha_{0s} + \alpha_{1s} \times year$

In this formulation, the values of β_{0s} and β_{1s} represent our prior medians. Because nationwide data on testing are sparse, we estimated β_{0s} as the number of CDC funded tests in 2020 divided by an estimate of the total number of HIV tests done in the US in 2020: the number of HIV tests performed at Quest or Labcorp laboratories divided by 0.44 (as approximately 44% of all laboratory tests in the US are performed by these two companies). β_{1s} was assumed to be zero. These represent rough prior estimates.

$$p_{cdc-tests} = \frac{\text{CDC Funded HIV Tests}}{\text{Total HIV Tests}} = \frac{2452507}{26427698} = 0.092800629$$

α_{0s} and α_{1s} were given normal distributions with mean zero and standard deviation 0.2.

1.2.2 The Proportion of New Diagnoses Made by CDC-Funded Tests

We formulated this component as a natural spline with knots at 2010, 2015, and 2020 on the logit scale. Knots differed for each stratum of age, race, sex, and HIV risk factor.

We derived prior medians for the knots in each stratum by fitting a spline to the positivity rate for all HIV tests funded by the CDC in the US from 2019-2021. The values for the knots were given a log-normal distribution with a standard deviation of 0.2.

1.3 Calibration

The distributional assumption of the likelihood for CDC HIV testing positvity is a binomial distribution and the distributional assumption of the likelihood for the number of CDC funded HIV tests is a poisson distribution. The joint likelihood is informed by combining these two corresponding multivariate normal distributions, in which a measurement error of both calibration targets is assumed (.015 for CDC funded HIV tests and 0.00015 for CDC HIV positivity).

1.3.1 Number of CDC-Funded HIV Tests

Our model simulated the number of CDC-funded HIV tests as the model-simulated total number of tests multiplied by the fraction of tests funded by the CDC. We assumed this calibration target followed a Poisson distribution centered at our simulated number of CDC-funded HIV tests:

$$y_{\text{cdc tests}} \sim Poisson(\text{Total HIV Tests} * p_{cdc-tests})$$

We further allowed that the reported number of CDC-funded tests might be impefectly measured, with a normally-distributed error with coefficient of variance of 0.015:

$$reported_{\text{cdc tests}} \sim Normal\Big(y_{\text{cdc tests}}, (0.015 \times reported_{\text{cdc tests}})^2\Big)$$

1.3.2 Number of New Diagnoses Made by CDC-Funded HIV Tests

Our model simulated the positivity rate among CDC-funded HIV tests as the model-simulated total new diagnoses multiplied by the fraction of diagnoses made with CDC-funded tests, divided by the simulated number of CDC-funded tests as given above.

$$positivity_{cdc} = \frac{\text{Total HIV Diagnoes} * p_{cdc-diagnoses}}{y_{\text{cdc tests}}}$$

We assumed that the number of diagnoses made by CDC funded tests (the positivity times number of tests) followed a binomial distribution:

$$y_{\text{cdc positivity}} \times y_{\text{cdc tests}} \sim Binomial(n = y_{\text{cdc tests}}, p = positivity_{cdc})$$

We further allowed the reported positivity of CDC-funded tests to be imperfectly measured, with a normally-distributed error of 0.00015:

$$reported_{\text{cdc positivity}} \sim Normal(y_{\text{cdc positivity}}, 0.000015^2)$$

2 Supplementary Figures

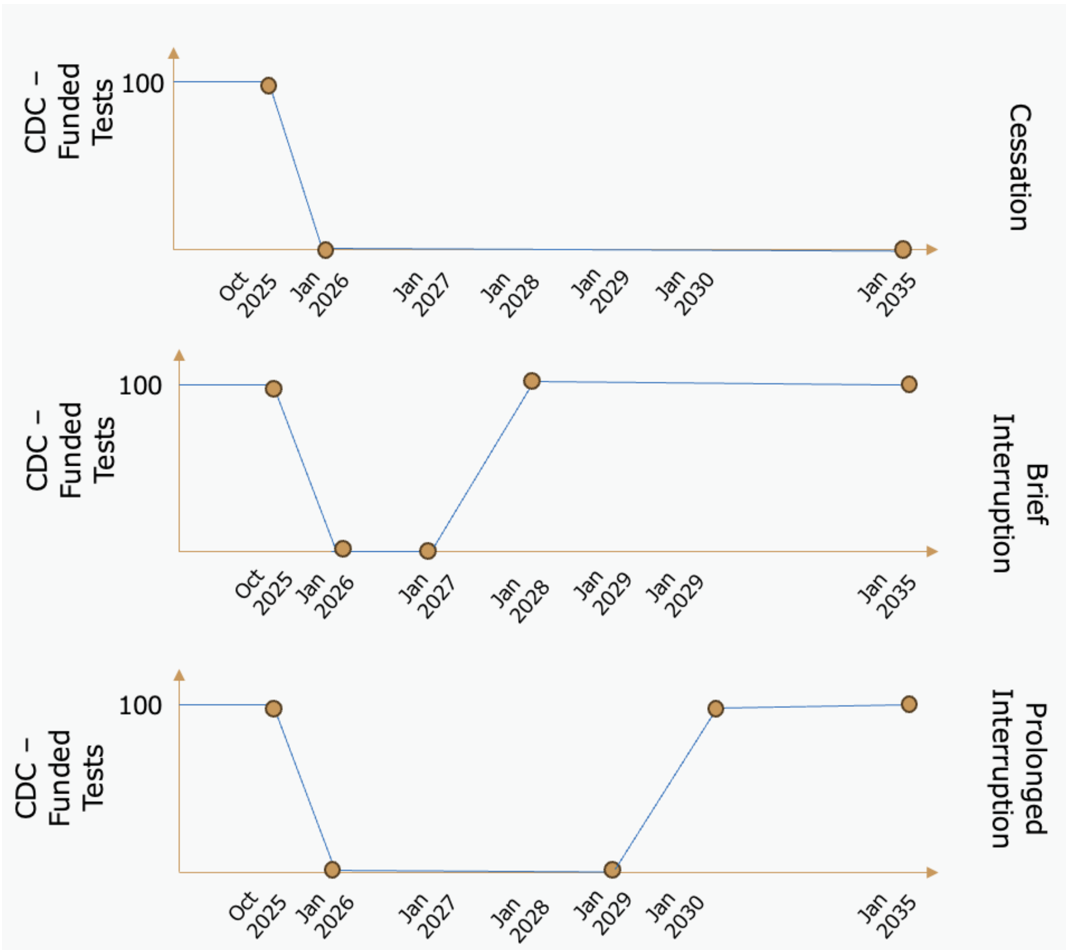

Figure 1: Schematic of CDC Testing Scenarios. The first panel describes the cessation intervention in which the CDC-funded testing is scaled down between October 2025- January 2026, and remains at this level until model projection ends in 2035. The second panel describes the brief interruption intervention in which the CDC-funded testing is scaled down between October 2025- January 2026 and returns from January 2027-January 2028. The last panel describes the prolonged interruption scenario in which CDC-funded testing is scaled down between October 2025- January 2026 and returns from January 2029-January 2030.

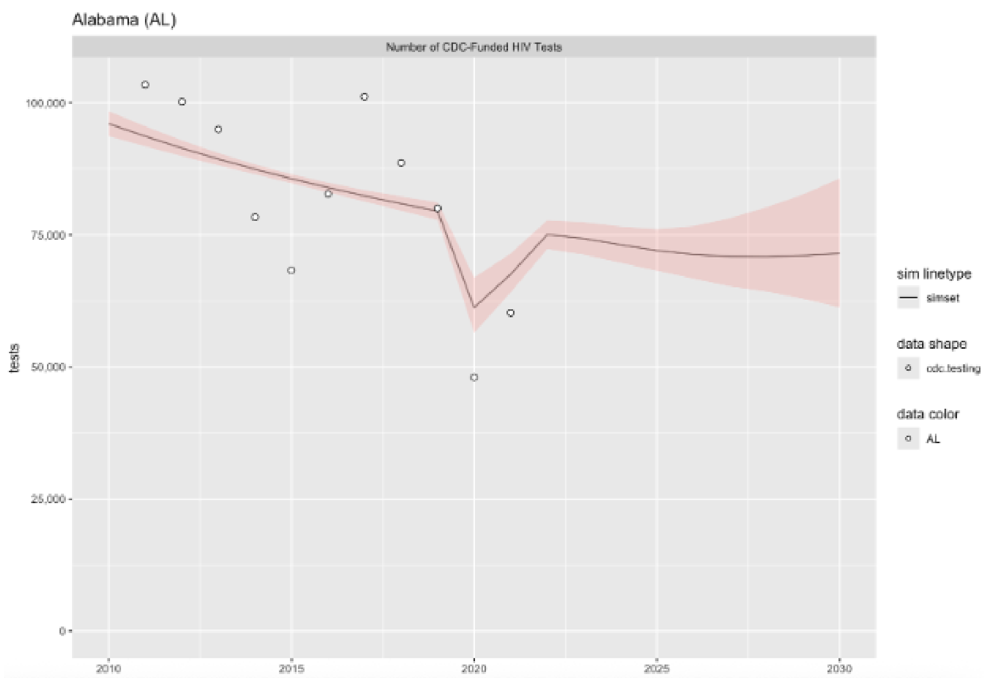

Figure 2: Calibration of model performance against number of CDC-Funded HIV tests for Alabama. The overlay of model simulations from the status quo simulation over time (x-axis) against the recorded number of CDC-funded HIV tests (y-axis) in Alabama is shown. White circles represent published data on the number of CDC-funded tests from 2011-2019. 2020 is excluded from historical trends due to the COVID-19 pandemic. The black line represents the average number of CDC-funded HIV tests across simulations, and the shaded red region represents all simulations.

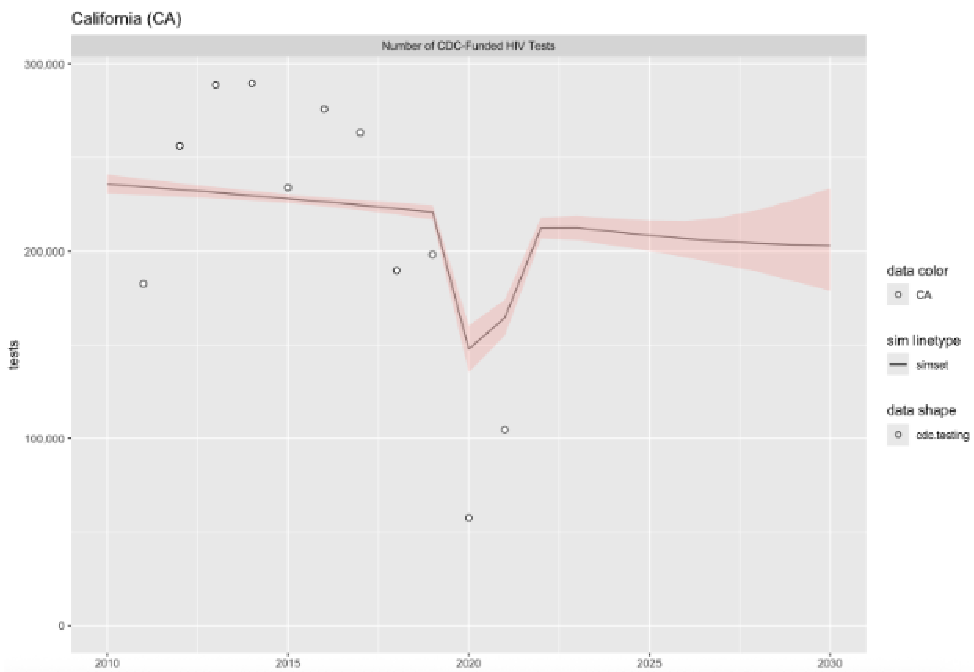

Figure 3: Calibration of model performance against number of CDC-Funded HIV tests for California. The overlay of model simulations from the status quo simulation over time (x-axis) against the recorded number of CDC-funded HIV tests (y-axis) in California is shown. White circles represent published data on the number of CDC-funded tests from 2011-2019. 2020 is excluded from historical trends due to the COVID-19 pandemic. The black line represents the average number of CDC-funded HIV tests across simulations, and the shaded red region represents all simulations.

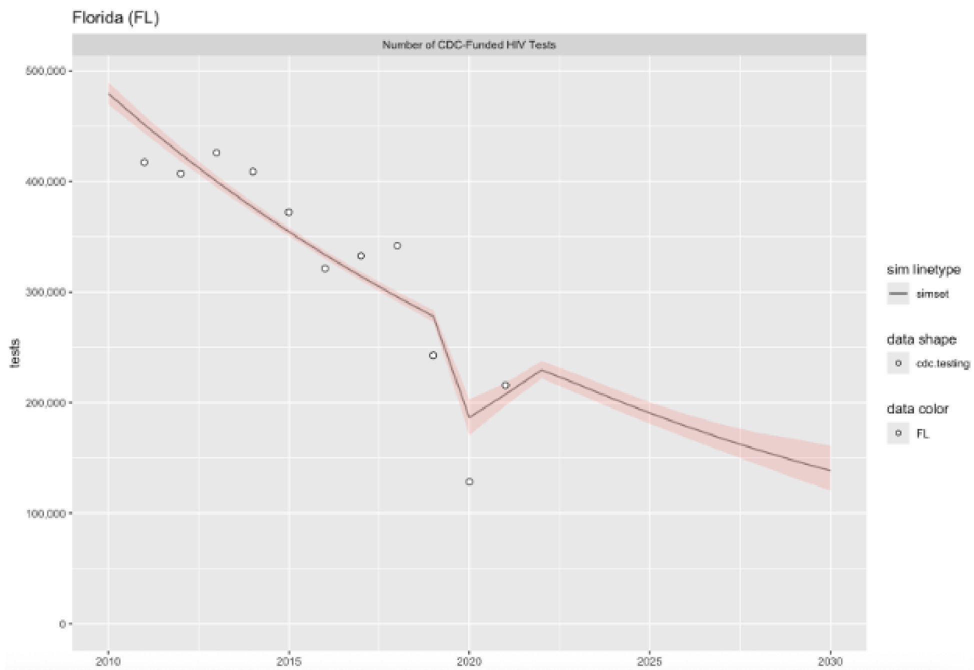

Figure 4: Calibration of model performance against number of CDC-Funded HIV tests for Florida. The overlay of model simulations from the status quo simulation over time (x-axis) against the recorded number of CDC-funded HIV tests (y-axis) in Florida is shown. White circles represent published data on the number of CDC-funded tests from 2011-2019. 2020 is excluded from historical trends due to the COVID-19 pandemic. The black line represents the average number of CDC-funded HIV tests across simulations, and the shaded red region represents all simulations.

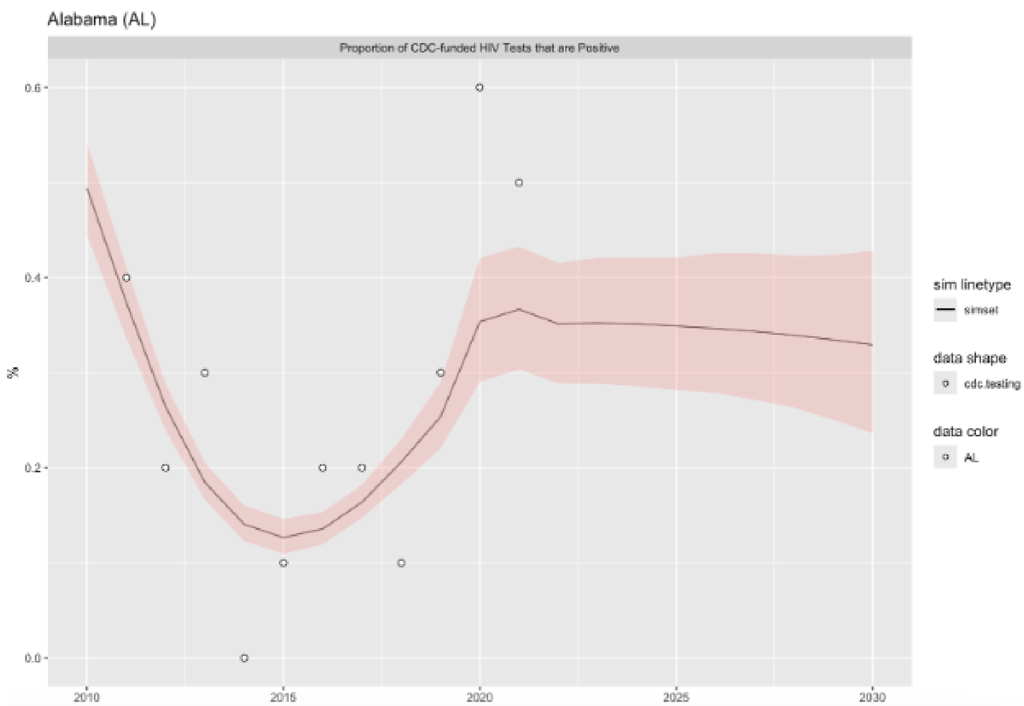

Figure 5: Calibration of model performance against CDC-funded HIV test positivity for Alabama. The overlay of model simulations from the status quo simulation over time (x-axis) against the recorded CDC-funded HIV test positivity (y-axis) in Alabama is shown. White circles represent published data on the number of CDC-funded tests from 2011-2019. 2020 is excluded from historical trends due to the COVID-19 pandemic. The black line represents the average number of CDC-funded HIV tests positivity across simulations, and the shaded red region represents all simulations.

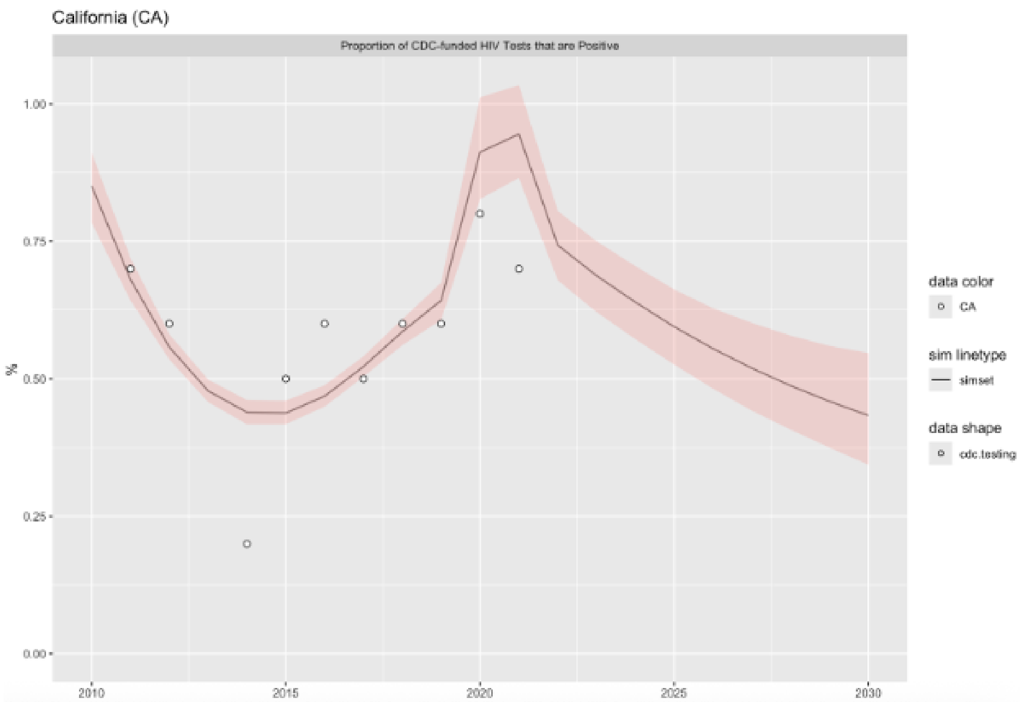

Figure 6: Calibration of model performance against CDC-funded HIV test positivity for California. The overlay of model simulations from the status quo simulation over time (x-axis) against the recorded CDC-funded HIV test positivity (y-axis) in California is shown. White circles represent published data on the number of CDC-funded tests from 2011-2019. 2020 is excluded from historical trends due to the COVID-19 pandemic. The black line represents the average number of CDC-funded HIV tests positivity across simulations, and the shaded red region represents all simulations.

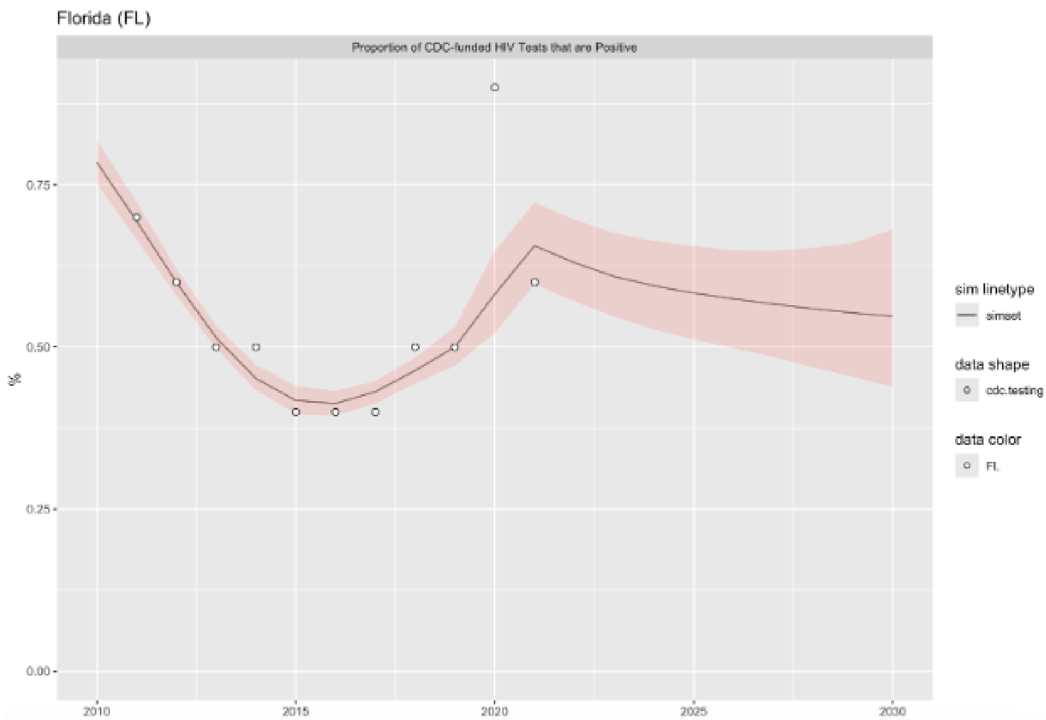

Figure 7: Calibration of model performance against CDC-funded HIV test positivity for Florida. The overlay of model simulations from the status quo simulation over time (x-axis) against the recorded CDC-funded HIV test positivity (y-axis) in Florida is shown. White circles represent published data on the number of CDC-funded tests from 2011-2019. 2020 is excluded from historical trends due to the COVID-19 pandemic. The black line represents the average number of CDC-funded HIV tests positivity across simulations, and the shaded red region represents all simulations.

	Continuation	Cessation		Prolonged Interruption		Brief Interruption	
State	Number of Incident Infections	Number of Excess Infections	Relative Excess Infections*	Number of Excess Infections	Relative Excess Infections*	Number of Excess Infections	Relative Excess Infections*
Louisiana	8,412 (6,593 - 10,294)	3,764 (1,068 - 8,105)	44.6% (13.3 - 93.2%)	1,232 (394 - 2,389)	14.7% (4.8 - 28.1%)	461 (164 - 831)	5.5% (2.0 - 9.7%)
Missouri	5,167 (4,158 - 6,189)	1,657 (425 - 3,656)	31.9% (9.2 - 68.0%)	646 (197 - 1,271)	12.5% (4.0 - 23.6%)	261 (91 - 479)	5.1% (1.9 - 8.9%)
Mississippi	4,634 (3,724 - 5,728)	1,271 (412 - 2,653)	27.5% (8.7 - 56.3%)	538 (169 - 1,046)	11.6% (3.8 - 22.8%)	231 (78 - 428)	5.0% (1.8 - 9.3%)
South Carolina	5,108 (4,284 - 6,014)	1,340 (389 - 2,862)	26.2% (8.1 - 54.6%)	605 (205 - 1,133)	11.9% (4.0 - 22.1%)	265 (97 - 470)	5.2% (2.0 - 9.2%)
Alabama	7,019 (5,817 - 8,144)	1,655 (534 - 3,355)	23.6% (7.6 - 46.1%)	639 (223 - 1,183)	9.1% (3.3 - 16.7%)	263 (99 - 458)	3.8% (1.5 - 6.6%)
Tennessee	9,489 (7,242 - 12,172)	2,095 (649 - 4,134)	22.2% (6.9 - 43.9%)	890 (299 - 1,608)	9.5% (3.2 - 18.0%)	373 (136 - 628)	4.0% (1.4 - 7.1%)
Georgia	20,609 (17,319 - 25,387)	4,006 (1,234 - 7,908)	19.2% (6.3 - 35.1%)	1,877 (638 - 3,463)	9.0% (3.2 - 15.4%)	841 (301 - 1,491)	4.0% (1.5 - 6.6%)
Arizona	6,754 (5,479 - 8,302)	1,260 (395 - 2,582)	18.7% (5.8 - 36.7%)	523 (179 - 969)	7.8% (2.7 - 13.8%)	225 (83 - 394)	3.3% (1.2 - 5.6%)
Texas	44,380 (37,281 - 54,387)	6,094 (2,088 - 11,546)	13.8% (4.8 - 25.2%)	2,255 (832 - 3,940)	5.1% (1.9 - 8.8%)	941 (365 - 1,573)	2.1% (0.8 - 3.5%)
California	27,817 (22,863 - 34,628)	3,809 (1,180 - 7,595)	13.6% (4.6 - 25.5%)	1,788 (616 - 3,332)	6.4% (2.3 - 11.3%)	812 (296 - 1,475)	2.9% (1.1 - 4.9%)
Ohio	7,533 (6,020 - 9,584)	996 (325 - 1,966)	13.2% (4.4 - 25.0%)	422 (151 - 780)	5.6% (2.0 - 9.9%)	185 (70 - 330)	2.5% (0.9 - 4.3%)
Florida	33,097 (28,007 - 40,112)	3,068 (1,052 - 5,870)	9.2% (3.1 - 16.7%)	1,578 (566 - 2,845)	4.8% (1.7 - 8.2%)	748 (285 - 1,302)	2.3% (0.9 - 3.7%)
New York	18,831 (15,542 - 23,487)	1,430 (453 - 2,893)	7.5% (2.5 - 14.2%)	632 (212 - 1,223)	3.3% (1.2 - 6.2%)	279 (97 - 524)	1.5% (0.5 - 2.7%)
Wisconsin	2,848 (2,107 - 3,503)	196 (63 - 393)	6.9% (2.2 - 13.5%)	85 (28 - 169)	3.0% (1.0 - 5.8%)	37 (12 - 73)	1.3% (0.4 - 2.5%)
Kentucky	2,115 (1,726 - 2,751)	125 (39 - 259)	5.8% (1.9 - 10.8%)	66 (23 - 133)	3.1% (1.1 - 5.6%)	32 (11 - 62)	1.5% (0.6 - 2.6%)
Illinois	8,416 (6,867 - 10,520)	433 (146 - 899)	5.1% (1.7 - 9.7%)	209 (71 - 413)	2.5% (0.9 - 4.4%)	97 (35 - 186)	1.1% (0.4 - 2.0%)
Washington	6,278 (4,707 - 7,960)	304 (112 - 534)	4.9% (1.7 - 8.5%)	166 (61 - 280)	2.7% (1.0 - 4.6%)	80 (30 - 134)	1.3% (0.5 - 2.2%)
Maryland	4,199 (3,334 - 5,420)	186 (67 - 333)	4.5% (1.6 - 7.9%)	103 (38 - 180)	2.5% (0.9 - 4.3%)	52 (19 - 88)	1.2% (0.5 - 2.1%)
Total	222,706 (210,324 - 237,189)	33,691 (11,327 - 60,161)	15.1% (5.2 - 26.9%)	14,254 (5,129 - 23,875)	6.4% (2.4 - 10.7%)	6,182 (2,371 - 9,890)	2.8% (1.1 - 4.5%)

0% ≥30%

Figure 8: Projected Excess HIV Infections if CDC-funded HIV Testing is Disrupted 2025-2035 Values denote the mean and 95 percent credible interval (across 1,000 simulations in each state) of the number of CDC-funded tests that would have been performed from 2025 to 2034 divided by the number of excess HIV infections that would result under three scenarios where funding is stopped in October 2025: "Cessation" (funding does not resume), "Prolonged Interruption" (testing returns to prior levels from January to December 2029), and "Brief Interruption" (testing recovers from January to December 2027). The columns labeled "Relative Excess Infections" give the percent change in projected incident infections, relative to "Continuation". Cells are shaded according to the number of tests not done per excess infection incurred.

State	Cessation	Prolonged Interruption	Brief Interruption
Ohio	137 (63 - 327)	125 (59 - 296)	129 (64 - 294)
Mississippi	310 (139 - 713)	274 (126 - 625)	281 (139 - 621)
New York	414 (186 - 1,012)	373 (168 - 909)	376 (173 - 901)
South Carolina	504 (218 - 1,247)	426 (192 - 1,037)	396 (196 - 905)
Missouri	630 (250 - 1,632)	541 (228 - 1,379)	535 (251 - 1,289)
Louisiana	633 (246 - 1,593)	553 (226 - 1,362)	578 (270 - 1,327)
Georgia	650 (310 - 1,579)	521 (252 - 1,251)	443 (223 - 1,025)
Tennessee	666 (288 - 1,623)	580 (256 - 1,383)	574 (280 - 1,311)
Florida	734 (348 - 1,702)	633 (305 - 1,453)	584 (296 - 1,303)
Alabama	751 (322 - 1,857)	633 (281 - 1,540)	604 (295 - 1,405)
Washington	767 (390 - 1,745)	608 (310 - 1,389)	490 (252 - 1,121)
California	884 (404 - 2,180)	725 (337 - 1,761)	633 (310 - 1,479)
Wisconsin	1,458 (646 - 3,376)	1,173 (526 - 2,692)	1,011 (470 - 2,298)
Arizona	1,643 (706 - 4,017)	1,333 (596 - 3,215)	1,172 (577 - 2,699)
Texas	1,647 (770 - 3,798)	1,367 (652 - 3,133)	1,266 (648 - 2,806)
Kentucky	2,135 (915 - 5,213)	1,721 (744 - 4,157)	1,430 (639 - 3,395)
Illinois	2,886 (1,272 - 6,757)	2,340 (1,050 - 5,498)	1,999 (938 - 4,558)
Maryland	4,396 (2,194 - 10,064)	3,561 (1,807 - 8,133)	2,959 (1,537 - 6,737)
Total	913 (453 - 2,145)	761 (387 - 1,764)	699 (379 - 1,570)

≤200 — ≥3,000

Figure 9: Number of CDC-funded Tests Not Performed per Excess Infection Values denote the mean and 95 percent credible interval (across 1,000 simulations in each state) of the number of CDC-funded tests that would have been performed from 2025 to 2030 divided by the number of excess HIV infections that would result under three scenarios where funding is stopped in October 2025: "Cessation" (funding does not resume), "Prolonged Interruption" (testing returns to prior levels from January to December 2029), and "Brief Interruption" (testing recovers from January to December 2027). The columns labeled "Relative Excess Infections" give the percent change in projected incident infections, relative to "Continuation". Cells are shaded according to the number of tests not done per excess infection incurred.

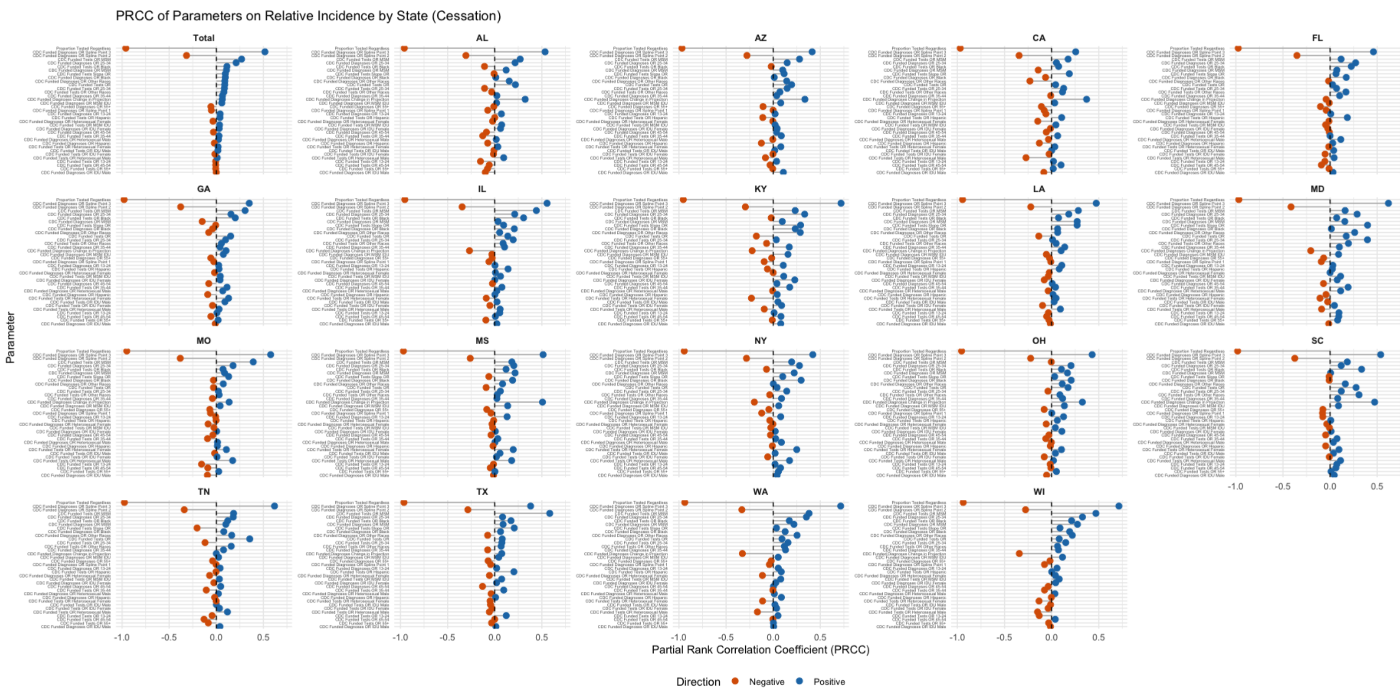

Figure 10: Impact of sampled CDC testing related parameters on relative excess incidence of HIV. The spearman's partial rank correlation coefficient (PRCC) (x-axis) for each of the 35 parameters governing CDC testing in our model is calculated, in comparison to the relative excess incidence of HIV comparing the cessation intervention with the status quo intervention (y-axis). This PRCC is calculated for each of the 11 states' 1000 simulations, and is denoted in red if the correlation is negative and blue if the correlation is positive. The first panel denotes the average PRCC for each parameter across all 18 states.

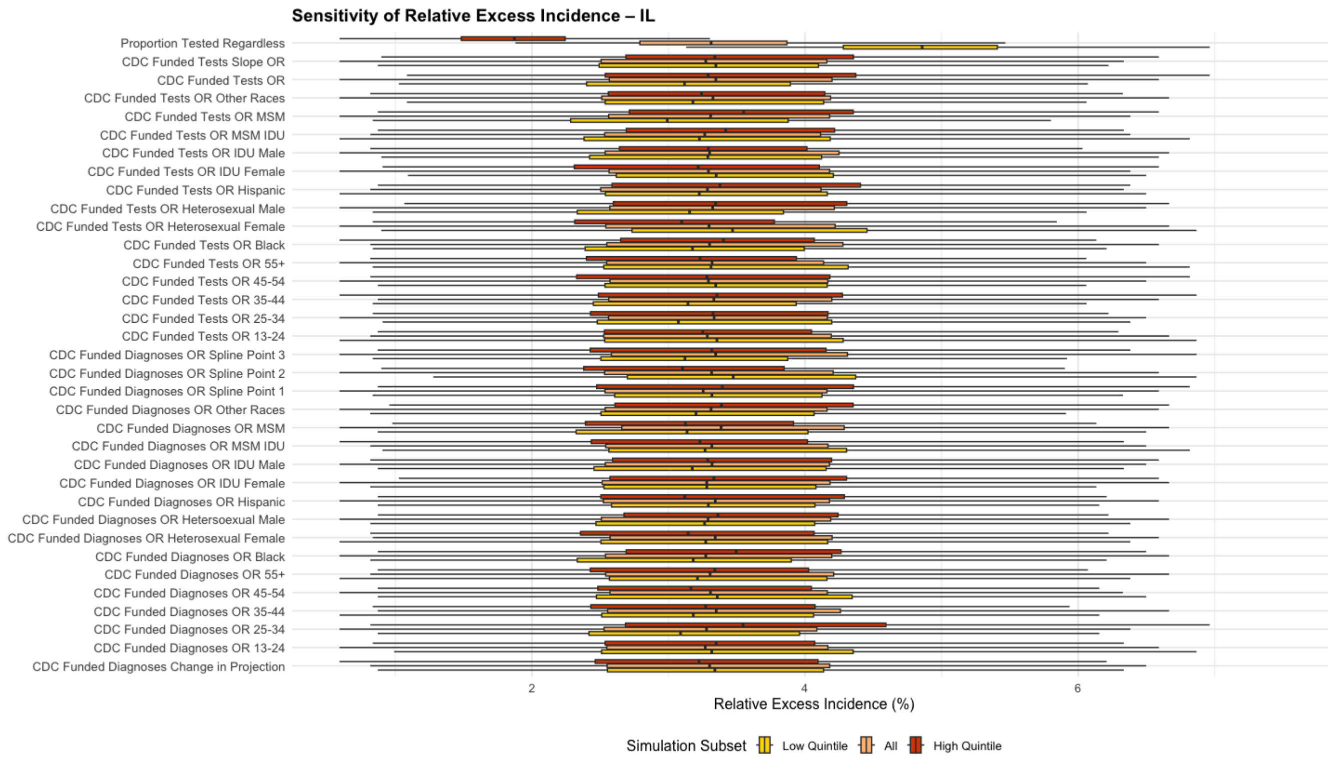

Figure 11: Sensitivity analyses for Illinois. On the x-axis we report the relative excess difference of HIV between the cessation intervention with the status quo intervention for the state of Illinois. Yellow bars show the distribution of outcomes among simulations for which the specified parameter is in the lowest quintile of its sampled values (out of 1000 simulations), and dark orange bars show the distribution of outcomes among simulations for which the specified parameter is in the highest quintile of its sampled values. The distribution of outcomes across all parameter values are shown in light orange. All distributions are represented as boxplots, with the endpoints of the colored bars indicating the interquartile range (IQR) and the error bars indicate the highest and lowest values no more than 1.5*IQR from the ends of the bars. Parameters are ordered from highest to lowest spearman's partial rank correlation coefficient.

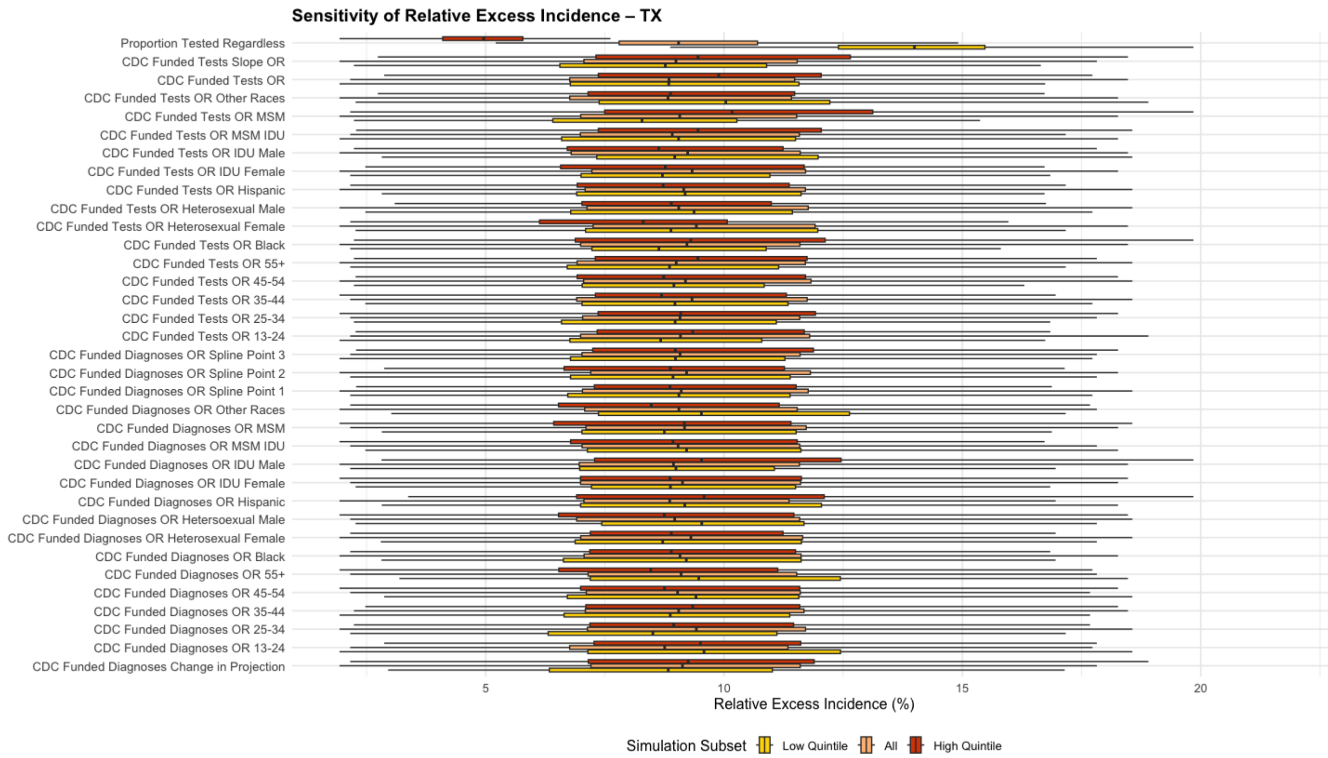

Figure 12: Sensitivity analyses for Texas. On the x-axis we report the relative excess difference of HIV between the cessation intervention with the status quo intervention for the state of Texas. Yellow bars show the distribution of outcomes among simulations for which the specified parameter is in the lowest quintile of its sampled values (out of 1000 simulations), and dark orange bars show the distribution of outcomes among simulations for which the specified parameter is in the highest quintile of its sampled values. The distribution of outcomes across all parameter values are shown in light orange. All distributions are represented as boxplots, with the endpoints of the colored bars indicating the interquartile range (IQR) and the error bars indicate the highest and lowest values no more than 1.5*IQR from the ends of the bars. Parameters are ordered from highest to lowest spearman's partial rank correlation coefficient.

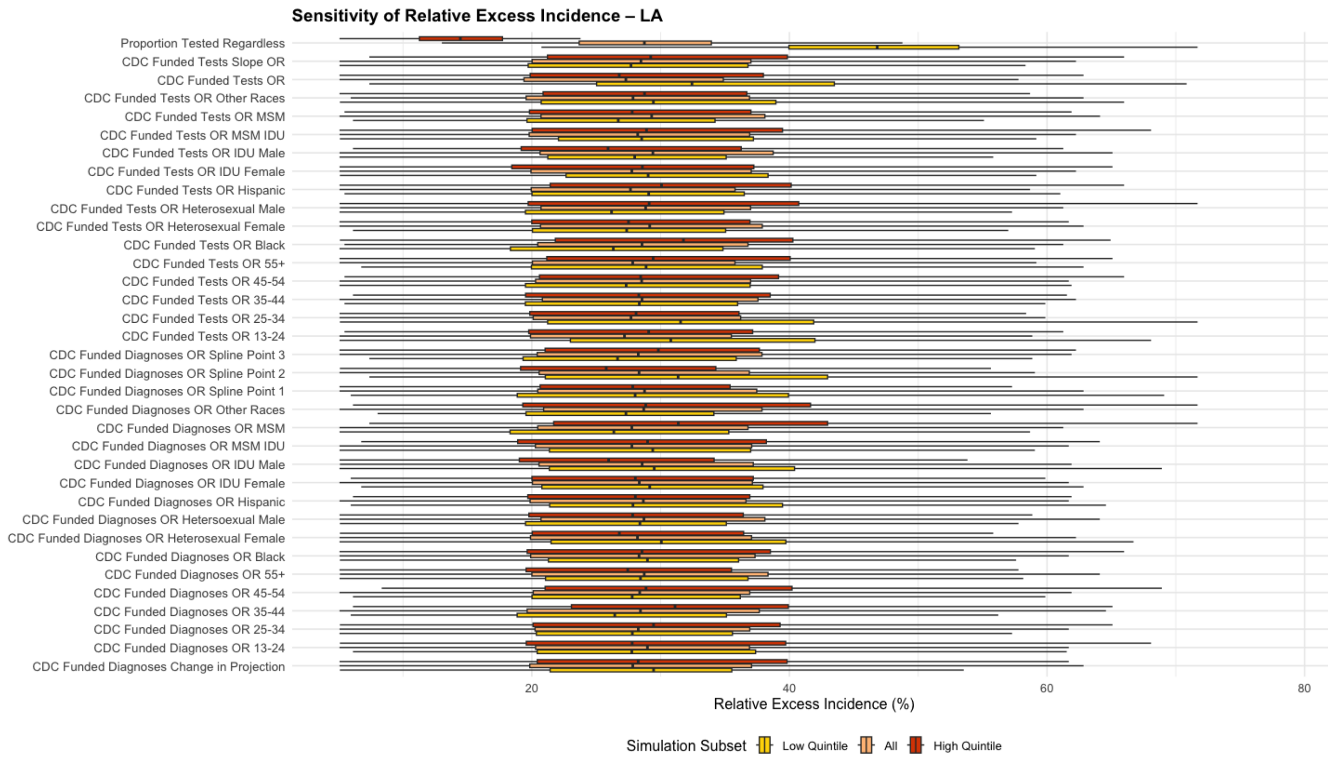

Figure 13: Sensitivity analyses for Louisiana. On the x-axis we report the relative excess difference of HIV between the cessation intervention with the status quo intervention for the state of Louisiana. Yellow bars show the distribution of outcomes among simulations for which the specified parameter is in the lowest quintile of its sampled values (out of 1000 simulations), and dark orange bars show the distribution of outcomes among simulations for which the specified parameter is in the highest quintile of its sampled values. The distribution of outcomes across all parameter values are shown in light orange. All distributions are represented as boxplots, with the endpoints of the colored bars indicating the interquartile range (IQR) and the error bars indicate the highest and lowest values no more than 1.5*IQR from the ends of the bars. Parameters are ordered from highest to lowest spearman's partial rank correlation coefficient.

3 References

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