Potential Effects of the COVID-19 Pandemic on HIV Transmission: A Modeling Study in 32 US Cities
Technical Supplement

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Contents

All code for this work is publicly available at https://github.com/tfojo1/ending_hiv

1 Identifying Ranges of Potential Pandemic Effects on Sexual Transmission, Viral Suppression, HIV Testing, and PrEP Use

1.1 Overview

We sought to generate ranges of possible effects on each of four parameters - sexual transmission, viral suppression among PWH, HIV testing, and PrEP use - due to the COVID-19 pandemic. These effects represent the maximal change in each parameter at the height of the pandemic, with lesser effects depending on mobility trends (see Section 2). Recognizing that there is a great deal of uncertainty about these effects, and that we would be generalizing from small, online or single-site studies to entire US cities, we sought to construct broad ranges that would include all plausible values.

We reviewed the published literature for studies that reported changes in any of our four key parameters from pre-pandemic to during the pandemic. For the reduction in each parameter, we chose a lower bound of zero (no change) and an upper bound that included the largest reported reduction in the parameter (rounded up to the nearest 10%).

1.2 Sexual Transmission

Our model represents sexual transmission between from one subgroup (of age, race, sex, and risk factor) to another subgroup as the product of a sexual transmission rate between the two subgroups and the prevalence of HIV in the first subgroup. In this sense, the sexual transmission rate represents an average number of unprotected sexual encounters per unit time between individuals in the two subgroups. This can be further conceptualized as the product of the average number of partnerships across the two subgroups and the average number of unprotected sexual encounters per partnership. For the pandemic effect, we presumed that sexual transmission rates for all pairs of subgroups were affected to the same degree.

Ascertaining a change in this parameter is challenging; many studies report a proportion of surveyed individuals who reported any reduction in sexual activity or number of sexual partners, but, for example, 50% of individuals reporting less sexual activity does not mean that the number of unprotected sexual encounters was reduced by 50%. When studies reported a change in unprotected sexual encounters, we used that quantity. If not, we used a reported reduction in the number of sexual partners, if available. If only a proportion reporting 'less sexual activity' was available.

We identified five studies that reported a change in sexual activity:

1. Stephenson et. al.[1] surveyed 518 gay, bisexual, and other men who have sex with men in the US in April and May, 2020. They reported a 0.1% increase in the number of unprotected anal sex partners (statistically indistinguishable from
textbfno change)

2. Sanchez et. al.[2] surveyed 1,051 MSM online in April, 2020. 51% reported fewer sexual partners and 9% reported more (net **42%**).

3. Starks et. al.[3] compared a survey of 455 sexual minority men respondents in the US May, 2020 to a survey of a matched pool of 455 men surveyed pre-pandemic. 72% of those in the pre-pandemic survey reported any condomless anal sex, compared to 26.4% during COVID. The frequency of condomless sex was not reported. This is a 66% reduction, in proportion reporting, but, assuming frequency of sex is higher in those reporting persistent condomless sex, likely overestimates the reduction in unprotected sexual encounters.

4. Craig-Kuhn et. al.[4] surveyed Black men who have sex with women in New Orleans, LA in May and June, 2020. The proportion reporting recent vaginal sex decreased from 96% to 48% (a **50%** decrease), with no change in the proportion reportion condomless sex among those who reported recent vaginal sex.

5. Gleason et. al.[5] surveyed 1,051 US adults in October 2020. Participants reported an average **21%** decrease in the number of sexual partners, and 27% reported a decrease in frequency of sex with their current partner, while 13% reported an increase in frequency (net **14%** reporting decreased frequency). Of those who previously had sex with casual partners, 54% reported a decrease in frequency and 10% reported an increase in frequency (net **44%** reporting decreased frequency). Similarly, among those who previously had hookup sex, 49% reported a decrease in frequency and 15% reported an increase (net **34%** reporting decreased frequency).

Based on these studies, we sampled reductions from 0% to 50%.

1.3 Viral Suppression

Our model includes a parameter that is the proportion of serostatus-aware PWH who are virally suppressed at a given point in time. We avoided studies that reported cross-sectional numbers of suppressed individuals, as they do not evaluate PWH who do not get a viral load drawn. We identified four studies that assessed changes in viral suppression OR that reported a change in ART adherence:

1. Hochstatter et. al.[6] repeatedly surveyed 64 PWH with a substance use disorder from January to May, 2021. The proportion of participants who missed one ART dose a week or less decreased from 95% pre-pandemic to 88% during, a **7% decrease**.

2. Sorbera et. al.[7] reviewed the charts of 211 PWH through July, 2020. Viral suppression (VL¡200) decreased from 89% before March 13, 2020 to 85% after, a **4% decrease**. Undetectable viral loads (VL¡20) decreased from 82% to 74%, a **9% decrease**.

3. Spinelli et. al.[8] found that, among 1,766 PWH at a San Francisco HIV clinic, the odds of viral non-suppression were **1.31-fold higher** in April, 2020 compared to Dec 2019 to Feb, 2020.

4. Hickey et. al.[9] found that viral suppression among homeless PWH in San Francisco was 48% from Dec, 2019 to March, 2020 and 47% from March to August, 2020, a **2% decrease**.

Based on these studies, we sampled reductions from 0% to 40%.

1.4 HIV Testing

We found one published study that reported on access to testing and two conference abstracts that compared rates of HIV testing before and during the pandemic:

1. Sanchez et. al.[2] surveyed 1,051 MSM online in April, 2020. 19% reported decreased access to HIV testing and 15% reported being tested less.

2. Curanovic et. al.[10] reported that, nationally, the number of HIV tests performed by LabCorp fell by 17.5% from March to October, 2020 compared to the same period in 2019. Regional reductions ranged from 11% in the South to 25% in the Mid-Atlantic.

3. Delaney et. al.[11] used data from a single commercial US laboratory. From March 13 to April 13, 2020, 45% fewer HIV screening tests were done than in the same period in 2019. By June, 2020, testing volumes were 8% lower than in 2019.

Based on these studies, we sampled reductions from 0% to 50%.

1.5 PrEP Use

The model incorporates "PrEP Coverage" - the proportion *of those at risk for HIV* who are enrolled in a PrEP program at a given point in time. Generally, studies report changes among individuals previously taking PrEP, which does not distinguish between a decrease in number at risk (due to decreased sexual encounters) or decreased use among those at risk. Nor does it take into account potentially fewer candidates initiating PrEP. Given this limitation, we identified four studies that evaluated changes in PrEP use among PrEP users:

1. Sanchez et. al.[2] surveyed 1,051 MSM online in April, 2020. **8%** of those who tried to get PrEP medications reported difficulty.

2. Hong et. al.[12] surveyed 239 young sexual minority men (YSMM) 17-24 years old between April and September 2020 in the U.S., and found that **14%** discontinued PrEP.

3. Pampati et. al.[13] reviewed an online cohort of 78 MSM who use PrEP in the Southern US from October, 2019 to July, 2020. **20%** either took less PrEP or discontinued it.

4. Brawley et. al.[14] Found that, among 409 US PrEP users, **32%** discontinued PrEP from March to June, 2020 (85% of those due to perceived low risk). 95% of 189 surveyed providers reported being able to still prescribe PrEP.

Based on these studies, we sampled reductions from 0% to 30%.

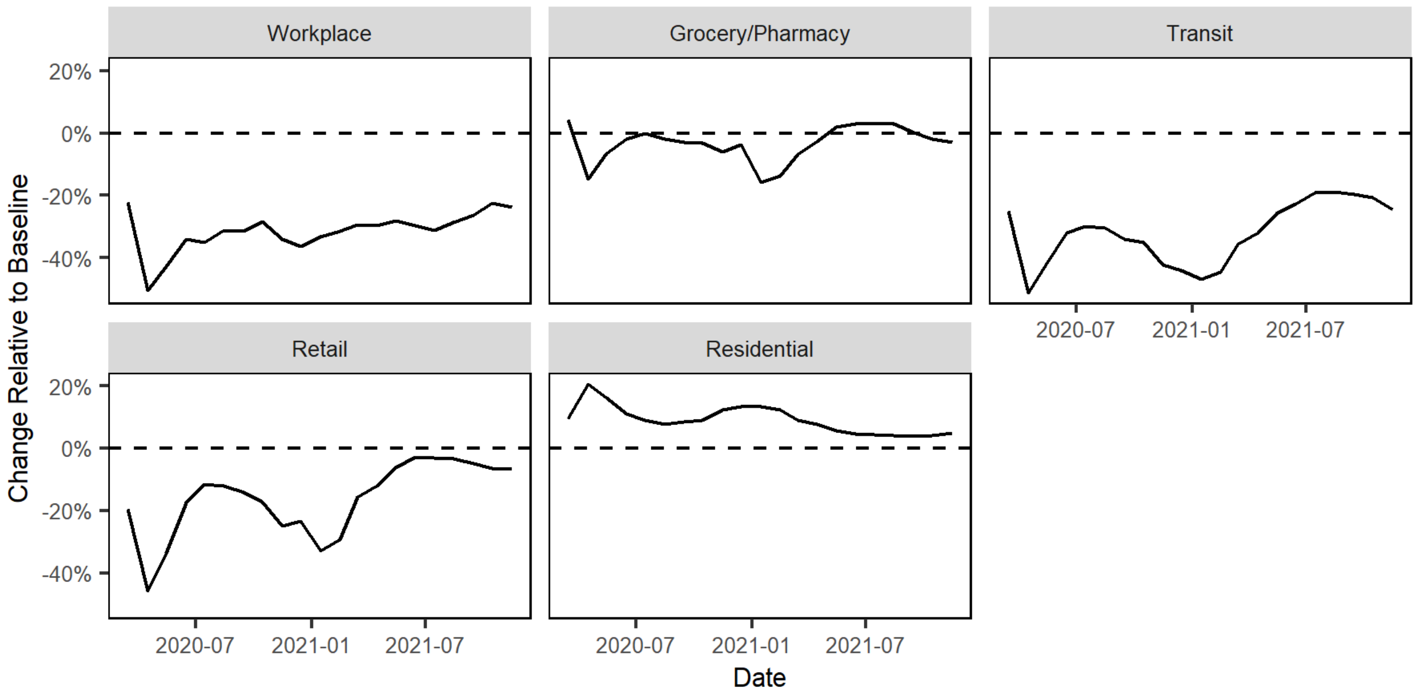
2 Indexing Pandemic Effects to Google Community Mobility Reports

We use Google Community Mobility Reports[15] to vary the effects of the pandemic on HIV epidemiology over time.

The data comprise daily percent changes in the number of people going to/spending time at different types of places, compared to the same day of the week for the period from Jan 3 – Feb 6, 2020, and are reported for each US county. The changes are available for (1) groceries and pharmacies, (2) workplaces, (3) transit, (4) retail, (5) residential, and (6) parks. Due to seasonal variations in park attendance, we use only the first five geographic categories.

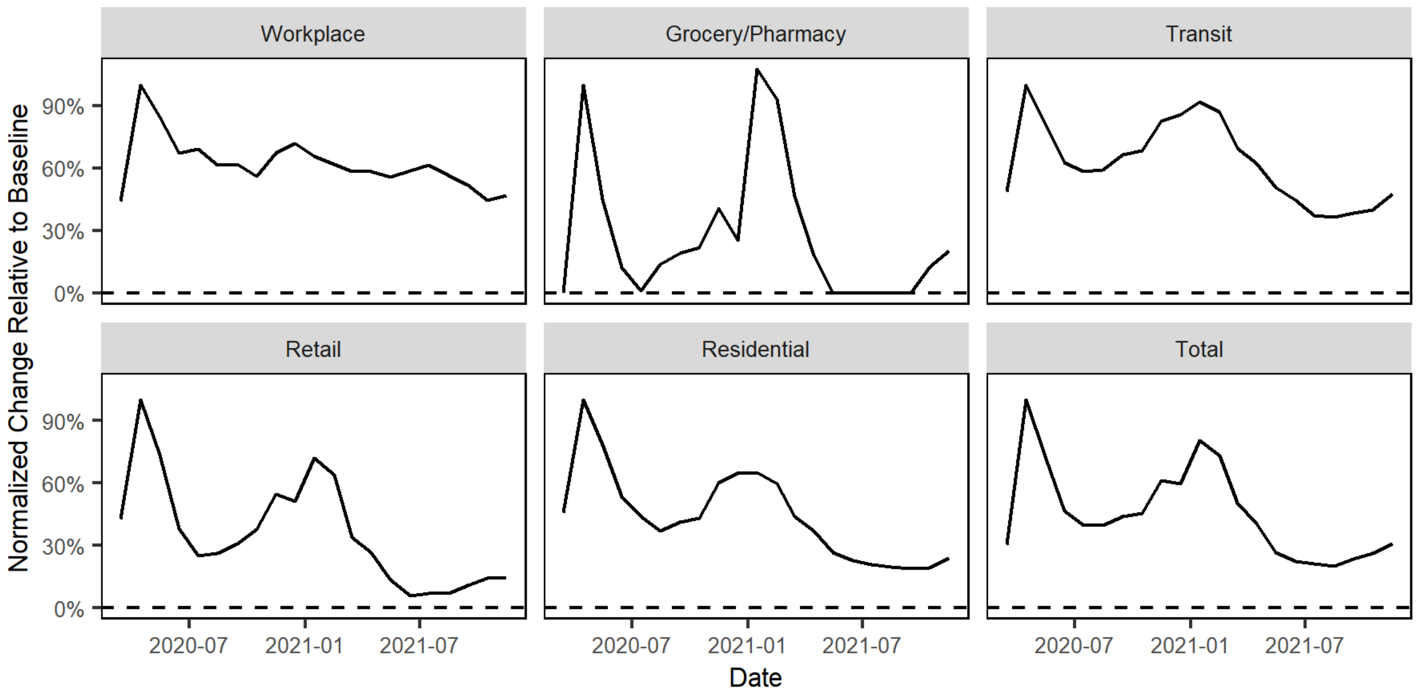
For each of the five categories, we took a population-weighted average of changes across all the counties in each MSA. We then took the average across all days in a month, to generate a monthly change from baseline. Figure S1 shows the monthly averages for the 14 counties in the Chicago-Naperville-Elgin, IL-IN-WI MSA.

Figure S1: Community Mobility Data for the Chicago-Naperville-Elgin, IL-IN-WI Metropolitan Statistical Area



We normalized the monthly changes by dividing the change in each month by the maximal change in any month (in practice, this was April, 2020) and truncated to be greater than zero. This yielded a proportion (bounded between 0 and 1) representing the degree to which mobility changed for each geographic category in each month, relative to the most it changed for any month. For each month, we averaged the five proportions (for five categories) to yield a single statistic, bounded on [0,1], represented the aggregate change in mobility for that month. This is shown in figure S2

Figure S2: Normalized Community Mobility Data for the Chicago-Naperville-Elgin, IL-IN-WI Metropolitan Statistical Area



We combined the monthly aggregate change in mobility - denoted δ_t for month t - with randomly sampled maximal reduction in each parameter - denoted γ'. If we assumed that the reduction in a parameter (eg, viral suppression) - denoted γ_t - correlated perfectly with the change in aggregate mobility, then we could multiply the monthly mobility by the sampled maximal change:

$$\gamma_t = \gamma' \times \delta_t$$

Conversely, if the monthly reduction in a parameter were static and unrelated to mobility, we could postulate:

$$\gamma_t = \gamma'$$

Because it is unclear how much mobility patterns mirror patterns in sexual transmission, viral suppression, HIV testing, and PrEP use, we postulated that there was a weight, w, bounded on [0,1], which determined how much mobility influenced the monthly reduction in each parameter:

$$\gamma_t = w \times \gamma' \times \delta_t + (1 - w) \times \gamma'$$

Across simulations, we randomly sampled the weight parameter from a $Beta(2, 2)$ distribution.

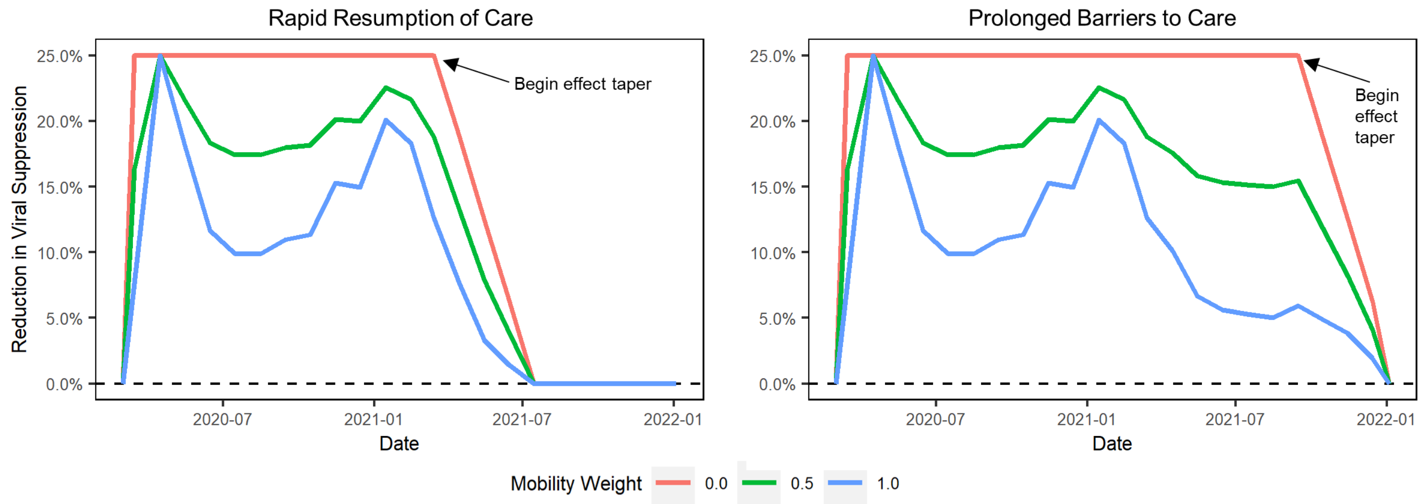
Lastly, we presumed that, after some point in time, $gamma_t$ tapered to zero over a period of several months. For sexual transmission, and for suppression, testing, and PrEP use in the ”Rapid Resumption of Care” scenario, this happened from March 8, 2021 to July 4, 2021. For suppression, testing, and PrEP use in the ”Prolonged Barriers to Care” scenario, this took place from Sept 8, 2021 to Jan 4, 2022.

This was achieved by multiplying by a factor θ_t. Prior to the beginning of the tapering period, $\theta_t = 1$ and after its end, $\theta_t = 0$, and decreases linearly from 1 to 0 over the course of the tapering period.

$$\gamma_t = \theta_t \big[w \times \gamma' \times \delta_t + (1 - w) \times \gamma' \big]$$

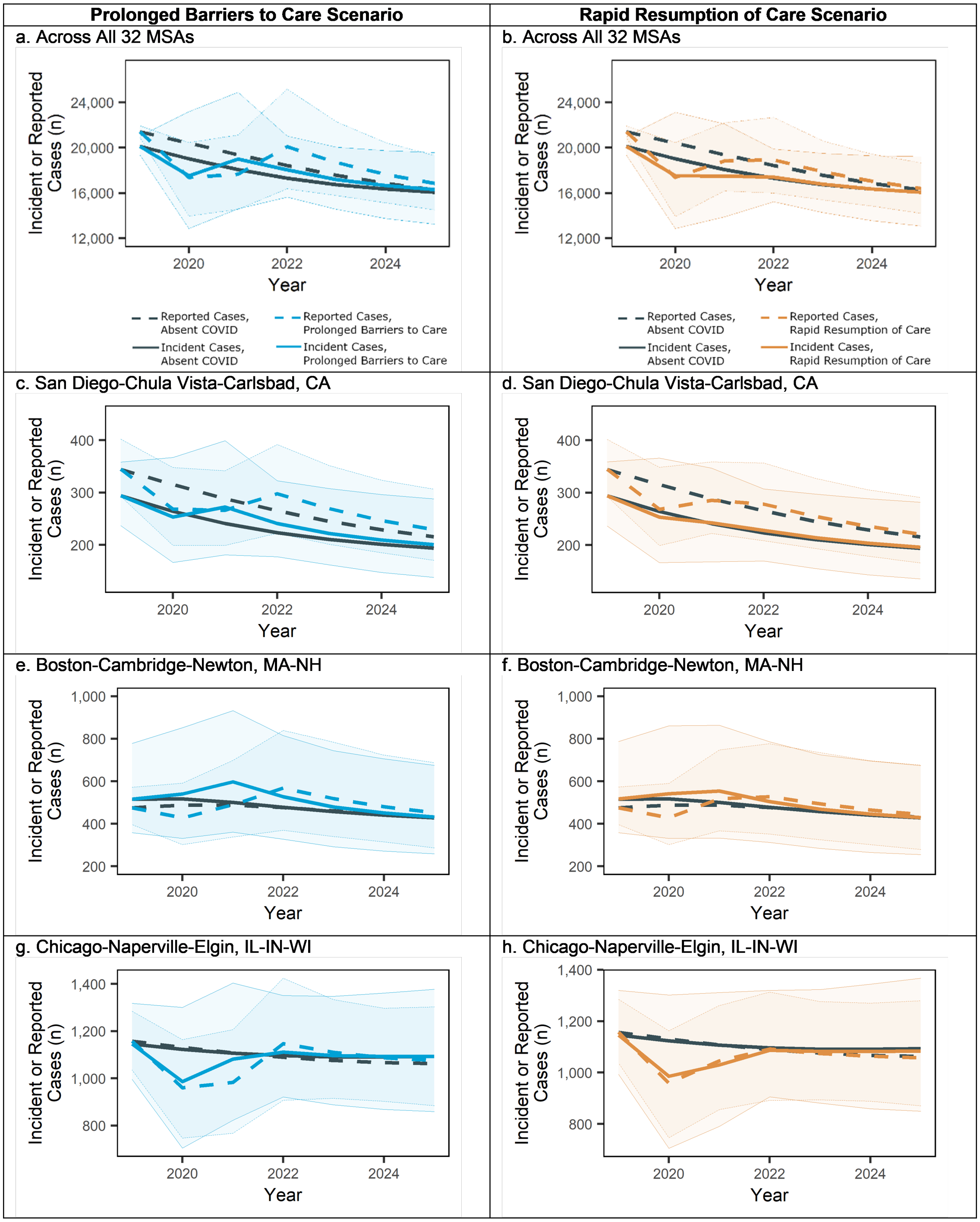
Figure S3 illustrates the monthly reduction in viral suppression, under both scenarios, if the sampled maximal reduction were 25%, under three values of the weight given to mobility data (1, 0.5, and 0), for the

Figure S3: Example Monthly Reduction in Viral Suppression Given Different Weights to Mobility Data, Chicago-Naperville-Elgin, IL-IN-WI Metropolitan Statistical Area



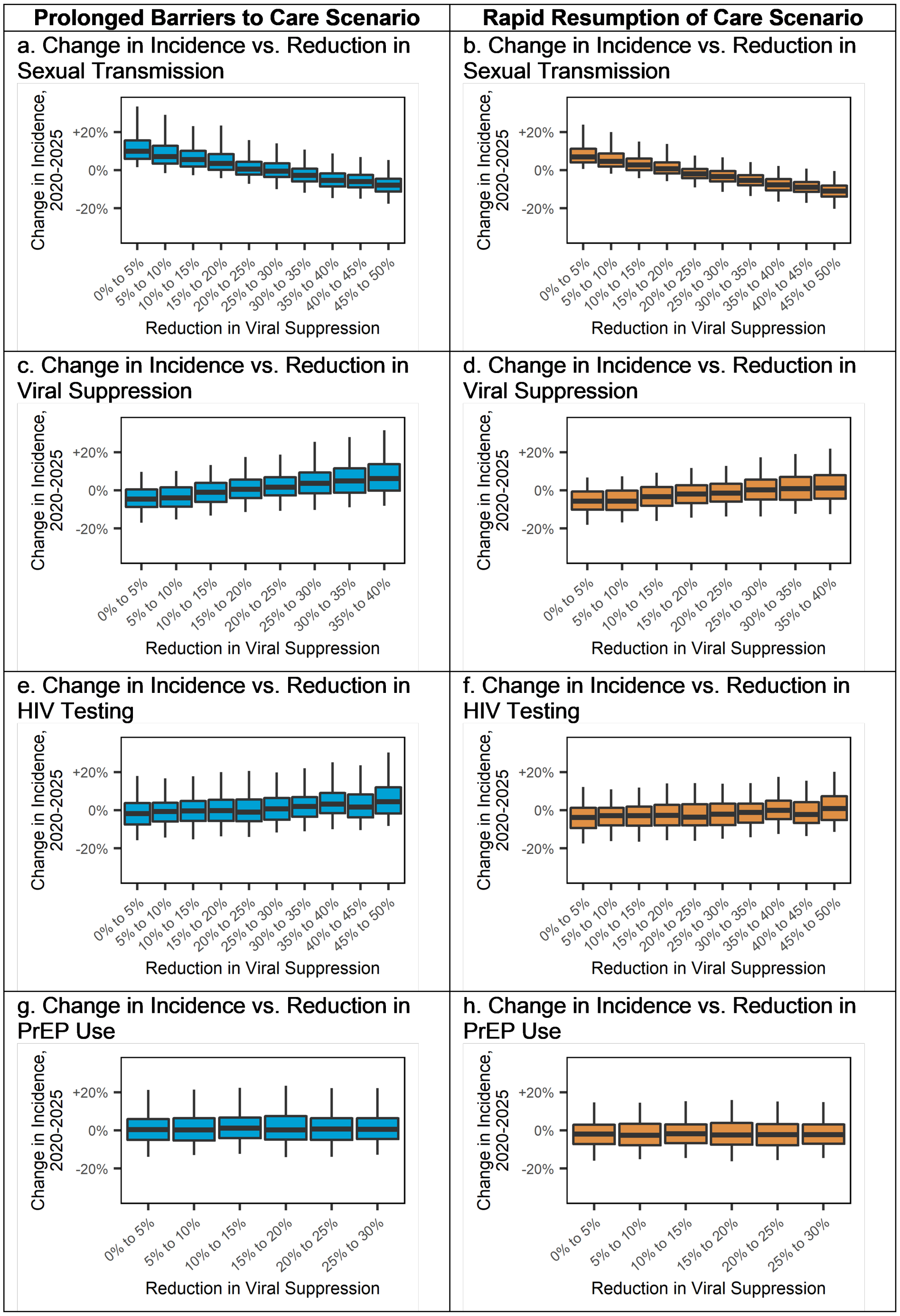
3 Additional Analyses

Figure S4: Figure S4: Projected Incidence and Reported Diagnoses Under Two Scenarios Representing the Potential Effects of the COVID-19 Pandemic



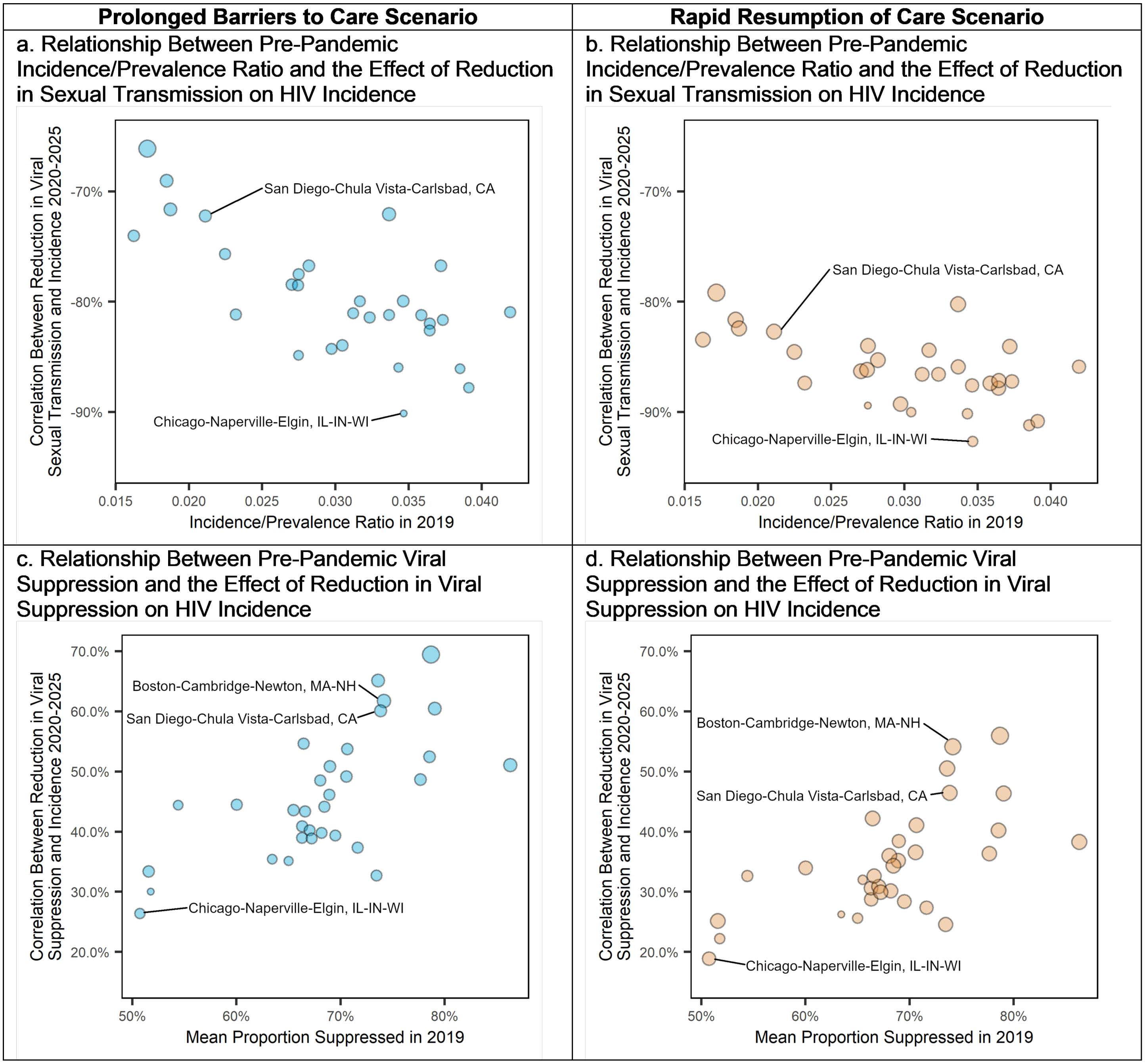
Solid lines denote the mean projected incidence across 1,000 simulations, whereas dashed lines denote the mean projected reported diagnoses. The shaded ribbons indicate the 95% credible interval. Blue lines in panels a, c, e, and g illustrate projections from the Prolonged Barriers to Care scenario (sexual transmission normalized by July 4, 2021; HIV testing, viral suppression, and PrEP use do not normalize until Feb 4, 2022); orange lines in panels b, d, f, and g illustrate the corresponding projections for the Rapid Resumption of Care scenario (sexual transmission, HIV testing, viral suppression, and PrEP use all normalize by July 4, 2021). Black lines in all panels illustrate projections if the COVID-19 pandemic had never occurred.

Figure S5: Relationship Between COVID Effects on Parameters and Change in Cumulative Incidence 2020-2025



The dark horizontal lines represent the median across 1,000 simulations in each of the 32 metropolitan statistical areas of the change incident cases from 2020-2025, calculated as the projected incident infections from 2020-2025 under the COVID scenario minus the incident infections if COVID had not occurred, divided by the cumulative incident infections if COVID had not occurred. The boxes denote the interquartile interval, and the whiskers denote the 95% credible interval. Panels a, c, e, and g (blue) show projections from the Prolonged Barriers to Care scenario (sexual transmission normalized by July 4, 2021; HIV testing, viral suppression, and PrEP use do not normalize until Feb 4, 2022); Panels b, d, f, and g (orange) show the corresponding projections for the Rapid Resumption of Care scenario (sexual transmission, HIV testing, viral suppression, and PrEP use all normalize by July 4, 2021).

Figure S6: Strength of Association Between Cumulative HIV Incidence 2020-2025 and the Reduction in Transmission and Viral Suppression due to the COVID-19 Pandemic



Each circle represents one metropolitan statistical area (MSA). The value on the x-axis is the mean (across 1,000 simulations in each MSA) pre-pandemic epidemiological quantity: incidence/prevalence ratio in panels a and b; proportion of diagnosed PWH who are suppressed in panels c and d. The value on the y-axis is the correlation, across all 1,000 simulations in one MSA, between the reduction sexual transmission (panels a and b) or viral suppression (panels c and d) and the relative change in cumulative incidence (under COVID vs. no COVID). The size of each circle is proportional to the relative change in cumulative incidence. Panels a and c (blue) show relationships from the Prolonged Barriers to Care scenario (sexual transmission normalized by July 4, 2021; HIV testing, viral suppression, and PrEP use do not normalize until Feb 4, 2022); Panels b and d (orange) show the corresponding relationships for the Rapid Resumption of Care scenario (sexual transmission, HIV testing, viral suppression, and PrEP use all normalize by July 4, 2021). Panels a and b do not show two outliers: Cincinnati, OH-KY-IN (Incidence/Prevalence > 0.06) and Boston-Cambridge-Newton, MA-NH (correlation $> -60\%$)

4 Calibration Targets

Table S1: Model Calibration Targets

	Target	Years	Level of Stratification	Data Source
1.	Reported diagnoses	2009 to 2017	sex, age, race, risk factor, sex*age, sex*race, sex*race, sex*risk, race*risk	CDC MSA reports[16,66–72]
2.	Estimated number of diagnosed PWH	2008 to 2016	sex, age, race, and risk factor sex*age, sex*race, sex*race, sex*risk, race*risk	CDC MSA reports[16,66–72]
3.	Mortality in PWH	2009 to 2016	sex	CDC MSA reports[66–72]
4˙	The proportion of PWH aware of their diagnosis (state-level)	2010 to 2018	total	HIV Atlas[16]
5.	The proportion of diagnosed PWH who were virally suppressed	2010 to 2018	total + age, race, sex, risk factor (when available)	local health departments
6.	The number of individuals receiving a prescription for emtricitabine/tenofovir for PrEP	2010 to 2018	sex, race	AIDSVu[73]
7.	The proportion receiving an HIV test	2013 to 2017	age, sex, race	BRFSS[43]
8.	The prevalence of injection drug use (sub-state estimates)	2014 to 2016	age	NSDUH[36]
9.	Cumulative AIDS mortality	up to 2002	age, race, sex, risk factor	AIDS Public Information Dataset[74]
10.	Reported AIDS diagnoses	1998 to 2002	total	AIDS Public Information Dataset[74]

5 Model Parameters and Their Prior Distributions

Table S2: Model Parameters and Sampling Distributions.

Parameter	Estimate	Uncertainty Range	Symbol/ Section	References
HIV TRANSMISSION RATES				
Male-to-male Sexual Transmission *(A composite of number of sexual encounters and rate of transmission per encounter)*				
Black, 2000	1	[0.003 - 354]	$\omega^{(MSM)}$ 10.2	
Black, ratio of rate by 2010 to 2000 rate	1	[0.257 - 3.891]		
Black, ratio of rate by 2020 to 2010 rate	1	[0.507 - 1.972]		
Hispanic, 2000	1	[0.003 - 354]		
Hispanic, ratio of rate by 2010 to 2000 rate	1	[0.257 - 3.891]		
Hispanic, ratio of rate by 2020 to 2010 rate	1	[0.507 - 1.972]		
Non-Black/Non-Hispanic, 2000	1	[0.003 - 354]		
Non-Black/Non-Hispanic, ratio of rate by 2010 to 2000 rate	1	[0.257 - 3.891]		
Non-Black/Non-Hispanic, ratio of rate by 2020 to 2010 rate	1	[0.507 - 1.972]		
Ratio of rate before 1980 to rate by 2000 (All Races)	3.1	[0.404 - 23.790]		HIV Atlas[16]
Heterosexual Transmission *(A composite of number of sexual encounters and rate of transmission per encounter)*				
Black, 2000	1	[0.003 - 354]	$\omega^{(het)}$ 10.2	
Black, ratio of rate by 2010 to 2000 rate	1	[0.257 - 3.891]		
Black, ratio of rate by 2020 to 2010 rate	1	[0.507 - 1.972]		
Hispanic, 2000	1	[0.003 - 354]		
Hispanic, ratio of rate by 2010 to 2000 rate	1	[0.257 - 3.891]		
Hispanic, ratio of rate by 2020 to 2010 rate	1	[0.507 - 1.972]		
Non-Black/Non-Hispanic, 2000	1	[0.003 - 354]		
Non-Black/Non-Hispanic, ratio of rate by 2010 to 2000 rate	1	[0.257 - 3.891]		
Non-Black/Non-Hispanic, ratio of rate by 2020 to 2010 rate	1	[0.507 - 1.972]		
Ratio of rate before 1980 to rate by 2000 (All Races)	2.2	[0.287 - 16.883]		HIV Atlas[16]
Transmission via Needle Sharing *(A composite of number of needle-sharing encounters and rate of transmission per encounter)*				
Black	1	[0.003 - 354]	$\omega^{(IDU)}$ 10.2	
Black, ratio of rate by 2010 to 2000 rate	1	[0.257 - 3.891]		
Black, ratio of rate by 2020 to 2010 rate	1	[0.507 - 1.972]		
Hispanic	1	[0.003 - 354]		
Hispanic, ratio of rate by 2010 to 2000 rate	1	[0.257 - 3.891]		
Hispanic, ratio of rate by 2020 to 2010 rate	1	[0.507 - 1.972]		
Non-Black/Non-Hispanic, 2000	1	[0.003 - 354]		
Non-Black/Non-Hispanic, ratio of rate by 2010 to 2000 rate	1	[0.257 - 3.891]		
Non-Black/Non-Hispanic, ratio of rate by 2020 to 2010 rate	1	[0.507 - 1.972]		
Ratio of rate before 1980 to rate by 2000 (All Races)	4.7	[0.612 - 36.068]		HIV Atlas[16]

**Uncertainty Range represents the 95% confidence interval for a Lognormal distribution unless otherwise indicated*

Table S2 (Model Parameters) continued				
Parameter	**Estimate**	**Uncertainty Range**	**Symbol/ Section**	**References**
SUSCEPTIBILTY TO HIV INFECTION BY AGE				
via Male-to-male Sexual Contact *(A composite of probability of being sexually active, number of encounters, and rate of transmission per encounter)*				
Age 13-24 prior to 2010 (relative to age 35-44)	0.67	[0.48 - 0.94]	$\omega^{(A)}$ (10.2)	Twenge 2017[17] Abma 2017[18]
Age 13-24 by 2020 (relative to age 35-44)	0.67	[0.48 - 0.94]		
Age 25-34 prior to 2010 (relative to age 35-44)	1.11	[0.79 - 1.56]		
Age 25-34 by 2020 (relative to age 35-44)	1.11	[0.79 - 1.56]		
Age 45-54 (relative to age 35-44)	0.72	[0.51 - 1.01]		
Age 55+ (relative to age 35-44)	0.35	[0.25 - 0.49]		
via Heterosexual Contact *(A composite of probability of being sexually active, number of encounters, and rate of transmission per encounter)*				
Age 13-24 (relative to age 35-44)	0.67	[0.48 - 0.94]	$\omega^{(A)}$ (10.2)	Twenge 2017[17] Abma 2017[18]
Age 25-34 (relative to age 35-44)	1.11	[0.79 - 1.56]		
Age 45-54 (relative to age 35-44)	0.72	[0.51 - 1.01]		
Age 55+ (relative to age 35-44)	0.35	[0.25 - 0.49]		
via Needle Sharing *(A composite of number of needle-sharing encounters and rate of transmission per encounter)*				
Age 13-24 (relative to age 35-44)	1.04	[0.74 - 1.46]	$\omega^{(A)}$ (10.2)	HIV Surveillance #24[19]
Age 25-34 (relative to age 35-44)	1.06	[0.75 - 1.49]		
Age 45-54 (relative to age 35-44)	0.84	[0.60 - 1.18]		
Age 55+ (relative to age 35-44)	0.70	[0.50 - 0.98]		
RELATIVE SUSCEPTIBILITY TO HIV ACQUISITION				
via needle sharing, MSM-IDU vs heterosexual male prior to 1990	3.30	[1.67 - 6.51]		Strathdee 1997[20]
via needle sharing, MSM-IDU vs heterosexual male by 2000	3.30	[1.67 - 6.51]		
via needle sharing, MSM-IDU vs heterosexual male by 2010	3.30	[1.67 - 6.51]		
via needle sharing, MSM-IDU vs heterosexual male by 2020	3.30	[1.67 - 6.51]		
via needle sharing, female vs heterosexual male	1.10	[0.56 - 2.17]		HIV Surveillance #24[19]
via heterosexual contact, male vs female	0.75	[0.38 - 1.48]		Shah 2016,[21] NHBS Report #19[22]
TRANSMISSIBILITY OF HIV BY HIV NATURAL HISTORY AND CARE/TREATMENT ENGAGEMENT				
Relative Risk of Transmission for Acute vs Chronic HIV	12	[8.54 - 16.85]		Shah 2016[21]
Relative Risk of Transmission by PWH with diagnosed vs undiagnosed HIV	0.3	[0.21 - 0.42]		Marks 2005,[23] Marks 2006[24]
Relative Risk of Transmission by PWH virally suppressed vs unsuppressed	0	*Not Sampled*		Eisinger 2019[25]
SEXUAL ASSORTATIVITY				
Proportion of female sexual partnerships with MSM, relative to the proportion of MSM in the population	0.0895	[0.045 - 0.177]		Pathela 2006[26]
Proportion of heterosexual male partnerships with other males	0.004	[0.002 - 0.008]		Pathela 2006[26]

**Uncertainty Range represents the 95% confidence interval for a Lognormal distribution unless otherwise indicated*

Table S2 (Model Parameters) continued				
Parameter	**Estimate**	**Uncertainty Range**	**Symbol/ Section**	**References**
Proportion of non-IDU sexual partnerships with active IDU, relative the the prevalence of active IDU in the population	0.2	[0.10 - 0.39]		Jenness 2010[27]
Proportion of Black sexual partnerships with Black partners, relative to the proportion Black in the population	3.76	[2.68 - 5.28]		Bohl 2011[28]
Proportion of Hispanic sexual partnerships with Hispanic partners, relative to the proportion Hispanic in the population	2.19	[1.56 - 3.08]		Mutanski 2014[29]
Proportion of Non-Black/Non-Hispanic sexual partnerships with Non-Black/Non-Hispanic partners, relative to the proportion Other in the population	1.55	[1.10 - 2.18]		Fujimoto 2015,[30] Hamilton 2015[31]
Dispersion of age of sexual partnerships	*Sex- and age-specific*	[0.71 - 1.40] $\times$ estimate		Chow 2016[32]
Ratio of proportion of 13yo who are sexually active to 20-24yo proportion	0.101	*Not Sampled*		Abma 2017[18]
Ratio of proportion of 14yo who are sexually active to 20-24yo proportion	0.144	*Not Sampled*		
Ratio of proportion of 15yo who are sexually active to 20-24yo proportion	0.173	*Not Sampled*		
Ratio of proportion of 16yo who are sexually active to 20-24yo proportion	0.346	*Not Sampled*		
Ratio of proportion of 17yo who are sexually active to 20-24yo proportion	0.546	*Not Sampled*		
Ratio of proportion of 18yo who are sexually active to 20-24yo proportion	0.733	*Not Sampled*		
Ratio of proportion of 19yo who are sexually active to 20-24yo proportion	0.906	*Not Sampled*		
Ratio of proportion of 65-74yo who are sexually active to 55-64yo proportion	0.721	*Not Sampled*		Lindau 2007[33]
Ratio of proportion of 75+yo who are sexually active to 55-64yo proportion	0.366	*Not Sampled*		
NEEDLE SHARING ASSORTATIVITY				
Proportion of Black needle-sharing partnerships with Black partners, relative to the proportion Black in the population	9.12	*Not Sampled*		Smith 2018[34]
Proportion of Hispanic needle-sharing partnerships with Hispanic partners, relative to the proportion Hispanic in the population	1.05	*Not Sampled*		
Proportion of Non-Black/Non-Hispanic needle-sharing partnerships with Non-Black/Non-Hispanic partners, relative to the proportion of Non-Black/Non-Hispanic in the population	1.05	*Not Sampled*		
Proportion of MSM needle-sharing partnerships with MSM partners, relative to the proportion MSM in the population	5.29	*Not Sampled*		Glick 2018[35]
Proportion of heterosexual male needle-sharing partnerships with heterosexual male partners, relative to the proportion heterosexual males in the population	0.82	*Not Sampled*		
**Uncertainty Range represents the 95% confidence interval for a Lognormal distribution unless otherwise indicated*				

Table S2 (Model Parameters) continued				
Parameter	**Estimate**	**Uncertainty Range**	**Symbol/ Section**	**References**
Proportion of female needle-sharing partnerships with female partners, relative to the proportion female in the population	0.51	*Not Sampled*		
Dispersion of age of sexual partnerships	Estimated based on sex and age	*Not Sampled*		Smith 2018[34]
Ratio of proportion of 13-14yo who share injection equipment to 19-24yo proportion	0.02	*Not Sampled*		
Ratio of proportion of 15-18yo who share injection equipment to 19-24yo proportion	0.18	*Not Sampled*		NSDUH 2015-2018[36]
Ratio of proportion of 65+ yo who share injection equipment to 55-64yo proportion	0.193	*Not Sampled*		NSDUH 2015 and 2016[36]
PROBABILITY OF RECEIVING HIV TEST WITHIN PAST YEAR				
MSM, 2010 Odds	0.67	[0.17 - 2.61]	β (10.5)	NHBS 2011-2018[19,22,37–42]
MSM, OR for every year after 2010	1.133	[0.989 - 1.298]		BRFSS 2013-2017[43]
Heterosexual, 2010 Odds	0.148	[0.04 - 0.58]		
Heterosexual, OR for every year after 2010	1.063	[0.928 - 1.218]		
IDU, 2010 Odds	0.369	[0.09 - 1.44]		
IDU, OR for every year after 2010	1.03	[0.899 - 1.180]		
MSM-IDU, 2010 Odds	0.67	[0.17 - 2.61]		
MSM-IDU, OR for every year after 2010	1.133	[0.989 - 1.298]		
Black vs Non-Black/Non-Hispanic, OR 2010	1.215	[0.31 - 4.73]		
Black vs Non-Black/Non-Hispanic, OR for every year after 2010	1.005	*Not Sampled*		
Hispanic vs Non-Black/Non-Hispanic, OR 2010	0.853	[0.22 - 3.32]		
Hispanic vs Non-Black/Non-Hispanic, OR for every year after 2010	1.015	*Not Sampled*		
Age 13-24 vs Age 35-44, OR 2010	1.267	[0.33 - 4.93]		
Age 13-24 vs Age 35-44, OR for every year after 2010	0.971	*Not Sampled*		
Age 25-34 vs Age 35-44, OR 2010	1.345	[0.35 - 5.23]		
Age 25-34 vs Age 35-44, OR for every year after 2010	0.983	*Not Sampled*		
Age 45-54 vs Age 35-44, OR 2010	0.836	[0.21 - 3.25]		
Age 45-54 vs Age 35-44, OR for every year after 2010	0.994	*Not Sampled*		
Age 55+ vs Age 35-44, OR 2010	0.749	[0.19 - 2.91]		
Age 55+ vs Age 35-44, OR for every year after 2010	0.991	*Not Sampled*		
Female vs Heterosexual Male, OR 2010	1.27	*Not Sampled*		
Female vs Heterosexual Male OR for every year after 2010	0.981	*Not Sampled*		
Relative Probability 1993 vs 2010	0.5	[0.36 - 0.70]		
PROBABILITY OF ACHIEVING VIRAL SUPPRESSION				
MSM, 2010 Odds	1.16	[0.30 - 4.51]	10.4	HIV Surveillance #18-2[44]
MSM, OR for every year after 2010	1.17	[1.021 - 1.340]		HIV Surveillance #18-5[45]
Heterosexual, 2010 Odds	0.885	[0.23 - 3.44]		HIV Surveillance #19-3[46]
Heterosexual, OR for every year after 2010	1.149	[1.003 - 1.316]		HIV Surveillance #20-2[47]
IDU, 2010 Odds	0.703	[0.18 - 2.74]		HIV Surveillance #21-4[48]
**Uncertainty Range represents the 95% confidence interval for a Lognormal distribution unless otherwise indicated*				

Table S2 (Model Parameters) continued				
Parameter	**Estimate**	**Uncertainty Range**	**Symbol/ Section**	**References**
IDU, OR for every year after 2010	1.143	[0.998 - 1.309]		HIV Surveillance #22-2[49]
MSM-IDU, 2010 Odds	0.975	[0.25 - 3.79]		HIV Surveillance #23-4[50]
MSM-IDU, OR for every year after 2010	1.179	[1.029 - 1.351]		HIV Surveillance #24-3[51]
Black vs. Non-Black/Non-Hispanic, OR 2010	0.543	[0.14 - 2.11]		HIV Surveillance #25-2[52]
Black vs. Non-Black/Non-Hispanic, OR for every year after 2010	0.997	[0.870 - 1.142]		
Hispanic vs. Non-Black/Non-Hispanic, OR 2010	0.759	[0.20 - 2.95]		
Hispanic vs. Non-Black/Non-Hispanic, OR for every year after 2010	0.985	[0.860 - 1.128]		
Age 13-24 vs Age 35-44, OR 2010	0.531	[0.14 - 2.07]		
Age 13-24 vs Age 35-44, OR for every year after 2010	1.059	[0.924 - 1.213]		
Age 25-34 vs Age 35-44, OR 2010	0.73	[0.19 - 2.84]		
Age 25-34 vs Age 35-44, OR for every year after 2010	1.028	[0.897 - 1.178]		
Age 45-54 vs Age 35-44, OR 2010	1.194	[0.31 - 4.65]		
Age 45-54 vs Age 35-44, OR for every year after 2010	1.007	[0.879 - 1.154]		
Age 55+ vs Age 35-44, OR 2010	1.301	[0.33 - 5.06]		
Age 55+ vs Age 35-44, OR for every year after 2010	0.999	[0.872 - 1.144]		
Female vs Male, Heteroexual, OR 2010	1.062	*Not Sampled*		
Female vs Male OR, Heterosexual, for every year after 2010	1.018	*Not Sampled*		
Female vs Male, IDU OR 2010	1.154	*Not Sampled*		
Female vs Male OR, IDU for every year after 2010	1.02	*Not Sampled*		
Additional OR for every year after 2020, all subgroups	1.05	[1.007 - 1.095]		
PrEP COVERAGE AMONG AT-RISK INDIVIDUALS				
Among Non-Black/Non-Hispanic MSM age 35-44 in 2014, proportion	0.005	[0.00 - 0.228]†		Finlayson 2019,[53] Holloway 2017,[54] HIV Surveillance #22[42]
Yearly increase among Non-Black/Non-Hispanic MSM age 35-44 in 2014, proportion	0.0045	[0.00 - 0.210]†		
Among Non-Black/Non-Hispanic Heterosexual Men age 35-44 in 2014, proportion	0.0009	[0.00 - 0.014]†		HIV Surveillance #19[22]
Yearly increase among Non-Black/Non-Hispanic Heterosexual Men age 35-44 in 2014, proportion	0.0002	[0.00 - 0.003]†		
Among Non-Black/Non-Hispanic PWID age 35-44 in 2014, proportion	0.0001	[0.00 - 0.002]†		HIV Surveillance #24[19]
Yearly increase among Non-Black/Non-Hispanic PWID age 35-44 in 2014, proportion	0.0002	[0.00 - 0.003]†		
Odds ratio of 2014 Coverage, Black vs. Non-Black/Non-Hispanic	0.5203	[0.336 - 0.806]		Finlayson 2019[53]
Odds ratio of Yearly Increase Black vs. Non-Black/Non-Hispanic	0.6559	[0.424 - 1.016]		Holloway 2017[54]
Odds ratio of 2014 Coverage, Hispanic vs. Non-Black/Non-Hispanic	0.4133	[0.267 - 0.640]		HIV Surveillance #22[42]
Odds ratio of Yearly Increase Hispanic vs. Non-Black/Non-Hispanic	0.7675	[0.496 - 1.189]		

**Uncertainty Range represents the 95% confidence interval for a Lognormal distribution unless otherwise indicated*

Table S2 (Model Parameters) continued				
Parameter	**Estimate**	**Uncertainty Range**	**Symbol/ Section**	**References**
Odds ratio of 2014 Coverage and Yearly Increase, age 13-24 vs 35-44	0.6886	[0.177 - 2.679]		HIV Surveillance #24[19]
Odds ratio of 2014 Coverage and Yearly Increase, age 25-34 vs 35-44	1.1511	[0.296 - 4.478]		HIV Surveillance #22[42]
Odds ratio of 2014 Coverage and Yearly Increase, age 45-54 vs 35-44	0.6217	[0.160 - 2.419]		
Odds ratio of 2014 Coverage and Yearly Increase, age 55+ vs 35-44	0.2048	[0.053 - 0.797]		
Odds ratio of 2014 Coverage and Yearly Increase, Female vs. Male	1.5411	*Not Sampled*		HIV Surveillance #24,[19] HIV Surveillance #22[42]
Adherence to PrEP	0.56	*Not sampled*		Coy 2019[55]
Relative risk of acquiring HIV, PrEP vs no PrEP, male-to-male sexual contact	0.14	*Not sampled*		McCormack 2016[56]
Relative risk of acquiring HIV, PrEP vs no PrEP, heterosexual contact	0.25	*Not sampled*		Baeten 2012[57]
Relative risk of acquiring HIV, PrEP vs no PrEP, needle-sharing	0.51	*Not sampled*		Choopanya 2013[58]
Frequency of HIV Screening while on PrEP	3mo	*Not sampled*		
DISTRIBUTION OF MSM IN THE POPULATION				
Total Proportion of Males who are MSM	*Location-specific*	[0.84 - 1.19] × estimate		Grey 2016[59]
Relative Proportion of Males who are MSM, Black vs. Non-Black/Non-Hispanic	1.28	*Not Sampled*		Lansky 2015[60]
Relative Proportion of Males who are MSM, Hispanic vs. Non-Black/Non-Hispanic	0.96	*Not Sampled*		
MORTALITY OF UNSUPPRESSED HIV				
Excess mortality rate among PWH with unsuppressed HIV before 1994	0.15	[0.71 - 1.40]	$\theta^{(HIV)}$	Bhaskaran 2008[61]
Excess mortality rate among PWH with unsuppressed HIV by 2000	0.036	[0.026 - 0.051]	(10.9)	
Excess mortality rate among PWH with unsuppressed HIV by 2010	0.023	[0.016 - 0.032]		
PROPORTION IN AGE BRACKET WHO WILL AGE UP TO NEXT BRACKET, per year				
MSM and MSM-IDU				
Age 13-24	0.27	[0.19 - 0.38]	$\alpha^{(H)}$	HIV Surveillance #24-5[62]
Age 25-34 prior to 2000	0.18	[0.09 - 0.36]	(10.8)	HIV Surveillance #14[63]
Age 25-34 after 2010	0.13	[0.07 - 0.26]		HIV Surveillance #23[64]
Age 35-44 prior to 2000	0.10	*Not Sampled*		
Age 35-44 after 2010	0.14	[0.07 - 0.28]		HIV Surveillance #23[64]
Age 45-54 prior to 2000	0.10	*Not Sampled*		
Age 45-54 after 2010	0.08	*Not Sampled*		
Heterosexual				
Age 13-24	0.25	[0.18 - 0.35]	$\alpha^{(H)}$	HIV Surveillance #24-5[62]
Age 25-34 prior to 2000	0.18	[0.09 - 0.36]	(10.8)	HIV Surveillance #14[63]
Age 25-34 after 2010	0.13	[0.07 - 0.26]		HIV Surveillance #23[64]
Age 35-44 prior to 2000	0.10	*Not Sampled*		
Age 35-44 after 2010	0.14	[0.07 - 0.28]		HIV Surveillance #23[64]
Age 45-54 prior to 2000	0.10	*Not Sampled*		
**Uncertainty Range represents the 95% confidence interval for a Lognormal distribution unless otherwise indicated*				

Table S2 (Model Parameters) continued				
Parameter	**Estimate**	**Uncertainty Range**	**Symbol/ Section**	**References**
Age 45-54 after 2010	0.08	*Not Sampled*		
PWID				
Age 13-24	0.32	[0.23 - 0.45]	$\alpha^{(H)}$ (10.8)	HIV Surveillance #24-5[62]
Age 25-34 prior to 2000	0.18	[0.09 - 0.36]		HIV Surveillance #14[63]
Age 25-34 after 2010	0.13	[0.07 - 0.26]		HIV Surveillance #23[64]
Age 35-44 prior to 2000	0.10	*Not Sampled*		
Age 35-44 after 2010	0.14	[0.07 - 0.28]		HIV Surveillance #23[64]
Age 45-54 prior to 2000	0.10	*Not Sampled*		
Age 45-54 after 2010	0.08	*Not Sampled*		
INJECTION DRUG USE				
Excess mortality rate among active IDU	0.0166	*Not Sampled*		Mathers 2014[65]
Incidence of IV Drug Use, base estimate	Location- and stratum-specific	-	10.7	NSDUH 2015-2018[36]
Multiplier, Incidence of IV Drug Use, Black, before 2000	1	[0.51 - 1.97]		
Multiplier,Incidence of IV Drug Use, Black, by 2020	1	[0.51 - 1.97]		
Multiplier,Incidence of IV Drug Use, Hispanic before 2000	1	[0.51 - 1.97]		
Multiplier,Incidence of IV Drug Use, Hispanic by 2020	1	[0.51 - 1.97]		
Multiplier,Incidence of IV Drug Use, Non-Black/Non-Hispanic before 2000	1	[0.51 - 1.97]		
Multiplier,Incidence of IV Drug Use, Non-Black/Non-Hispanic by 2020	1	[0.51 - 1.97]		
Multiplier,Incidence of IV Drug Use, MSM before 2000	1	[0.51 - 1.97]		
Multiplier,Incidence of IV Drug Use, MSM by 2020	1	[0.51 - 1.97]		
Rate of Remission of IV Drug Use	Location- and stratum-specific	[0.51 - 1.97] × estimate		
Rate of Relapse of IV Drug Use	Location- and stratum-specific	[0.51 - 1.97] × estimate		
FUTURE UNCERTAINTY				
Continued changes in MSM tranmission rates from 2020-2030, as proportion of changes from 2010-2020	0.1	[0.03 - 0.39]	p_2 (10.1.2.2)	
Continued changes in heterosexual tranmission rates from 2020-2030, as proportion of changes from 2010-2020	0.1	[0.03 - 0.39]		
Continued changes in IDU tranmission rates from 2020-2030, as proportion of changes from 2010-2020	0.1	[0.03 - 0.39]		
Improvements in testing continue until year	uniform on [2020-2025]			
Improvements in viral suppression continue until year	uniform on [2020-2025]			
**Uncertainty Range represents the 95% confidence interval for a Lognormal distribution unless otherwise indicated*				

Table S2 (Model Parameters) continued				
Parameter	**Estimate**	**Uncertainty Range**	**Symbol/ Section**	**References**
Improvements in PrEP coverage continue until year	uniform on [2020-2025]			

6 Model Structure and Differential Equations

6.1 Terminology

- In general, we partition the population into A age brackets (indexed $a = 1, ..., A$), R races (indexed $r = 1, ..., R$), S sex/sexual behavioral categories (indexed $s = 1, ..., S$), and k states of intravenous drug use (indexed $k = 1, ..., K$).
- For each stratum a, r, s, k of age $\times$ race $\times$ sex/sexual behavior $\times$ IV drug use status, we define seven states with respect to HIV status.
- We let $U_{a,r,s,k}(t)$ denote those within the stratum who are uninfected
- We let $IA_{a,r,s,k}$ and $IC_{a,r,s,k}$ denote those ***i**nfected* with hiv but unaware of their diagnosis with ***a**cute* and ***c**hronic* HIV respectively
- We let $PA_{a,r,s,k}$ and $PC_{a,r,s,k}$ denote those infected with HIV, unaware of their diagnosis, but enrolled in a ***P**rEP* with ***a**cute* and ***c**hronic* HIV respectively
- We let $DA_{a,r,s,k}$ and $DC_{a,r,s,k}$ denote those aware of their ***d**iagnosis* with ***a**cute* and ***c**hronic* HIV respectively
- We assume there are M modes of HIV transmission, indexed $1, ..., m$. In this work, $M = 2$ (sexual and intravenous)

6.1.1 Partitions of Age, Race, Sex/Sexual Behavior, and IV Drug Use

The terminology above allows for an arbitrary number of partitions by age, race, sex/sexual behavior, and IV drug use status. In this work, we use the following partitions:

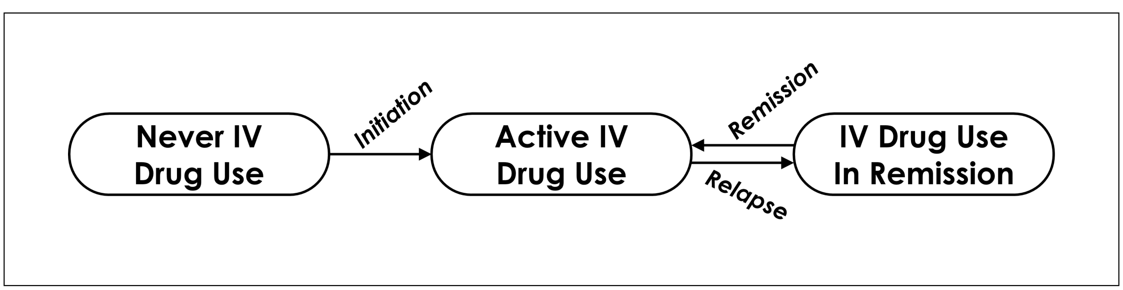
6.1.1.1 Age To align with CDC reporting, we split the adult population into age strata of 13-24yo, 25-34yo, 35-44yo, 45-54yo, and $\geq$55 years old.

6.1.1.2 Race We split the population into three race strata: Black, Hispanic, and Other (non-Black/non-Hispanic), since Black and Hispanic individuals account for a disproportionate number of new HIV infections.

6.1.1.3 Sex/Sexual Behavior We separate the population into three strata vis-a-vis sex and sexual behaviors: female, heterosexual male, and men who have sex with men (MSM). In combination with IV drug use strata (below), this allows us to fully represent all risk categories captured by the CDC (male and female heterosexual contact, MSM, heterosexual IV drug use, and MSM plus IV drug use).

6.1.1.4 Intravenous Drug Use We partition strata of age, sex/sexual behavior, and race into 3 strata with respect to IV drug use: "Never Use", "Active Use", and "IV Drug Use in Remission". As shown in the figure below, there are three transitions possible with respect to IV drug use: *initiation* of use, *remission* from use, and *relapse*:

Figure S7: IV Drug Use Transitions



6.1.2 Time-Varying Parameters

Many of the parameters in our differential equations are time-varying. We present the differential equations here using general formulations for time-varying parameters (e.g., $\theta(t)$ for mortality rate). In section 10 - "Functional Forms for Parameters" - we present the specific functional forms we used to allow parameters to vary over time.

6.2 HIV Transmission

For shorthand, here we will replace a, r, s, k by i and j to index strata of age × race × sex/sexual behavior × IV drug use, where there are $N = A \cdot R \cdot S \cdot K$ total strata $(i, j = 1, ..., N)$

The rate of new infections into stratum i at time t - denoted $\Delta_i(t)$ - is the sum of the rates of new infections by each of the M modes of transmission:

$$\Delta_i(t) = \sum_{m=1}^{M} \Delta_{i,m}(t) \tag{1}$$

where $\Delta_{i,m}(t)$ is the rate of new infections into stratum i by transmission mode m at time t, which is the sum over all strata j of the rate of new infections into stratum i from contact with stratum j via mode m of transmission:

$$\Delta_{i,m}(t) = \sum_{j=1}^{N} \Delta_{i,j,m}(t) \tag{2}$$

where $\Delta_{i,j,m}(t)$ is the rate of new infections in stratum i due to contact with those infected in stratum j via a mode of transmission m at time t. Broadly speaking, this is the product of:

- The *transmissibility* from stratum j at time t, which is a function of the prevalence of unsuppressed PWH in the stratum.
- The proportion of stratum i's partners who come from stratum j (for transmission mode m) at time t, denoted $\Phi_{i,j,m}(t)$
- The rate of transmission from stratum j to stratum i via mode m at time t, denoted $\Gamma_{i,j,m}(t)$
- The *susceptibility* of stratum i to infection at time t (in this work, this is a function of PrEP coverage within the stratum)

$$\Delta_{i,j,m} = transmissibility_{j,m}(t) \times \Phi_{i,j,m}(t) \times \Gamma_{i,j,m}(t) \times susceptibility_{i,m}(t) \tag{3}$$

We describe *transmissibility* and *susceptibility* in further detail:

6.2.1 Transmissibility

The transmissibility of HIV from stratum j via mode of transmission m at time t is a function of the prevalence of unsuppressed HIV in stratum j, allowing for PWH in the acute phase of HIV to transmit more and for those who are diagnosed to reduce transmission behaviors:

$$transmissibility_{j,m}(t) = \frac{\eta \cdot IA_j(t) + IC_j(t) + \eta \cdot PA_j(t) + PC_j(t) + \eta \cdot \upsilon_j(t) \cdot DA_j(t) \cdot [1 - \rho_j(t)] + \upsilon_j(t) \cdot DC_j(t) \cdot [1 - \rho_j(t)]}{U_j(t) + IA_j(t) + IC_j(t) + PA_j(t) + PC_j(t) + DA_j(t) + DC_j(t)} \tag{4}$$

where

- η is the ratio of transmissibility in the acute phase of HIV relative to the chronic phase
- $\rho_j(t)$ is the proportion of diagnosed PWH in stratum j who are virally suppressed at time t
- $\upsilon_j(t)$ is the degree (relative rate) to which PWH who are aware of their diagnosis reduce their transmission behaviors, on average, relative to PWH who are unaware of their diagnosis

6.2.2 Susceptibility

$$susceptibility_{i,m}(t) = [1 - \pi_i(t)] + \pi_i(t) \times \kappa_i \tag{5}$$

- $\pi_i(t)$ is the proportion uninfected individuals at risk for HIV in stratum i at time t who are enrolled in a PrEP program
- κ_i is the relative risk of HIV infection for those on PrEP (relative to no PrEP) in stratum i

6.3 Uninfected $\left(U_{a,r,s,k}(t)\right)$

The inflows into each stratum a, r, s, k of uninfected are those entering the model at the youngest age bracket or aging into age stratum a and those moving into IV drug use state k. The outflows are those who become infected with HIV, as well as those who die, age out of age stratum a, or move out of IV drug use state k.

$$
\begin{aligned}
\frac{\partial U_{a,r,s,k}(t)}{\partial t} &= \mathbb{1}_{a=1} \times \lambda_r \times P_r(t) + \mathbb{1}_{a>1} \times \alpha^U_{a-1,r,s,k}(t) \times U_{a-1,r,s,k}(t) \\
&+ \mathbb{1}_{k=active\_use} \times [\zeta_{a,r,s}(t) \times U_{a,r,s,never\_use}(t) + \xi_{a,r,s}(t) \times U_{a,r,s,prior\_use}(t)] \\
&\quad + \mathbb{1}_{k=prior\_use} \times \psi_{a,r,s}(t) \times U_{a,r,s,active\_use}(t) \\
&- \Delta_{a,r,s,k}(t) \\
&- \theta^G_{a,r,s,k} \times U_{a,r,s,k}(t) - \mathbb{1}_{k=active\_use} \times \theta^{IDU} \times U_{a,r,s,k}(t) \\
&- \alpha^U_{a,r,s,k}(t) \times U_{a,r,s,k}(t) \\
&- U_{a,r,s,k}(t) \times \left[\mathbb{1}_{k=never\_use} \times \zeta_{a,r,s}(t) + \mathbb{1}_{k=active\_use} \times \psi_{a,r,s}(t) + \mathbb{1}_{k=prior\_use} \times \xi_{a,r,s}(t)\right]
\end{aligned}
$$

where

- $\mathbb{1}_{a=1}$ evaluates to 1 if a is the first age bracket and 0 otherwise, and $\mathbb{1}_{a>1}$ evaluates to 0 if a is the first age bracket and 1 otherwise
- $\lambda_(t)$ denotes the birth rate for race r at time t
- $P_r(t)$ is the total size of all strata where race $= r$ at time t. i.e.

$$P_r(t) = \sum_{a,s,k} U_{a,r,s,k}(t) + IA_{a,r,s,k}(t) + IC_{a,r,s,k}(t) + PA_{a,r,s,k}(t) + PC_{a,r,s,k}(t) + DA_{a,r,s,k}(t) + DC_{a,r,s,k}(t)$$

- $\alpha^U_{a-1,r,s,k}$ denotes the aging rate at time t of uninfected individuals in the age stratum before a - the average rate at which uninfected individuals move from age stratum $a-1$ to a
- $\mathbb{1}_{k=active\_use}$ evaluates to 1 if k denotes a compartment of active IV drug use and 0 otherwise, and $\mathbb{1}_{k=prior\_use}$ evaluates to 1 if k denotes a compartment of prior IV drug use
- $\zeta_{a,r,s}(t)$ denotes the rate of first-time initiation of IV drug use at time t in stratum a, r, s
- $\xi_{a,r,s}(t)$ denotes the rate of relapse into IV drug use among prior users of IV drugs at time t in stratum a, r, s
- $\psi_{a,r,s}(t)$ denotes the rate of remission of IV drug use among active users at time t in stratum a, r, s
- $U_{a,r,s,never\_use}$, $U_{a,r,s,prior\_use}$, $U_{a,r,s,active\_use}$ denote the compartments with the same age, race, and sex/sexual behavior as a, r, s, k but whose IV drug use stratum is "never use", "prior use", or "active use" respectively
- $\Delta_{a,r,s,k}(t)$ denotes the number of new HIV infections in stratum a, r, s, k at time t. This is detailed in Section 6.2 on page 21
- $\theta^G_{a,r,s,k}$ denotes the general mortality rate of individuals in stratum a, r, s, k
- θ^{IDU} denotes the excess mortality rate due to active IV drug use
- $\alpha^U_{a,r,s,k}(t)$ denotes the aging rate at time t for uninfected individuals in stratum a, r, s, k

6.4 Undiagnosed, Acute HIV $\left(IA_{a,r,s,k}(t)\right)$

The inflows into each stratum a, r, s, k of acute, undiagnosed HIV are the new infections among those who were not on PrEP, those aging into age stratum a, and those moving into IV drug use state k. The outflows are those who get diagnosed or progress to chronic HIV, as well as those who die (from HIV or other causes), age out of age stratum a, or move out of IV drug use state k.

$$
\begin{aligned}
\frac{\partial IA_{a,r,s,k}(t)}{\partial t} &= \Delta_{a,r,s,k}(t) \times [1 - \mu_{a,r,s,k}(t)] \\
&+ \mathbb{1}_{a>1} \times \alpha^H_{a-1,r,s,k}(t) \times IA_{a-1,r,s,k}(t) \\
&+ \mathbb{1}_{k=active\_use} \times [\zeta_{a,r,s}(t) \times IA_{a,r,s,never\_use}(t) + \xi_{a,r,s}(t) \times IA_{a,r,s,prior\_use}(t)] \\
&\quad + \mathbb{1}_{k=prior\_use} \times \psi_{a,r,s}(t) \times IA_{a,r,s,active\_use}(t) \\
&- \beta_{a,r,s,k}(t) \times IA_{a,r,s,k}(t) \\
&- \tau \times IA_{a,r,s,k}(t) \\
&- \theta^{HIV}(t) \times IA_{a,r,s,k}(t) - \theta^G_{a,r,s,k} \times IA_{a,r,s,k}(t) - \mathbb{1}_{k=active\_use} \times \theta^{IDU} \times IA_{a,r,s,k}(t) \\
&- \alpha^H_{a,r,s,k}(t) \times IA_{a,r,s,k}(t) \\
&- IA_{a,r,s,k}(t) \times \left[\mathbb{1}_{k=never\_use} \times \zeta_{a,r,s}(t) + \mathbb{1}_{k=active\_use} \times \psi_{a,r,s}(t) + \mathbb{1}_{k=prior\_use} \times \xi_{a,r,s}(t)\right]
\end{aligned}
$$

where

- $\mu_{a,r,s,k}(t)$ denotes the proportion of new infections in stratum a, r, s, k at time t that were among individuals on PrEP.

$$
\mu_{a,r,s,k}(t) = \frac{\pi_{a,r,s,k}(t) \times \kappa_{a,r,s,k}}{[1 - \pi_{a,r,s,k}(t)] + \pi_{a,r,s,k}(t) \times \kappa_{a,r,s,k}}
$$

  where $\pi_{a,r,s,k}(t)$ is the proportion uninfected individuals at risk for HIV in stratum a, r, s, k at time t who are enrolled in a PrEP program, and $\kappa_{a,r,s,k}$ is the relative risk of HIV infection for PrEP use in stratum a, r, s, k

- $\alpha^H_{a-1,r,s,k}(t)$ denotes the aging rate of HIV-positive individuals in the age stratum prior to a
- $\beta_{a,r,s,k}(t)$ is the rate of diagnosis of HIV for those in stratum a, r, s, k at time t
- τ is the rate of progression from acute to chronic HIV
- $\theta^{HIV}(t)$ is the (time-varying) rate of excess mortality from unsuppressed HIV
- $\alpha^H_{a,r,s,k}(t)$ is the aging rate at time t for PWH in stratum a, r, s, k

6.5 Undiagnosed, Acute HIV, Enrolled in a PrEP Program $\left(PA_{a,r,s,k}(t)\right)$

The inflows into each stratum a, r, s, k of acute, undiagnosed HIV among those enrolled in a PrEP program are the proportion of new infections among those who were on PrEP, those aging into age stratum a, and those moving into IV drug use state k. The outflows are those who get diagnosed or progress to chronic HIV, as well as those who die (from HIV or other causes), age out of age stratum a, or move out of IV drug use state k.

$$
\begin{aligned}
\frac{\partial PA_{a,r,s,k}(t)}{\partial t} &= \Delta_{a,r,s,k}(t) \times \mu_{a,r,s,k}(t) \\
&+ \mathbb{1}_{a>1} \times \alpha^H_{a-1,r,s,k}(t) \times PA_{a-1,r,s,k}(t) \\
&+ \mathbb{1}_{k=active\_use} \times [\zeta_{a,r,s}(t) \times PA_{a,r,s,never\_use}(t) + \xi_{a,r,s}(t) \times PA_{a,r,s,prior\_use}(t)] \\
&\quad + \mathbb{1}_{k=prior\_use} \times \psi_{a,r,s}(t) \times PA_{a,r,s,active\_use}(t) \\
&- \beta^{PrEP} \times PA_{a,r,s,k}(t) \\
&- \tau \times PA_{a,r,s,k}(t) \\
&- \theta^{HIV}(t) \times PA_{a,r,s,k}(t) - \theta^G_{a,r,s,k} \times PA_{a,r,s,k}(t) - \mathbb{1}_{k=active\_use} \times \theta^{IDU} \times PA_{a,r,s,k}(t) \\
&- \alpha^H_{a,r,s,k}(t) \times PA_{a,r,s,k}(t) \\
&- PA_{a,r,s,k}(t) \times \left[\mathbb{1}_{k=never\_use} \times \zeta_{a,r,s}(t) + \mathbb{1}_{k=active\_use} \times \psi_{a,r,s}(t) + \mathbb{1}_{k=prior\_use} \times \xi_{a,r,s}(t)\right]
\end{aligned}
$$

where

- β^{PrEP} is the rate of diagnosis of HIV among those enrolled in a PrEP program

6.6 Diagnosed, Acute HIV $\left(DA_{a,r,s,k}(t)\right)$

The inflows into each stratum a, r, s, k of acute, diagnosed HIV are new HIV diagnoses among those with undiagnosed, acute HIV (those enrolled in a PrEP program and not), those aging into age stratum a, and those moving into IV drug use state k. The outflows are those who progress to chronic HIV, as well as those who die (from unsuppressed HIV or other causes), age out of age stratum a, or move out of IV drug use state k.

$$\begin{aligned}
\frac{\partial DA_{a,r,s,k}(t)}{\partial t} &= \beta_{a,r,s,k}(t) \times IA_{a,r,s,k}(t) + \beta^{PrEP} \times PA_{a,r,s,k}(t) \\
&+ \mathbb{1}_{a>1} \times \alpha^{H}_{a-1,r,s,k}(t) \times DA_{a-1,r,s,k}(t) \\
&+ \mathbb{1}_{k=active_use} \times [\zeta_{a,r,s}(t) \times DA_{a,r,s,never_use}(t) + \xi_{a,r,s}(t) \times DA_{a,r,s,prior_use}(t)] \\
&\quad + \mathbb{1}_{k=prior_use} \times \psi_{a,r,s}(t) \times DA_{a,r,s,active_use}(t) \\
&- \beta_{a,r,s,k}(t) \times DA_{a,r,s,k}(t) \\
&- \tau \times DA_{a,r,s,k}(t) \\
&- \theta^{HIV}(t) \times DA_{a,r,s,k}(t) \times [1 - \rho_{a,r,s,k}(t)] - \theta^{G}_{a,r,s,k} \times DA_{a,r,s,k}(t) - \mathbb{1}_{k=active_use} \times \theta^{IDU} \times DA_{a,r,s,k}(t) \\
&- \alpha^{H}_{a,r,s,k}(t) \times DA_{a,r,s,k}(t) \\
&- DA_{a,r,s,k}(t) \times \left[\mathbb{1}_{k=never_use} \times \zeta_{a,r,s}(t) + \mathbb{1}_{k=active_use} \times \psi_{a,r,s}(t) + \mathbb{1}_{k=prior_use} \times \xi_{a,r,s}(t)\right]
\end{aligned}$$

where

- $\rho_{a,r,s,k}(t)$ is the proportion of those with diagnosed HIV in stratum a, r, s, k who are virally suppressed at time t.

6.7 Undiagnosed, Chronic HIV $\left(IC_{a,r,s,k}(t)\right)$

The inflows into each stratum a, r, s, k of chronic, undiagnosed HIV are those who progress from acute to chronic HIV, those aging into age stratum a, and those moving into IV drug use state k. The outflows are those who get diagnosed, as well as those who die (from HIV or other causes), age out of age stratum a, or move out of IV drug use state k.

$$\begin{aligned}
\frac{\partial IC_{a,r,s,k}(t)}{\partial t} &= \tau \times IA_{a,r,s,k}(t) \\
&+ \mathbb{1}_{a>1} \times \alpha^{H}_{a-1,r,s,k}(t) \times IC_{a-1,r,s,k}(t) \\
&+ \mathbb{1}_{k=active_use} \times [\zeta_{a,r,s}(t) \times IC_{a,r,s,never_use}(t) + \xi_{a,r,s}(t) \times IC_{a,r,s,prior_use}(t)] \\
&\quad + \mathbb{1}_{k=prior_use} \times \psi_{a,r,s}(t) \times IC_{a,r,s,active_use}(t) \\
&- \beta_{a,r,s,k}(t) \times IC_{a,r,s,k}(t) \\
&- \theta^{HIV}(t) \times IC_{a,r,s,k}(t) - \theta^{G}_{a,r,s,k} \times IC_{a,r,s,k}(t) - \mathbb{1}_{k=active_use} \times \theta^{IDU} \times IC_{a,r,s,k}(t) \\
&- \alpha^{H}_{a,r,s,k}(t) \times IC_{a,r,s,k}(t) \\
&- IC_{a,r,s,k}(t) \times \left[\mathbb{1}_{k=never_use} \times \zeta_{a,r,s}(t) + \mathbb{1}_{k=active_use} \times \psi_{a,r,s}(t) + \mathbb{1}_{k=prior_use} \times \xi_{a,r,s}(t)\right]
\end{aligned}$$

6.8 Undiagnosed, Chronic HIV, Enrolled in a PrEP Program $\left(PC_{a,r,s,k}(t)\right)$

The inflows into each stratum a, r, s, k of chronic, undiagnosed HIV among those enrolled in a PrEP program are those who progress from acute to chronic HIV, those aging into age stratum a, and those moving into IV drug use state k. The outflows are those who get diagnosed, as well as those who die (from HIV or other causes), age out of age stratum a, or move out of IV drug use state k.

$$\begin{aligned}
\frac{\partial PC_{a,r,s,k}(t)}{\partial t} &= \tau \times PA_{a,r,s,k}(t) \\
&+ \mathbb{1}_{a>1} \times \alpha^{H}_{a-1,r,s,k}(t) \times PC_{a-1,r,s,k}(t) \\
&+ \mathbb{1}_{k=active_use} \times [\zeta_{a,r,s}(t) \times PC_{a,r,s,never_use}(t) + \xi_{a,r,s}(t) \times PC_{a,r,s,prior_use}(t)] \\
&\quad + \mathbb{1}_{k=prior_use} \times \psi_{a,r,s}(t) \times PC_{a,r,s,active_use}(t) \\
&- \beta^{PrEP} \times PC_{a,r,s,k}(t) \\
&- \theta^{HIV}(t) \times PC_{a,r,s,k}(t) - \theta^{G}_{a,r,s,k} \times PC_{a,r,s,k}(t) - \mathbb{1}_{k=active_use} \times \theta^{IDU} \times PC_{a,r,s,k}(t) \\
&- \alpha^{H}_{a,r,s,k}(t) \times PC_{a,r,s,k}(t) \\
&- PC_{a,r,s,k}(t) \times \left[\mathbb{1}_{k=never_use} \times \zeta_{a,r,s}(t) + \mathbb{1}_{k=active_use} \times \psi_{a,r,s}(t) + \mathbb{1}_{k=prior_use} \times \xi_{a,r,s}(t)\right]
\end{aligned}$$

6.9 Diagnosed, Chronic HIV $\left(DC_{a,r,s,k}(t)\right)$

The inflows into each stratum a, r, s, k of chronic, diagnosed HIV are new HIV diagnoses among those with undiagnosed, chronic HIV (those enrolled in a PrEP program and not), those who progress from acute to chronic HIV, those aging into age stratum a, and those moving into IV drug use state k. The outflows are those who die (from unsuppressed HIV or other causes), age out of age stratum a, or move out of IV drug use state k.

$$
\begin{aligned}
\frac{\partial DC_{a,r,s,k}(t)}{\partial t} &= \beta_{a,r,s,k}(t) \times IC_{a,r,s,k}(t) + \beta^{PrEP} \times PC_{a,r,s,k}(t) \\
&+ \tau \times DA_{a,r,s,k}(t) \\
&+ \mathbb{1}_{a>1} \times \alpha^{H}_{a-1,r,s,k}(t) \times DC_{a-1,r,s,k}(t) \\
&+ \mathbb{1}_{k=active\_use} \times [\zeta_{a,r,s}(t) \times DC_{a,r,s,never\_use}(t) + \xi_{a,r,s}(t) \times DC_{a,r,s,prior\_use}(t)] \\
&\quad + \mathbb{1}_{k=prior\_use} \times \psi_{a,r,s}(t) \times DC_{a,r,s,active\_use}(t) \\
&- \beta_{a,r,s,k}(t) \times DC_{a,r,s,k}(t) \\
&- \theta^{HIV}(t) \times DC_{a,r,s,k}(t) \times [1 - \rho_{a,r,s,k}(t)] - \theta^{G}_{a,r,s,k} \times DC_{a,r,s,k}(t) - \mathbb{1}_{k=active\_use} \times \theta^{IDU} \times DC_{a,r,s,k}(t) \\
&- \alpha^{H}_{a,r,s,k}(t) \times DC_{a,r,s,k}(t) \\
&- DC_{a,r,s,k}(t) \times \left[\mathbb{1}_{k=never\_use} \times \zeta_{a,r,s}(t) + \mathbb{1}_{k=active\_use} \times \psi_{a,r,s}(t) + \mathbb{1}_{k=prior\_use} \times \xi_{a,r,s}(t)\right]
\end{aligned}
$$

7 Running And Calibrating the Model

7.1 Initializing and Running the Model

We initialize the model with population sizes from 2007, and seed three HIV cases, one to each race, in the stratum of MSM aged 35-44yo.

We let the model start running at 1970 with this initial state, and run forward to 2007. From 1970 to 2007, we keep the sizes of each stratum of age × race × sex/sexual behavior constant; the prevalence of HIV and IV drug use states can vary within these strata. (Fixing strata sizes allowed us to avoid having to replicate birth patterns prior to the 2010-2030 time period).

We continue running the model from 2007 to 2030, without the requirement that strata sizes remain constant.

7.2 Calibration Method

To fit our 131 sampled parameters in each MSA, we use Adaptive Metropolis Sampling, a Markov-chain Monte-Carlo technique first described by Haario et. al.[75] We use a variation of algorithm 5 (”componentwise” sampling) in Andrieu et. al,[76] in which we sample blocks of 1 to 6 parameters at a time in a ”blockwise” fashion.

For each iteration of the MCMC, we:

1. Sample the new parameters for the block
2. Run a simulation using the parameters (the new values for parameters in the block, and prior values for parameters not in the block)
3. Compute the likelihood (and prior for the parameters) and accept or reject

7.2.1 Finding Initial Parameter Values

For each location, we developed a set of starting parameter values by manually calibrating transmission rates and age susceptibilities so that the marginal reported diagnoses and prevalence by age, by race, and by risk factor visually approximated the calibration targets. All other parameter values were left at their ”best guess” values (the median for parameters following a Log-normal prior).

Using these starting values, we ran an exploratory, single-chain Adaptive Metropolis Sampling Process for 20,000 iterations with a target acceptance rate of 0.10. We discarded the first 10,000 parameter sets and thinned the remainder to every 20th set, yielding 500 parameter sets. For each parameter value, we calculated a mean and standard deviation on the log scale across the 500 values, as well as correlations with all other parameters. We used the resulting Log-Multivariate-Normal distribution to sample initial parameters for the MCMC runs described below.

7.2.2 Likelihood and Priors

In our deterministic, compartmental model, there is a one-to-one correlation between parameters and simulations. The likelihood function can only be computed on a simulation once it has run. Our log-likelihood is actually the sum of ten independent sub-likelihoods, detailed in Section 8.

The prior distributions for parameters are mostly Log-Normal distributions (a few are Logit-Normal or Uniform), as detailed in Table S2.

7.2.3 MCMC Sampling

For each location, we ran four chains, sampling starting parameter values for each chain from the Log-Multivariate-Normal distribution described above in section 7.2.1. For each chain, we ran 50,000 burn-in iterations followed by 50,000 sampling iterations. We thinned to every 200th iteration, leaving us with a set of 1,000 simulations. We used a target acceptance rate of 0.234.

We assessed for convergence using the split-$\hat{r}$ described in Gelman,[77] as well as visual inspection of trace plots for important or poorly mixing parameters.

8 The Likelihood

Our likelihood decomposes into 10 independent likelihoods for each of the 10 calibration targets: new diagnoses, prevalence, HIV mortality, proportion of PWH aware of their diagnosis, proportion of PWH virally suppressed, number of at-risk individuals receiving prescriptions for emtricitabine/tenofovir, probability of receiving an HIV test, prevalence of injection drug use, historical AIDS mortality (prior to 2002), and historical reported diagnoses (1998-2002).

8.1 Calibrating Model Rates to Observed Data: Binomial Likelihood

In general, for each of our outcome targets, we will use some variation of a binomial likelihood that maps the probability of an outcome in stratum i in a simulation to the number of events in reported data.

$$y_{i,t} \sim Binomial(n_t, p_{i,t}) \tag{6}$$

where

- $y_{i,t}$ is the reported outcome in subgroup i at time t
- n_t is the total population size at time t
- $p_{i,t}$ is the simulated outcomes in subgroup i at time t divided by the simulated total population size at time t

Note that we scale our outcome probabilities - even for a subgroup - relative to the total population. For example, if we were calibrating to the number of reported diagnoses in MSM in 2015, $p_{i,t}$ would be the simulated number of new infections among MSM in 2015 divided by the *total* simulated population in 2015. Similarly, the n_t used in our likelihood represents the *total* population, even when calibrating a subgroup.

Formulating the likelihood in this way allows us to avoid conditioning on subgroup numbers that are not known or known imperfectly. For example, the true number of MSM is not recorded by the US census. While estimates are available, they are imprecise and not stratified by race.

In actuality, we use the Normal approximation to the binomial, which is computationally more efficient and allows us to formulate multivariate likelihoods easily:

$$y_{i,t} \sim Normal\Big(n_t \cdot p_{i,t}, n_t \cdot p_{i,t} \cdot (1 - p_{i,t})\Big) \tag{7}$$

8.2 Mapping Outcomes in Stratified Compartments to Reported Marginal Observations

Our model produces estimates of each outcome in 135 strata per year of age (5 brackets), race (Black, Hispanic, Other), sex/sexual behavior (MSM, heterosexual male, female), and IV drug use (never use, active use, prior use). Calibration targets are rarely reported as fully stratified. To calibrate to marginal data, we use a multivariate likelihood which uses matrix multiplication to aggregate strata into marginal subgroups.

To illustrate, we use a simplified example in which a model partitions the population four strata of age (young vs. old) and sex (male vs. female), but calibrates to marginal outcomes at time t: $y_{young,t}$, $y_{old,t}$, $y_{male,t}$, $y_{female,t}$.

We presume that:

$$\begin{aligned} y_{young,t} &= y_{young,male,t} + y_{young,female,t} \\ y_{old,t} &= y_{old,male,t} + y_{old,female,t} \\ y_{male,t} &= y_{young,male,t} + y_{old,male,t} \\ y_{female,t} &= y_{young,female,t} + y_{old,female,t} \end{aligned}$$

$y_{young,male,t}$, $y_{young,female,t}$, $y_{old,male,t}$, $y_{old,female,t}$ are not actually reported. However, we formulate the likelihood we would use if they were, using an independent, binomial likelihood for each of the four stratified outcomes:

$$\begin{aligned} y_{young,male,t} &\sim Binomial(n_t, p_{young,male,t}) \\ y_{young,female,t} &\sim Binomial(n_t, p_{young,female,t}) \\ y_{old,male,t} &\sim Binomial(n_t, p_{old,male,t}) \\ y_{old,female,t} &\sim Binomial(n_t, p_{old,female,t}) \end{aligned}$$

For computational efficiency and to facilitate multivariate formulation, we use the normal approximation to the binomial:

$$\begin{aligned} y_{young,male,t} &\sim Normal\big(n_t \times p_{young,male,t}, n_t \times p_{young,male,t} \times (1 - p_{young,male,t})\big) \\ y_{young,female,t} &\sim Normal\big(n_t \times p_{young,female,t}, n_t \times p_{young,female,t} \times (1 - p_{young,female,t})\big) \\ y_{old,male,t} &\sim Normal\big(n_t \times p_{old,male,t}, n_t \times p_{old,male,t} \times (1 - p_{old,male,t})\big) \\ y_{old,female,t} &\sim Normal\big(n_t \times p_{old,female,t}, n_t \times p_{old,female,t} \times (1 - p_{old,female,t})\big) \end{aligned}$$

We write this as a multivariate normal distribution with a mean vector corresponding to the four individual means and a diagonal variance-covariance matrix whose diagonal elements are the four individual variances:

$$\boldsymbol{y_t'} = \begin{bmatrix} y_{young,male,t} \\ y_{young,female,t} \\ y_{old,male,t} \\ y_{old,female,t} \end{bmatrix} \sim Multivariate\text{-}Normal(\boldsymbol{\mu_t}, \boldsymbol{\Sigma_t}) \tag{8}$$

Next, we formulate a matrix, $\boldsymbol{M}$, that maps from the unobserved, stratified outcomes to the marginal outcomes which we do observe:

$$\boldsymbol{y_t} = \begin{bmatrix} y_{young,t} \\ y_{old,t} \\ y_{male,t} \\ y_{female,t} \end{bmatrix} = \begin{bmatrix} 1 & 1 & 0 & 0 \\ 0 & 0 & 1 & 1 \\ 1 & 0 & 1 & 0 \\ 0 & 1 & 0 & 1 \end{bmatrix} \begin{bmatrix} y_{young,male,t} \\ y_{young,female,t} \\ y_{old,male,t} \\ y_{old,female,t} \end{bmatrix} = \boldsymbol{M_t} \begin{bmatrix} y_{young,male,t} \\ y_{young,female,t} \\ y_{old,male,t} \\ y_{old,female,t} \end{bmatrix} = \boldsymbol{M_t y_t'} \tag{9}$$

Using this matrix, we can map the likelihood over the unobserved, stratified outcomes to a likelihood over the observed, marginal outcomes:

$$\boldsymbol{y_t} \sim Multivariate\text{-}Normal\big(\boldsymbol{M_t \mu_t}, \boldsymbol{M \Sigma_t M_t^T}\big) \tag{10}$$

This formulation preserves the correlations induced by calibrating to marginal outcomes. For example, if a simulation over-estimated the young, male stratum, we would expect the overestimation of both the total young and overestimation of the total male to be related.

We can extend this approach to formulate a matrix $\boldsymbol{M}$ that maps our 135 strata to any set of marginal outcomes. We can map to two-level marginals (e.g., new diagnoses reported by sex and age bracket).

We can also extend this approach across multiple years by assuming that the errors in any one year are independent of other years:

$$\boldsymbol{y} = \begin{bmatrix} \boldsymbol{y_{t1}} \\ \boldsymbol{y_{t2}} \\ \vdots \\ \boldsymbol{y_{tT}} \end{bmatrix} \sim Multivariate\text{-}Normal\big(\boldsymbol{M\mu}, \boldsymbol{M\Sigma M}^T\big) \tag{11}$$

where

- T is the number of years we include
- $\boldsymbol{\mu} = \begin{bmatrix} \boldsymbol{\mu_{t1}} \\ \boldsymbol{\mu_{t2}} \\ \vdots \\ \boldsymbol{\mu_{tT}} \end{bmatrix}$
- $\boldsymbol{M} = \begin{bmatrix} \boldsymbol{M_{t1}} & \boldsymbol{0} & \dots & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{M_{t2}} & \dots & \boldsymbol{0} \\ \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{0} & \boldsymbol{0} & \dots & \boldsymbol{M_{tT}} \end{bmatrix}$
- $\boldsymbol{\Sigma} = \begin{bmatrix} \boldsymbol{\Sigma_{t1}} & \boldsymbol{0} & \dots & \boldsymbol{0} \\ \boldsymbol{0} & \boldsymbol{\Sigma_{t2}} & \dots & \boldsymbol{0} \\ \vdots & \vdots & \ddots & \vdots \\ \boldsymbol{0} & \boldsymbol{0} & \dots & \boldsymbol{\Sigma_{tT}} \end{bmatrix}$

8.3 Incorporating Measurement Error

The formulation described in Section 8.2 above captures error that stems from the degree to which model simulations depart from reported outcomes. However, we also consider that reported outcomes are imperfect measures of a "true" outcome, and adjust our likelihoods accordingly. For this formulation, we introduce $y^*_{i,t}$ - the true (unobserved) outcome for subgroup i at time t, and use it to decomponse the relationship between $y_{i,t}$ - the reported outcome - and simulated outcomes.

For every subgroup i and time t, we write:

$$y_{i,t} = y^*_{i,t} + Bias_{i,t} + \epsilon_{i,t} \tag{12}$$

- $y_{i,t}$ is the reported (measured) outcome for subgroup i at time t to which we calibrate
- $y^*_{i,t}$ is the true (unobserved) outcome
- $Bias_{i,t}$ represents the bias. We set this term to zero for most reported outcomes. However, some outcomes are expected to differ systematically from the truth. For example, with respect to HIV mortality, it is known that a small proportion of deaths in PWH are not reported to the National Death Index.[78,79]
- $\epsilon_{i,t}$ The measurement error for outcome $y_{i,t}$

We can vectorize Equation 12

$$\boldsymbol{y} = \boldsymbol{y^*} + \boldsymbol{Bias} + \boldsymbol{\epsilon} \tag{13}$$

We let

$$\boldsymbol{Bias} \sim Multivariate\text{-}Normal\Big(\boldsymbol{B}, \boldsymbol{\Sigma_B}\Big) \tag{14}$$

$$\boldsymbol{\epsilon} \sim Multivariate\text{-}Normal\Big(\boldsymbol{0}, \boldsymbol{\Sigma_\epsilon}\Big) \tag{15}$$

And we replace $\boldsymbol{y}$ in Equation 11 with $\boldsymbol{y^*}$:

$$\boldsymbol{y^*} \sim Multivariate\text{-}Normal\big(\boldsymbol{M\mu}, \boldsymbol{M\Sigma M}^T\big) \tag{16}$$

We can combine Equations 14, 15, and 16 to yield a likelihood that incorporates different sources of error: the degree to which the model deviate from the truth, measurement error of reported outcomes, and bias.

$$\boldsymbol{y} \sim Multivariate\text{-}Normal\Big(\boldsymbol{M\mu} + \boldsymbol{B}, \boldsymbol{M\Sigma M}^T + \boldsymbol{\Sigma_B} + \boldsymbol{\Sigma_\epsilon}\Big) \tag{17}$$

8.3.1 Correlated Measurement Errors

We also allow for measurement errors and bias to be correlated over time. For example, if estimated prevalent HIV cases among MSM are overestimated in 2015, they are likely to be overestimated in 2016 and 2017 when using the same methods.[80] To represent these correlations, we decompose $\boldsymbol{\Sigma_\epsilon}$ and $\boldsymbol{\Sigma_B}$ into a vector of standard deviations, $\boldsymbol{\sigma}$ and a correlation matrix, $\boldsymbol{\Lambda}$:

$$\boldsymbol{\Sigma_\epsilon} = \boldsymbol{\sigma_\epsilon \Lambda_\epsilon \sigma_\epsilon^T} \tag{18}$$

$$\boldsymbol{\Sigma_B} = \boldsymbol{\sigma_B \Lambda_B \sigma_B^T} \tag{19}$$

In most cases, we give $\boldsymbol{\Lambda_\epsilon}$ and $\boldsymbol{\Lambda_B}$ a compound symmetry (AKA exchangeable) structure:

$$\Lambda_{ij} = \begin{cases} 1 & \text{if } i = j \\ \rho & \text{if } i \neq j \end{cases} \tag{20}$$

In general we formulate the standard deviations, σ using a coefficient of variance: $\sigma_{i,t} = y_{i,t} \times cv_{i,t}$. We estimate the coefficients of variance and correlation parameters based off of reported data where possible.

8.4 Reported Diagnoses 2008-2018

8.4.1 Calibration Targets

We calibrate to reported diagnoses from 2008-2018 as reported by the CDC in HIV Atlas[16] and Metropolitan Statistical Area Reports.[66–72] We fit to total as well as stratified data when available (the years 2010,2011, and 2013-2017):

- Total diagnoses for all years 2008-2018
- Stratified by age × sex for 2010, 2011, and 2013-2017
- Stratified by race × sex for 2010, 2011, and 2013-2017
- Stratified by risk factor × sex for 2010, 2011, and 2013-2017
- Stratified by race × risk factor for 2010, 2011, and 2013-2017

When the sum of stratified diagnoses from MSA reports did not equal the reported total diagnoses from HIV Atlas, we scaled the stratified diagnoses such that they summed to the total, but maintained the relative proportions of the MSA report.

8.4.2 Measurement Error

Because HIV Atlas estimates differed from those in the MSA reports, we were able to estimate the standard deviations of measurement errors by treating the HIV Atlas estimates as truth and the MSA reports as a measured quantity. We formulated the standard deviation as a coefficient of variance multiplied by the estimate, and derived a frequentist maximum likelihood estimate of 0.065 for the coefficient of variance.

Because there was a change in the method of reporting from 2014 to 2015, we assumed that 2008-2014 errors were strongly correlated with a correlation of 0.65, as were 2015-2018 errors, but that errors from the years 2008-2014 had a weaker correlation of 0.25 with errors from 2015-2018.

8.4.3 Likelihood Formulation

Using the error terms above, we formulated a multivariate normal likelihood based off of a binomial (Section 8.1) with a mapping to account for correlations between overlapping strata (Section 8.2) and correlated measurement errors (Section 8.3.1) using the error terms described above.

8.4.4 Variance Inflation

To improve parameter mixing in the MCMC, we inflate the variances for this likelihood by a factor of 4.

8.5 Estimated Prevalence 2008-2018

8.5.1 Calibration Targets

We calibrate to the estimated prevalence (of those aware of their diagnosis) from 2008-2018 as reported by the CDC in HIV Atlas[16] and Metropolitan Statistical Area Reports.[66–72] We fit to total as well as stratified data when available (the years 2009, 2010, and 2012-2016):

- Total diagnoses for all years 2008-2018
- Stratified by age × sex for 2009, 2010, and 2012-2016
- Stratified by race × sex for 2009, 2010, and 2012-2016
- Stratified by risk factor × sex for 2009, 2010, and 2012-2016
- Stratified by race × risk factor for 2009, 2010, and 2012-2016

When the sum of stratified prevalence from MSA reports did not equal the reported total prevalence from HIV Atlas, we scaled the stratified prevalences such that they summed to the total, but maintained the relative proportions of the MSA report.

8.5.2 Measurement Error

As with reported diagnoses, we were able to estimate the standard deviations of measurement errors by treating the HIV Atlas estimates as truth and the MSA reports as a measured quantity. We formulated the standard deviation as a coefficient of variance multiplied by the estimate, and derived a frequentist maximum likelihood estimate of 0.09 for the coefficient of variance.

Because there was a change in the method of reporting from 2014 to 2015, we assumed that 2008-2013 errors were strongly correlated with a correlation of 0.65, as were 2014-2018 errors, but that errors from the years 2008-2013 had a weaker correlation of 0.25 with errors from 2014-2018.

8.5.3 Likelihood Formulation

As with reported diagnoses, we formulated a multivariate normal likelihood based off of a binomial (Section 8.1) with a mapping to account for correlations between overlapping strata (Section 8.2) and correlated measurement errors (Section 8.3.1) using the error terms described above.

8.5.4 Variance Inflation

To improve parameter mixing in the MCMC and to prevent the likelihood for prevalence from dominating the likelihood for reported diagnoses (prevalence has a much larger p than reported diagnoses, so a much smaller binomial variance), we inflate the variances for this likelihood by a factor that is equal to the square-root of the average total prevalence from 2010-2018 divided by the square-root of the average number of reported diagnoses from 2010-2018.

8.6 Mortality in PWH 2009-2016

8.6.1 Calibration Targets

We calibrate to the mortality among PWH aware of their diagnosis in 2009, 2010, and 2012-2016 as reported by the CDC in Metropolitan Statistical Area Reports.[66–72] We fit to total mortality as well as mortality stratified by sex.

8.6.2 Measurement Error

We took the standard deviation to be a product of the coefficient of variance and the mortality estimate. We used the same coefficient of variance calculated for prevalence (0.09), as well as correlation coefficients (0.65 for 2009-2013 errors with 2009-2013 errors, 0.65 for 2014-2016 errors with 2014-2016 errors, and 0.25 for 2009-2013 errors with 2014-2016 errors).

8.6.3 Bias

Because a small proportion of deaths in PWH are not captured by the National Death Index,[78,79] we presumed that mortality was biased down by 2.6% with a standard deviation of 1.3%.[78,79]

8.6.4 Likelihood Formulation

We formulate a multivariate normal likelihood analagous to the likelihood for reported diagnoses and mortality, with the addition of the bias term as outlined in Section 8.3.

8.6.5 Variance Inflation

To improve parameter mixing in the MCMC, we inflate the variances for this likelihood by a factor of 2.

8.7 Awareness of Diagnosis Among PWH 2010-2018

8.7.1 Calibration Targets

We calibrate to the proportion of PWH who are aware of their disease. For five MSAs (Houston-The Woodlands-Sugar Land, TX; Los Angeles-Long Beach-Anaheim, CA; Memphis, TN-MS-AR; New York-Newark-Jersey City, NY-NJ-PA; Seattle-Tacoma-Bellevue, WA) estimates of the proportion aware for at least 3 years from 2010-2018 were publicly available from local public health websites. For the remaining 27 MSAs, we used the state-level estimates of proportion aware of their diagnoses available through HIV Atlas.[16] For MSAs that spanned multiple states, we calibrated to the weighted average of the proportion aware, where weights were the population within in the MSA that falls into each state from 2010-2018.

8.7.2 Formulation of Binomial Likelihood Component

For each year t, we postulated that:

$$y_t \sim Binomial(\frac{y_t}{\pi_t}, p_t) \tag{21}$$

where:

- y_t is the prevalence of PWH aware of their diagnosis in year t as reported by the CDC
- π_t represents our calibration target, the proportion of PWH aware of their diagnosis in year t as reported by the CDC or local health department
- $\frac{y_t}{\pi_t}$ is the estimated number of all PWH (both those aware and unaware of their diagnosis) in year t
- p_t is the simulated proportion of PWH aware of their diagnosis in year t

In order to generalize to a multivariate likelihood, we used the normal approximation to the binomial:

$$y_t \sim Normal\Big(\frac{y_t}{\pi_t} \cdot p_t, \frac{x_t}{\pi_t} \cdot p_t \cdot (1 - p_t)\Big) \tag{22}$$

8.7.3 Measurement Error

We included a measurement error as described in section 8.3.1. We assumed that the reported proportion of PWH aware of their diagnosis had a standard deviation of 0.005 when based on county- or MSA-level data data, and a standard deviation of 0.015 when based on state-level data.

We furthermore presumed that measurement errors were correlated across time, using a compound symmetry correlation structure with $\rho = 0.5$

8.7.4 Likelihood Formulation

We incorporated the Binomial component and measurement error into a multivariate normal likelihood as described in 8.2.

8.7.5 Variance Inflation

To improve parameter mixing in the MCMC, we inflate the variances for this likelihood by a factor of 8.

8.8 Viral Suppression Among PWH 2010-2018

The likelihood for suppression had two independent components: a multivariate-normal component targeting the reported proportion of PWH who were suppressed, and a Bernoulli component to weight whether suppression was increasing or decreasing.

8.8.1 Calibration Targets

We calibrated to the proportion of PWH who were suppressed, as reported on local health department websites, for all years between 2010 and 2018 where data were available. If multiple jurisdictions within an MSA reported proportions, we took the weighted average. If no data was available at the county- or MSA-level we used state-level proportions. A total proportion suppressed was available for all 32 MSAs; we also included estimates stratified by age, by race, by sex, and by HIV-acquisition risk factor if they were available.

8.8.2 Binomial Likelihood Component

We formulated a multivariate-normal approximation to a Binomial likelihood, similar to the one detailed in Section 8.1 with the exceptions that (1) the response was the CDC-reported prevalence of HIV multiplied by the reported proportion suppressed and (2) that the n was the simulated prevalence of diagnosed HIV instead of the total population. We used the matrix mapping described in Section 8.2 to account for correlations in overlapping stratifications.

8.8.3 Measurement Error

We included a measurement error as described in section 8.3.1. We assumed that the reported proportion of PWH aware of their diagnosis had a standard deviation of 0.01 when based on county- or MSA-level data data, and a standard deviation of 0.03 when based on state-level data.

We furthermore presumed that measurement errors were correlated across time, using a compound symmetry correlation structure with $\rho = 0.5$

8.8.4 Multivariate Normal Likelihood Formulation

We incorporated the Binomial component and measurement error into a multivariate normal likelihood as described in 8.2.

8.8.5 Bernoulli Likelihood for Increasing vs. Decreasing Suppression

In general, suppression is increasing or stable over time in most locations across most subgroups. In order to discourage solutions where one race or age subgroup had decreasing suppression over time but total suppression followed overall trends (which was possible in locations where stratified data on suppression were unavailable), we also included a Bernoulli likelihood. This likelihood specified that the probability that, for each stratum of age, race, sex, and IV drug use, the probability that simulated suppression had a decreasing slope on the logit scale was 0.05 (which we estimated from the average number of reported suppressed proportions that decreased from one year to the next in all locations and all stratifications for which we had data). ie:

$$\prod_{a,r,s,k} 0.05^{\text{suppression in stratum } a,r,s,k \text{ is decreasing}} \times 0.95^{\text{suppression in stratum } a,r,s,k \text{ is not decreasing}} \tag{23}$$

8.9 Pharmacy Fills of Prescriptions for PrEP 2012-2018

8.9.1 Calibration Targets

We calibrated to the number of prescriptions for Emtricitabine/Tenofovir for use as PrEP from 2012 to 2018, as reported by AIDSVu.[73] We used both total numbers as well as numbers stratified by age and by sex (although, due to data suppression rules, stratified estimates were sometimes missing).

8.9.2 Differences between Model Representation and Reported Data

The concept of PrEP in our model differs from the data reported by AIDSVu in a number of ways, and our likelihood has to make adjustments for these discrepancies.

Our model simulations produce a proportion of at-risk individuals who are currently enrolled in a PrEP program (since most prescriptions for PrEP are written on a 3-month basis, we take this to correspond to a prescription in the past 3 months).

The AIDSVu data report the number of individuals who filled at least one prescription for emtricitabine/tenofovir in the past year, and who were not using it (as judged by a validated algorithm[81]) for treatment of HIV infection or viral hepatitis. Pharmacy records come from a commercial dataset that captures 83% of prescriptions nationally.[82]

This introduces several discrepancies:

1. Not all individuals who have a prescription for PrEP will be captured in the dataset
2. Some individuals who take emtricitabine/tenofovir for indications other than PrEP (HIV treatment, viral hepatitis) will be incorrectly classified as taking it for PrEP

3. Not all individuals who filled a PrEP prescription in the past year will have filled in the past 3 months (ie, have an "active" prescription)

8.9.3 Adjusting the Calibration Target to Account for Discrepancies

We mapped our model output to the calibration target - the number of pharmacy fills for emtricitabine/tenofovir - using four adjustment factors, as follows:

$$y_i' = y_i \times \frac{\pi \cdot \phi \cdot \rho}{\theta} \tag{24}$$

where:

- $y_{i,t}$ Represents the reported number of pharmacy fills in the past year for a stratum i at time t t
- $y_{i,t}'$ Represents our adjusted response - the number of individuals on PrEP at time t
- π denotes the proportion of emtricitabine/tenofovir prescriptions classified as for PrEP that are truly for PrEP and not some other indication (the positive predictive value of the algorithm)
- ρ denotes the ratio of the number of people with a pharmacy fill in the past three months to the number of people with a pharmacy fill in the past year
- θ denotes the proportion of pharmacy fills that are captured in the dataset

As each of the four adjustment factors is itself uncertain, we represented each with a Lognormal distribution:

$$\begin{aligned}
Ln(\pi) &\sim Normal(\pi_0', \sigma_\pi'^2)\\
Ln(\rho) &\sim Normal(\rho_0', \sigma_\rho'^2)\\
Ln(\theta) &\sim Normal(\theta_0', \sigma_\theta'^2)
\end{aligned}$$

We derived estimates of the mean and variance for each of the factors from the literature (Table S3 below). We converted these to the mean and distribution of a Lognormal distribution using the approximation that the log-sd is approximately equation to the coefficient of variance:

$$\begin{aligned}
\pi_0' &= Ln(\pi_0)\\
\sigma_\pi' &= \frac{\sigma_\pi}{\pi_0}
\end{aligned}$$

where π_0 is the mean and σ_π is the standard deviation for π (NOT on the log scale), with analagous calculations for ρ and θ.

This formulation allowed us to articulate a Lognormal distribution for $y_{i,t}'$ - the number of people on PrEP at time t - that is a function of our reported calibration target - $y_{i,t}$ - and the adjustment factors:

$$\begin{aligned}
Ln(y_{i,t}') &= Ln(y_{i,t}) + Ln(\pi) + Ln(\phi) + Ln(\rho) - Ln(\theta) &(25)\\
&\sim Normal\Big(Ln(y_{i,t}) + \pi_0' + \rho_0' - \theta_0', \sigma_\pi'^2 + \sigma_\rho'^2 + \sigma_\theta'^2\Big) &(26)
\end{aligned}$$

We used approximations to give $y_{i,t}'$ a Normal distribution that will allow us to more easily fold it into a multivariate likelihood, with mean and variance:

$$\begin{aligned}
E\big[y_{i,t}'\big] &= y_{i,t} \times \frac{\pi \cdot \rho}{\theta}\\
Var\big[y_{i,t}'\big] &= \big(\sigma_\pi'^2 + \sigma_\rho'^2 + \sigma_\theta'^2\big) \times E\big[y_{i,t}'\big]
\end{aligned}$$

We imposed a correlation in the effects of these factors across time, by defining the vector $\boldsymbol{y_i'}$ of all $y'i,t$ to have a compound symmetry matrix with correlation coefficient of 0.5.

Table S3: Means and Standard Deviations of PrEP Likelihood Adjustment Factors

Adjustment Factor	Mean	Standard Deviation	Reference
Proportion of prescriptions correctly classified as PrEP (π)	0.901	0.035	MacCannell 2015[81]
Ratio of PrEP within 3mo to PrEP within 1yr (ρ)	0.523	0.038	Siegler 2018,[83] AIDSVu[73]
Proportion of pharmacy fills captured in dataset (θ)	0.83	0.05	Sullivan 2018[82]

8.9.4 Measurement Error

On top of the adjustments mapping pharmacy fills to enrollment in a PrEP program, we allowed for the reported pharmacy fills to have a measurement error standard deviation equal to $\sqrt{y_{i,t}}$. This is based on the assumption that the observed number of pharmacy fills follows a binomial distribution, and when p is small, the variance of a binomial distribution $n \cdot p \cdot (1-p) \approx n \cdot p$.

8.9.5 Adjusting the probability of taking PrEP to Account for who is 'At-Risk' for HIV

We postulated that the number of people on PrEP, $y'_{i,t}$, followed a binomial distribution. We took the whole population to be the n of the binomial, which required that the p be the probability of being at risk for HIV AND being on PrEP.

Our model simulations output a probability of being on PrEP for those at risk for acquiring HIV. We multiplied this probability by the probability of being at risk for acquiring HIV to get the overall p for the binomial distribution.

We estimated the proportion at risk for acquiring HIV by calculating the proportion of MSM, PWID, and heterosexuals who meet CDC criteria for PrEP[84] for each stratum of age and race from NHBS surveillance reports (Tables S4, S5, S6).[19,22,42] For MSM and heterosexuals, we multiplied this by the proportion in each age bracket who are sexually active (Table S7).

We used the normal approximation to the binomial to formulate these as a multivariate normal, as described in Section 8.2. Because the proportion indicated for PrEP in a location is likely correlated from year to year, we imposed an autoregressive correlation structure on the distribution with a $\rho = 0.9$.

Table S4: Estimated Proportion of Sexually Active MSM with Indication for PrEP*

	Black	Hispanic	Other
13-24 years	0.363	0.416	0.476
25-34 years	0.429	0.492	0.562
35-44 years	0.420	0.482	0.551
45-54 years	0.370	0.424	0.485
55+ years	0.305	0.350	0.401

*Estimated as the proportion reporting condomless sex with a casual partner from the 2017 NHBS Report[42]

Table S5: Estimated Proportion of PWID with Indication for PrEP*

	Black	Hispanic	Other
13-24 years	0.606	0.703	0.831
25-34 years	0.593	0.689	0.814
35-44 years	0.566	0.656	0.776
45-54 years	0.502	0.582	0.688
55+ years	0.419	0.486	0.575

*Estimated as the proportion reporting needle-sharing from the 2018 NHBS Report[19]

Table S6: Estimated Proportion of Heterosexuals with Indication for PrEP*

	Black	Hispanic	Other
13-24 years	0.1305	0.0611	0.0595
25-34 years	0.1225	0.0574	0.0558
35-44 years	0.0641	0.0300	0.0292
45-54 years	0.0538	0.0252	0.0245
55+ years	0.0435	0.0204	0.0198

*Estimated as the proportion reporting a recent STI in the 2016 NHBS Report[22]

Table S7: Estimated Proportion of Individuals Who Are Sexually Active, by Age and Race

	Female	Male
13-24 years	0.659	0.626
25-34 years	0.975	0.953
35-44 years	0.986	0.977
45-54 years	0.987	0.982
55+ years	0.390	0.656

Proportions for 13-54 year olds derived from Mosher 2005,[85] for 55+ from Lindau 2007[33]

8.9.6 Likelihood Formulation

We combined these three elements - a multivariate normal deriving from the adjustment factors, a multivariate normal encapsulating the measurement errors, and a multivariate normal approximation of the binomial by adding the mean vectors and covariance matrices.

8.9.7 Variance Inflation

To improve parameter mixing in the MCMC, we inflated the variances for this likelihood by a factor of 2.

8.10 Receipt of HIV Test 2013-2017

8.10.1 Calibration Targets

We calibrated testing rates to several targets:

1. The total proportion of individuals reporting ever taking an HIV test in the MSA in 2013, 2014, 2016, and 2017, as reported by the Behavioral Risk Factor Surveillance System (BRFSS)[43]
2. The relative likelihood (odds ratio) by race/ethnicity of reporting ever receiving a test at the state level for Black vs. Non-Black/Non-Hispanic and Hispanic vs. Non-Black/Non-Hispanic as reported by BRFSS.
3. The relative likelihood (odds ratio) by sex of reporting ever receiving a test at the state level (female vs. male) as reported by BRFSS.
4. The relative likelihood (odds ratio) by age of reporting ever receiving a test at the state level for 13-24 vs 35-44 years, 25-34 vs 35-44 years, 45-54 vs 35-44 years, and 55+ vs 35-44 years as reported by BRFSS.

We presumed each of these targets to follow an independent likelihood, which we combined

8.10.2 Likelihood Component for Total Proportion Ever Tested

The portion of the likelihood which calibrated to the total proportion of individuals reporting ever taking an HIV test incorporated three sources of uncertainty:

1. The uncertainty in relating our simulated parameter - the rate of testing in subgroups - to a proportion ever tested
2. A binomial component which captures the uncertainty in mapping from model simulations to observed calibration targets
3. Measurement error in the observed calibration targets

We describe these three components in the next three paragraphs.

8.10.3 Mapping Model Testing Rates to Proportion Ever Tested

Our model simulations produce rates of testing for each compartment, which we needed to map to the probability of ever receiving an HIV test.

We first translated the testing rate for stratum i at time t, $r_{i,t}$, to the probability of receiving a test in the past year, $p_{i,t}$, under the assumption that testing follows a Poisson process:

$$p_{i,t} = 1 - e^{-r_{i,t}} \tag{27}$$

We related the probability of receiving a test in the past year to the probability of ever receiving a test under the following model:

$$Ln(1 - p_{i,t}^{ever}) = \sim Normal\big(\beta \cdot Ln(1 - p_{i,t}), \sigma^2\big) \tag{28}$$

which postulates that the log-probability of never receiving a test is proportional to the log probability of not receiving at test in the past year. We fit this model using data from NHBS surveys from 2011-2018,[19,22,37–42] which reported both the proportion ever receiving a test and the proportion receiving a test in the past year in 23 US metropolitan statistical areas, yielding $\beta = 2.49$, $\sigma = 0.046$.

Combining equations 27 and 28 yields:

$$Ln\big(1 - p_{i,t}^{ever}\big) \sim Normal\big(\beta \cdot r_{i,t}, \sigma'^2\big) \tag{29}$$

By the properties of the log-normal distribution, we have

$$E\big[1 - p_{i,t}^{ever}\big] = \mu_{i,t} = e^{\beta r_{i,t} \cdot \frac{\sigma'^2}{2}} \tag{30}$$

$$Var\big(1 - p_{i,t}^{ever}\big) = \sigma_{i,t}^2 = \big(e^{\sigma'^2} - 1\big) \cdot e^{2\beta r_{i,t} + \sigma'^2} \tag{31}$$

For feasibility integrating with other components in the likelihood, we approximated this Log-normal for $1 - p_i^{ever}$ distribution by a Normal distribution:

$$1 - p_{i,t}^{ever} \sim Normal\big(\mu_{i,t}, \sigma_{i,t}^2\big) \tag{32}$$

$$p_{i,t}^{ever} \sim Normal\big(1 - \mu_{i,t}, \sigma_{i,t}^2\big) \tag{33}$$

8.10.4 Binomial Likelihood Component for Total Proportion Ever Tested

We defined $\hat{p}_{i,t}$ to be the 'true' proportion of individuals in stratum i ever tested for HIV at time t, and formulated a binomial likelihood in terms of $p_{i,t}^{ever}$:

$$n_{i,t} \cdot \hat{p}_{i,t} | p_{i,t}^{ever} \sim Binomial\big(n_{i,t}, p_{i,t}^{ever}\big) \tag{34}$$

Where $n_{i,t}$ is the simulated size of stratum i at time t.

Using a normal approximation to the binomial gives us:

$$n_{i,t} \cdot \hat{p}_{i,t} \sim Normal\big(n_{i,t} \cdot p_{i,t}^{ever}, n_{i,t} \cdot p_{i,t}^{ever} \cdot (1 - p_{i,t}^{ever})\big) \tag{35}$$

To correspond to the observed total proportion ever tested, we summed across strata:

$$n_t \cdot \hat{p}_t = \sum_i n_{i,t} \cdot \hat{p}_{i,t} \sim Normal\Big(\sum_i n_{i,t} \cdot p_{i,t}^{ever}, \sum_i n_{i,t} \cdot p_{i,t}^{ever} \cdot (1 - p_{i,t}^{ever})\Big) \tag{36}$$

$$\hat{p}_t \sim Normal\left(\frac{\sum_i n_{i,t} \cdot p_{i,t}^{ever}}{n_t}, \frac{\sum_i n_{i,t} \cdot p_{i,t}^{ever} \cdot (1 - p_{i,t}^{ever})}{n_t^2}\right) \tag{37}$$

$$\tag{38}$$

where $n_t = \sum_i n_{i,t}$

8.10.5 Measurement Error for Total Proportion Ever Tested

We calibrated to the reported proportion ever tested for HIV at a given time t for each MSA, which we denote p_t^{obs}.

We postulated that this is a noisy measurement of the true proportion ever tested, $\hat{p}_t$:

$$p_t^{obs} | \hat{p}_t \sim Normal(\hat{p}_t, \tau^2) \tag{39}$$

Where τ^2 comes from the Wald interval for the sample data, ie:

$$\tau^2 = n_t^{obs} \cdot p_t^{obs} \cdot (1 - p_t^{obs}) \tag{40}$$

We vectorized the observed probabilities, and allowed the measurement errors to be correlated across the resulting multivariate normal distribution:

$$\boldsymbol{p^{obs}} \sim Multivariate\text{-}Normal\big(\boldsymbol{\hat{p}}, \boldsymbol{\tau \Gamma \tau}^T\big) \tag{41}$$

Where $\boldsymbol{\Gamma}$ is a compound symmetry (exchangeable) correlation matrix with $\rho = 0.5$

8.10.6 Likelihood Components for Odds Ratios of Ever-Testing by Sex, Age, and Race

We included three likelihood components for the odds ratios of ever receiving a test by sex, age, and race at the state level. These include two sources of uncertainty: measurement error for the reported proportion ever tested, and a binomial error mapping the simulated outputs to observed data.

8.10.7 Binomial Component for Odds Ratios

In general, we wanted to compare the proportion ever receiving an HIV test in two subgroups (which we denote 1 and 2) at time t.

We defined $\bar{p}_{1,t}$ to be the estimated proportion ever tested in subgroup 1 and $\bar{p}_{2,t}$ to be the estimated proportion ever tested in subgroup 2 at time t, and assigned them a binomial distribution:

$$\bar{p}_{1,t} \cdot n_{1,t} \sim Binomial(n_{1,t}, \bar{\mu}_{1,t}) \tag{42}$$

$$\bar{p}_{2,t} \cdot n_{2,t} \sim Binomial(n_{2,t}, \bar{\mu}_{2,t}) \tag{43}$$

$$\tag{44}$$

Where we formulated $\bar{\mu}_{1,t}$ and $\bar{\mu}_{2,t}$ using the quantity $\mu_{i,t}$ defined in Section 8.10.3, equation 30,

$$\bar{\mu}_{1,t} = 1 - \frac{\sum_i \mu_{i,t} \cdot n_{i,t} \cdot \mathbb{1}_{i \in \text{subgroup 1}}}{\sum_i n_i \cdot \mathbb{1}_{i \in \text{subgroup 1}}} \tag{45}$$

$$\bar{\mu}_{2,t} = 1 - \frac{\sum_i \mu_{i,t} \cdot n_{i,t} \cdot \mathbb{1}_{i \in \text{subgroup 2}}}{\sum_i n_i \cdot \mathbb{1}_{i \in \text{subgroup 2}}} \tag{46}$$

Using the normal approximation to tbe binomial gives us:

$$\bar{p}_{1,t} \cdot n_{1,t} \sim Normal\Big(n_{1,t} \cdot \bar{\mu}_{1,t}, n_{1,t} \cdot \bar{\mu}_{1,t} \cdot (1 - \bar{\mu}_{1,t})\Big) \tag{47}$$

$$\bar{p}_{1,t} \sim Normal\left(\bar{\mu}_{1,t}, \frac{\bar{\mu}_{1,t} \cdot (1 - \bar{\mu}_{1,t})}{n_{1,t}}\right) \tag{48}$$

$$\bar{p}_{2,t} \sim Normal\left(\bar{\mu}_{2,t}, \frac{\bar{\mu}_{2,t} \cdot (1 - \bar{\mu}_{2,t})}{n_{2,t}}\right) \tag{49}$$

$$\tag{50}$$

We used the delta method to derive a distribution for the log odds ratio:

$$Ln\big(\bar{OR}_{12,t}\big) = Ln\left(\frac{\bar{p}_{1,t}}{1 - \bar{p}_{1,t}} \cdot \frac{1 - \bar{p}_{2,t}}{\bar{p}_{2,t}}\right) \sim Normal\left(Ln\left(\frac{\bar{\mu}_{1,t}}{1 - \bar{\mu}_{1,t}} \cdot \frac{1 - \bar{\mu}_{2,t}}{\bar{\mu}_{2,t}}\right), \gamma^2_{12,t}\right) \tag{51}$$

where

$$\gamma^2_{12,t} = \frac{\bar{\mu}_{1,t} \cdot (1 - \bar{\mu}_{1,t})}{n_{1,t}} \times \left(\frac{1}{\bar{\mu}_{1,t}} - \frac{1}{1 - \bar{\mu}_{1,t}}\right)^2 + \frac{\bar{\mu}_{2,t} \cdot (1 - \bar{\mu}_{2,t})}{n_{2,t}} \times \left(\frac{1}{\bar{\mu}_{2,t}} - \frac{1}{1 - \bar{\mu}_{2,t}}\right)^2 \tag{52}$$

8.10.8 Measurement Error for Odds Ratios

We defined our response, $OR_{12,t}$, as the odds ratio of the reported proportions ever tested in subgroups 1 and 2 at time t (denoted $p^{obs}_{1,t}$ and $p^{obs}_{2,t}$):

We gave the log odds ratio derived from $\bar{p}_{1,t}$ and $\bar{p}_{2,t}$ a normal distribution centered at $\bar{OR}_{12,t}$ as defined above:

$$Ln\big(OR_{12,t}\big) \sim Normal\big(\bar{OR}_{12,t}, \sigma^2_{12,t}\big) \tag{53}$$

$\sigma_{12,t}$ is the standard deviation of the log odds ratio calculated from the sample:

$$\sigma_{12,t} = \sqrt{\frac{1}{p^{obs}_{1,t} \cdot n^{obs}_{1,t}} + \frac{1}{(1 - p^{obs}_{1,t}) \cdot n^{obs}_{1,t}} + \frac{1}{p^{obs}_{2,t} \cdot n^{obs}_{2,t}} + \frac{1}{(1 - p^{obs}_{2,t}) \cdot n^{obs}_{1,t}}} \tag{54}$$

We allowed measurement errors to be correlated over time by vectorizing, and using a multivariate-normal distribution:

$$\boldsymbol{Ln\big(OR_{12}\big)} \sim Multivariate\text{-}Normal\big(\boldsymbol{\bar{OR}_{12}}, \boldsymbol{\sigma_{12,t}\Gamma\sigma^T_{12,t}}\big) \tag{55}$$

where Γ is a compound symmetry correlation matrix with $\rho = 0.5$.

8.10.9 Variance Inflation

To improve parameter mixing in the MCMC, we inflate the variances for this likelihood by a factor of 64.

8.11 Injection Drug Use 2014-2016

8.11.1 Calibration Targets

We calibrated simulated IV drug use to four targets each for active use and prior use, drawn from the NSDUH 2014-2016:[36]

1. The total prevalence of active IV drug use, calculated as the NSDUH substate estimate for heroin use in the past year multiplied by the national ratio of use of any injection drug within 30 days to use of heroin within the past year
2. The total prevalence of prior IV drug use, calculated as the NSDUH substate estimate for heroin use in the past year multiplied by the national ratio of use of any injection drug more than 30 days prior to use of heroin within the past year
3. The odds ratio of the prevalence of drug use within 30 days for Black vs. non-Black/non-Hispanic and non-Black/non-Hispanic, based on national NSDUH surveys
4. The odds ratio of the prevalence of drug use more than 30 days prior for Black vs. non-Black/non-Hispanic and non-Black/non-Hispanic, based on national NSDUH surveys
5. The odds ratio of the prevalence of drug use within 30 days for female vs. heterosexual male and MSM vs. heterosexual male, based on national NSDUH surveys
6. The odds ratio of the prevalence of drug use more than 30 days prior for female vs. heterosexual male and MSM vs. heterosexual male, based on national NSDUH surveys
7. The odds ratio of the prevalence of drug use within 30 days for 13-24yo vs. 35-44yo, 25-34yo vs 35-44yo, 45-54yo vs 35-44yo, and 55+yo vs. 35-44yo, based on national NSDUH surveys
8. The odds ratio of the prevalence of drug use more than 30 days prior for 13-24yo vs. 35-44yo, 25-34yo vs 35-44yo, 45-54yo vs 35-44yo, and 55+yo vs. 35-44yo, based on national NSDUH surveys

These values were summed across 2014-2016. We treated the likelihoods for each of these targets as independent.

8.11.2 Log-Normal Likelihood

For the first two targets (prevalence of active and prior IV drug use), we used a Lognormal likelihood centered at the simulated prevalence, with a standard deviation of $\frac{Ln(2)}{2}$ (which gives a 95% interval from half to twice the median estimate).

$$Ln\big(p^{obs}\big) \sim Normal\big(p^{sim}, \sigma^2\big) \tag{56}$$

For the remaining targets (odds ratios by race, sex/sexual behavior, and age), we used a Lognormal distribution centered at the odds ratio from simulations, also with a standard deviation of $\frac{Ln(2)}{2}$:

$$Ln\big(OR^{obs}\big) \sim Normal\big(OR^{sim}, \sigma^2\big) \tag{57}$$

8.12 Cumulative AIDS Mortality prior to 2002

To help with estimation of parameters in the early part of the simulation, we included a calibration target of the total mortality due to AIDS from 1981 to 2000, stratified by race, sex, and HIV-acquisition risk factor.

We treated each of the 24 strata (three races, two sexes, four risk factors) as independent. Our likelihood took into account that not all deaths were captured during this time period.[63]

We let:

- y_i denote our response, the observed cumulative number of AIDS death in stratum i of race, sex, and risk factor from 1981 to 2000
- p_i denote the simulated rate of deaths
- n_i denote the sum of the total population over 13 years old (by US census data) from 1981 to 2000 in the location we are calibrating to

- ϕ denote the proportion of AIDS deaths that were captured by reporting systems. We use $\phi = 0.85 \times 0.9 = 0.765$; the technical appendix to the 2001-2002 CDC HIV/AIDS report[63] estimates that 85% of AIDS cases and 90% of deaths in people with reported AIDs were captured.

- $sigma_i^2$ denote the measurement error around y_i. We used $\sigma_i = y_i \times 0.09$ as for reported prevalence (Section 8.5.2).

As with other elements of the likelihood, we decomposed into a term that captures the difference between model simulations and truth (y_i') and measurement error (ϵ_i):

$$y_i = y_i' + \epsilon_i \tag{58}$$
$$y_i' \sim Binomial(n_i, p_i\phi) \tag{59}$$
$$\epsilon_i \sim Normal(0, \sigma_i^2) \tag{60}$$

Using the Normal approximation to the Binomial allowed us to combine this into one Normal distribution:

$$y_i \sim Normal\big(n_i \cdot p_i\phi, n_i \cdot p_i\phi \cdot (1 - p_i\phi_i) + \sigma_i^2\big) \tag{61}$$

8.12.1 Variance Inflation

To improve parameter mixing in the MCMC, we inflate the variances for this likelihood by a factor of 2.

8.13 Reported AIDS Diagnoses from 1999-2002

In addition to the cumulative AIDS mortality, we also helped estimation of parameters early in the simulation by including as a calibration target the total number of AIDS diagnoses in each year from 1999 to 2002. This particularly helped estimate the early trends that produce the prevalence during 2010-2020.

8.13.1 AIDS Diagnoses vs. HIV Diagnoses

Our model does not explicitly capture AIDS - only all HIV infections. We worked around this by postulating that the number of AIDS diagnoses in a year was a multiple of the number of HIV diagnoses in that year:

$$y_t' = \gamma_t \times \phi_t \tag{62}$$

where

- y_t' is the 'true' number of AIDS diagnoses in year t
- γ_t is the number of HIV diagnoses in year t
- ϕ_t is the ratio of AIDS to HIV diagnoses in year t

Because ϕ_t, the ratio of AIDS to HIV diagnoses entails uncertainty, we represented it with a Lognormal distribution:

$$Ln(\phi_t) \sim Normal\big(Ln(\bar{\phi}_t), \tau^2\big) \tag{63}$$

We estimated the values of $\bar{\phi}_t$ from the 2001-2002 CDC HIV/AIDS report,[63] which reported both number of AIDS diagnoses and HIV diagnoses for 30 areas with confidential name based reporting from the previous five years. Specifically, $\bar{\phi}_{1999} = 1.45$, $\bar{\phi}_{2000} = 1.56$, $\bar{\phi}_{2001} = 1.51$, and $\bar{\phi}_{2002} = 1.39$. We chose $\tau = \frac{log(1.1)}{2}$, which gives a 95% interval of 0.9 to 1.1 times $\bar{\phi}_t$.

8.13.2 Measurement Error

We also allowed the reported number of AIDS cases in year t, y_t, to have a measurement error on the log scale:

$$Ln(y_t) \sim Normal(Ln(y_t'), \lambda^2) \tag{64}$$

We chose $\lambda = 0.09$ (essentially a coefficient of variance of 0.09) to align with the measurement error for prevalence given in Seciton 8.5.2.

Combining equations 62, 63, and 64 gives us:

$$Ln(y_t) \sim Normal\big(Ln(\gamma_t) + Ln(\bar{\phi}_t), \tau^2 + \lambda^2\big) \tag{65}$$

By the properties of the Lognormal distribution, we have:

$$E[y_t] = \mu_t = \gamma_t \phi_t \cdot e^{\frac{\tau^2+\lambda^2}{2}} \tag{66}$$

$$Var(y_t) = \sigma_t^2 = \left(e^{\tau^2+\lambda^2} - 1\right) \cdot \left(\gamma_t \phi_t\right)^2 \cdot e^{\tau^2+\lambda^2} \tag{67}$$

$$\tag{68}$$

To more easily integrate this aspect of the likelihood with a binomial component below, we approximated the distribution in 65 with a Normal distribution:

$$y_t \sim Normal(\mu_t, \sigma_t^2) \tag{69}$$

Since measurement errors in the ratio of AIDS to HIV diagnoses, ϕ_i are likely correlated within a location from year to year, we vectorized this to a multivariate normal distribution:

$$\boldsymbol{y} \sim Multivariate\text{-}Normal\left(\boldsymbol{\mu}, \boldsymbol{\sigma}\boldsymbol{\Lambda}\boldsymbol{\sigma}^T\right) \tag{70}$$

where $\boldsymbol{\Lambda}$ is a compound symmetry (exchangeable) correlation matrix with $\rho = 0.5$

8.13.3 Formulation of Binomial Likelihood Component

Lastly, we mapped the model-simulated rate of HIV diagnoses, p_t to the number of HIV diagnoses, γ_t with a binomial distribution:

$$\gamma_t \sim Binomial(n_t, p_t) \tag{71}$$

where n_t is the total population (per US Census Bureau) of 13+ year olds in year t in the location we are calibrating to. We used the normal approximation to the binomial to give us:

$$\gamma_t \sim Normal\left(n_t \cdot p_t, n_t \cdot p_t \cdot (1 - p_t)\right) \tag{72}$$

Combining with equation 70 gives us our likelihood

9 Projected Outcomes Under Different Scenarios for How COVID-19 Pandemic Affects HIV Transmission

9.1 Projected Incidence in 2020, 2021, and 2025

Table S8: Projected Incidence in 2020 by Metropolitan Statistical Area, Absent Pandemic, Prolonged Barriers to Care, and Rapid Resumption of Care Scenarios

Location	Absent Pandemic, 2020	Prolonged Barriers to Care, 2020	Rapid Resumption of Care, 2020
New York-Newark-Jersey City, NY-NJ-PA	2,170 [1,884 to 2,453]	2,191 [1,518 to 3,064]	2,191 [1,516 to 3,076]
Miami-Fort Lauderdale-Pompano Beach, FL	1,681 [1,264 to 2,070]	1,473 [966 to 2,077]	1,473 [967 to 2,074]
Los Angeles-Long Beach-Anaheim, CA	1,845 [1,614 to 2,082]	1,657 [1,179 to 2,232]	1,657 [1,180 to 2,243]
Atlanta-Sandy Springs-Alpharetta, GA	1,415 [1,242 to 1,614]	1,275 [923 to 1,735]	1,275 [921 to 1,725]
Houston-The Woodlands-Sugar Land, TX	1,247 [1,029 to 1,470]	1,098 [771 to 1,482]	1,099 [774 to 1,495]
Dallas-Fort Worth-Arlington, TX	1,108 [934 to 1,292]	1,020 [715 to 1,430]	1,020 [714 to 1,433]
Chicago-Naperville-Elgin, IL-IN-WI	1,124 [966 to 1,305]	986 [705 to 1,301]	986 [705 to 1,301]
Washington-Arlington-Alexandria, DC-VA-MD-WV	567 [476 to 691]	557 [379 to 794]	557 [377 to 797]
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	565 [466 to 678]	518 [361 to 721]	518 [361 to 720]
Orlando-Kissimmee-Sanford, FL	536 [434 to 676]	476 [320 to 675]	477 [323 to 679]
San Francisco-Oakland-Berkeley, CA	448 [348 to 571]	435 [271 to 639]	435 [273 to 638]
Phoenix-Mesa-Chandler, AZ	444 [343 to 585]	395 [259 to 586]	395 [259 to 581]
Tampa-St. Petersburg-Clearwater, FL	452 [347 to 616]	403 [267 to 581]	403 [268 to 583]
Riverside-San Bernardino-Ontario, CA	494 [356 to 678]	433 [264 to 665]	433 [263 to 663]
Detroit-Warren-Dearborn, MI	416 [318 to 527]	383 [250 to 546]	383 [250 to 545]
Baltimore-Columbia-Towson, MD	265 [203 to 333]	251 [170 to 351]	251 [170 to 351]
Las Vegas-Henderson-Paradise, NV	365 [297 to 443]	313 [217 to 429]	312 [216 to 426]
Boston-Cambridge-Newton, MA-NH	517 [335 to 804]	541 [332 to 860]	541 [329 to 852]
San Diego-Chula Vista-Carlsbad, CA	265 [212 to 329]	253 [166 to 366]	253 [167 to 366]
Charlotte-Concord-Gastonia, NC-SC	312 [253 to 383]	280 [191 to 388]	280 [190 to 389]
San Antonio-New Braunfels, TX	310 [253 to 380]	280 [190 to 390]	280 [190 to 389]
Jacksonville, FL	270 [197 to 372]	243 [156 to 367]	243 [155 to 366]
New Orleans-Metairie, LA	235 [185 to 294]	217 [146 to 305]	217 [146 to 306]
Memphis, TN-MS-AR	235 [175 to 300]	209 [135 to 302]	209 [135 to 302]
Seattle-Tacoma-Bellevue, WA	361 [216 to 531]	347 [188 to 571]	346 [187 to 566]
Austin-Round Rock-Georgetown, TX	207 [168 to 259]	194 [127 to 284]	194 [127 to 285]
Indianapolis-Carmel-Anderson, IN	226 [180 to 278]	208 [146 to 284]	208 [145 to 284]
Cincinnati, OH-KY-IN	320 [242 to 443]	302 [204 to 430]	301 [204 to 431]
Columbus, OH	168 [127 to 224]	156 [102 to 226]	156 [102 to 225]
Baton Rouge, LA	160 [118 to 224]	147 [101 to 214]	147 [100 to 214]
Sacramento-Roseville-Folsom, CA	187 [142 to 239]	163 [104 to 238]	163 [104 to 239]
Cleveland-Elyria, OH	111 [85 to 142]	105 [70 to 149]	105 [70 to 149]
Total	19,023 [18,154 to 20,050]	17,509 [12,871 to 23,123]	17,508 [12,837 to 23,144]

Table S9: Projected Incidence in 2021 by Metropolitan Statistical Area, Absent Pandemic, Prolonged Barriers to Care, and Rapid Resumption of Care Scenarios

Location	Absent Pandemic, 2021	Prolonged Barriers to Care, 2021	Rapid Resumption of Care, 2021
New York-Newark-Jersey City, NY-NJ-PA	2,016 [1,721 to 2,326]	2,355 [1,678 to 3,267]	2,086 [1,579 to 2,752]
Miami-Fort Lauderdale-Pompano Beach, FL	1,579 [1,145 to 2,001]	1,585 [1,098 to 2,180]	1,481 [1,022 to 2,027]
Los Angeles-Long Beach-Anaheim, CA	1,785 [1,539 to 2,057]	1,839 [1,386 to 2,410]	1,701 [1,311 to 2,188]
Atlanta-Sandy Springs-Alpharetta, GA	1,377 [1,192 to 1,584]	1,400 [1,090 to 1,786]	1,311 [1,042 to 1,639]
Houston-The Woodlands-Sugar Land, TX	1,202 [968 to 1,445]	1,191 [876 to 1,598]	1,123 [828 to 1,489]
Dallas-Fort Worth-Arlington, TX	1,053 [866 to 1,248]	1,105 [804 to 1,509]	1,020 [758 to 1,356]
Chicago-Naperville-Elgin, IL-IN-WI	1,107 [939 to 1,308]	1,082 [822 to 1,398]	1,030 [791 to 1,312]
Washington-Arlington-Alexandria, DC-VA-MD-WV	507 [409 to 630]	588 [404 to 839]	518 [380 to 704]
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	530 [425 to 654]	550 [394 to 760]	512 [371 to 692]
Orlando-Kissimmee-Sanford, FL	504 [397 to 646]	514 [367 to 717]	479 [343 to 670]
San Francisco-Oakland-Berkeley, CA	413 [310 to 544]	480 [296 to 698]	419 [275 to 599]
Phoenix-Mesa-Chandler, AZ	415 [309 to 575]	428 [287 to 622]	394 [264 to 572]
Tampa-St. Petersburg-Clearwater, FL	427 [315 to 610]	435 [294 to 617]	404 [280 to 579]
Riverside-San Bernardino-Ontario, CA	475 [321 to 697]	477 [289 to 764]	439 [266 to 699]
Detroit-Warren-Dearborn, MI	395 [290 to 518]	418 [273 to 602]	381 [253 to 540]
Baltimore-Columbia-Towson, MD	238 [175 to 312]	261 [173 to 371]	236 [164 to 327]
Las Vegas-Henderson-Paradise, NV	339 [265 to 416]	328 [236 to 438]	313 [226 to 416]
Boston-Cambridge-Newton, MA-NH	501 [315 to 792]	598 [361 to 930]	554 [333 to 858]
San Diego-Chula Vista-Carlsbad, CA	241 [189 to 306]	272 [182 to 398]	242 [168 to 346]
Charlotte-Concord-Gastonia, NC-SC	303 [236 to 384]	305 [214 to 423]	285 [203 to 386]
San Antonio-New Braunfels, TX	298 [239 to 375]	306 [211 to 422]	284 [200 to 384]
Jacksonville, FL	261 [181 to 378]	263 [173 to 402]	247 [164 to 374]
New Orleans-Metairie, LA	217 [164 to 282]	231 [159 to 324]	212 [149 to 294]
Memphis, TN-MS-AR	220 [155 to 290]	217 [136 to 325]	202 [128 to 305]
Seattle-Tacoma-Bellevue, WA	354 [191 to 566]	410 [202 to 745]	357 [185 to 621]
Austin-Round Rock-Georgetown, TX	191 [151 to 244]	210 [137 to 308]	189 [127 to 273]
Indianapolis-Carmel-Anderson, IN	217 [166 to 274]	223 [159 to 306]	209 [149 to 282]
Cincinnati, OH-KY-IN	314 [232 to 441]	324 [225 to 466]	312 [215 to 446]
Columbus, OH	159 [117 to 220]	167 [111 to 243]	155 [107 to 223]
Baton Rouge, LA	150 [107 to 217]	154 [108 to 226]	146 [102 to 213]
Sacramento-Roseville-Folsom, CA	185 [136 to 243]	181 [116 to 269]	168 [108 to 250]
Cleveland-Elyria, OH	99 [72 to 132]	107 [71 to 154]	98 [68 to 140]
Total	18,073 [16,856 to 19,491]	19,003 [14,622 to 24,860]	17,507 [13,917 to 22,078]

Table S10: Projected Incidence in 2025 by Metropolitan Statistical Area, Absent Pandemic, Prolonged Barriers to Care, and Rapid Resumption of Care Scenarios

Location	Absent Pandemic, 2025	Prolonged Barriers to Care, 2025	Rapid Resumption of Care, 2025
New York-Newark-Jersey City, NY-NJ-PA	1,720 [1,293 to 2,156]	1,762 [1,319 to 2,228]	1,735 [1,305 to 2,196]
Miami-Fort Lauderdale-Pompano Beach, FL	1,322 [815 to 1,861]	1,344 [831 to 1,891]	1,323 [807 to 1,865]
Los Angeles-Long Beach-Anaheim, CA	1,654 [1,300 to 2,057]	1,679 [1,317 to 2,093]	1,651 [1,305 to 2,063]
Atlanta-Sandy Springs-Alpharetta, GA	1,315 [1,050 to 1,585]	1,316 [1,051 to 1,605]	1,311 [1,047 to 1,588]
Houston-The Woodlands-Sugar Land, TX	1,113 [797 to 1,470]	1,121 [798 to 1,475]	1,108 [787 to 1,457]
Dallas-Fort Worth-Arlington, TX	935 [698 to 1,193]	946 [705 to 1,214]	934 [696 to 1,200]
Chicago-Naperville-Elgin, IL-IN-WI	1,093 [858 to 1,377]	1,092 [862 to 1,380]	1,084 [849 to 1,364]
Washington-Arlington-Alexandria, DC-VA-MD-WV	399 [263 to 570]	408 [270 to 574]	402 [265 to 570]
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	458 [309 to 637]	461 [315 to 642]	456 [313 to 633]
Orlando-Kissimmee-Sanford, FL	431 [295 to 592]	436 [302 to 595]	430 [294 to 588]
San Francisco-Oakland-Berkeley, CA	337 [215 to 500]	351 [222 to 520]	341 [218 to 500]
Phoenix-Mesa-Chandler, AZ	356 [211 to 571]	361 [214 to 582]	354 [210 to 576]
Tampa-St. Petersburg-Clearwater, FL	371 [227 to 611]	375 [234 to 622]	369 [227 to 608]
Riverside-San Bernardino-Ontario, CA	432 [231 to 791]	440 [236 to 812]	427 [228 to 784]
Detroit-Warren-Dearborn, MI	358 [219 to 548]	367 [226 to 553]	358 [221 to 543]
Baltimore-Columbia-Towson, MD	189 [114 to 283]	192 [118 to 284]	190 [116 to 281]
Las Vegas-Henderson-Paradise, NV	282 [190 to 383]	283 [188 to 388]	279 [187 to 383]
Boston-Cambridge-Newton, MA-NH	428 [255 to 681]	433 [258 to 674]	430 [256 to 673]
San Diego-Chula Vista-Carlsbad, CA	194 [134 to 278]	201 [138 to 289]	196 [135 to 282]
Charlotte-Concord-Gastonia, NC-SC	287 [198 to 405]	289 [199 to 404]	286 [197 to 401]
San Antonio-New Braunfels, TX	277 [194 to 373]	279 [196 to 373]	275 [193 to 367]
Jacksonville, FL	244 [140 to 412]	246 [145 to 407]	242 [143 to 408]
New Orleans-Metairie, LA	181 [116 to 261]	185 [117 to 266]	182 [115 to 263]
Memphis, TN-MS-AR	190 [112 to 274]	192 [114 to 278]	190 [113 to 274]
Seattle-Tacoma-Bellevue, WA	326 [135 to 678]	347 [144 to 750]	329 [135 to 695]
Austin-Round Rock-Georgetown, TX	154 [105 to 214]	159 [108 to 223]	156 [105 to 218]
Indianapolis-Carmel-Anderson, IN	198 [133 to 276]	201 [136 to 276]	198 [134 to 273]
Cincinnati, OH-KY-IN	297 [190 to 439]	301 [197 to 439]	298 [194 to 437]
Columbus, OH	139 [91 to 210]	141 [93 to 215]	139 [91 to 210]
Baton Rouge, LA	132 [84 to 209]	134 [85 to 210]	133 [84 to 209]
Sacramento-Roseville-Folsom, CA	185 [113 to 283]	188 [113 to 284]	182 [110 to 278]
Cleveland-Elyria, OH	78 [46 to 117]	79 [47 to 119]	78 [47 to 118]
Total	16,073 [13,206 to 19,034]	16,308 [13,304 to 19,557]	16,064 [13,181 to 19,239]

9.2 Projected Reported Diagnoses in 2020, 2021, and 2025

Table S11: Projected Reported Diagnoses in 2020 by Metropolitan Statistical Area, Absent Pandemic, Prolonged Barriers to Care, and Rapid Resumption of Care Scenarios

Location	Absent Pandemic, 2020	Prolonged Barriers to Care, 2020	Rapid Resumption of Care, 2020
New York-Newark-Jersey City, NY-NJ-PA	2,493 [2,266 to 2,733]	2,167 [1,727 to 2,604]	2,167 [1,725 to 2,605]
Miami-Fort Lauderdale-Pompano Beach, FL	1,878 [1,640 to 2,111]	1,580 [1,218 to 1,954]	1,580 [1,216 to 1,950]
Los Angeles-Long Beach-Anaheim, CA	1,876 [1,665 to 2,091]	1,575 [1,231 to 1,944]	1,574 [1,235 to 1,947]
Atlanta-Sandy Springs-Alpharetta, GA	1,462 [1,324 to 1,635]	1,241 [979 to 1,516]	1,241 [978 to 1,518]
Houston-The Woodlands-Sugar Land, TX	1,260 [1,117 to 1,412]	1,066 [826 to 1,306]	1,066 [828 to 1,305]
Dallas-Fort Worth-Arlington, TX	1,187 [1,039 to 1,349]	1,011 [789 to 1,249]	1,011 [785 to 1,245]
Chicago-Naperville-Elgin, IL-IN-WI	1,131 [1,002 to 1,269]	960 [747 to 1,163]	960 [747 to 1,166]
Washington-Arlington-Alexandria, DC-VA-MD-WV	722 [634 to 825]	621 [478 to 767]	621 [479 to 768]
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	652 [570 to 742]	557 [433 to 680]	557 [434 to 679]
Orlando-Kissimmee-Sanford, FL	589 [503 to 695]	498 [376 to 620]	498 [376 to 622]
San Francisco-Oakland-Berkeley, CA	513 [436 to 599]	434 [328 to 552]	434 [327 to 549]
Phoenix-Mesa-Chandler, AZ	501 [420 to 593]	420 [316 to 536]	420 [315 to 539]
Tampa-St. Petersburg-Clearwater, FL	482 [409 to 579]	407 [303 to 518]	407 [302 to 518]
Riverside-San Bernardino-Ontario, CA	510 [413 to 616]	431 [321 to 553]	431 [322 to 552]
Detroit-Warren-Dearborn, MI	418 [356 to 484]	359 [271 to 439]	359 [270 to 439]
Baltimore-Columbia-Towson, MD	338 [290 to 388]	290 [223 to 357]	290 [224 to 357]
Las Vegas-Henderson-Paradise, NV	403 [346 to 469]	339 [261 to 428]	339 [260 to 428]
Boston-Cambridge-Newton, MA-NH	489 [379 to 656]	428 [302 to 589]	428 [303 to 591]
San Diego-Chula Vista-Carlsbad, CA	316 [262 to 377]	269 [199 to 348]	268 [198 to 346]
Charlotte-Concord-Gastonia, NC-SC	318 [271 to 368]	270 [205 to 336]	270 [205 to 334]
San Antonio-New Braunfels, TX	314 [271 to 358]	266 [208 to 329]	266 [207 to 330]
Jacksonville, FL	279 [235 to 337]	239 [180 to 304]	239 [180 to 305]
New Orleans-Metairie, LA	256 [223 to 292]	218 [168 to 269]	218 [168 to 269]
Memphis, TN-MS-AR	274 [235 to 315]	226 [169 to 287]	226 [169 to 287]
Seattle-Tacoma-Bellevue, WA	369 [263 to 482]	314 [213 to 438]	314 [212 to 436]
Austin-Round Rock-Georgetown, TX	228 [196 to 265]	194 [148 to 240]	194 [148 to 240]
Indianapolis-Carmel-Anderson, IN	218 [185 to 253]	188 [144 to 234]	188 [144 to 234]
Cincinnati, OH-KY-IN	270 [225 to 322]	233 [177 to 294]	232 [177 to 294]
Columbus, OH	178 [149 to 212]	153 [114 to 193]	153 [113 to 193]
Baton Rouge, LA	177 [154 to 209]	152 [117 to 189]	152 [118 to 190]
Sacramento-Roseville-Folsom, CA	180 [147 to 216]	151 [112 to 198]	151 [112 to 199]
Cleveland-Elyria, OH	135 [114 to 158]	118 [90 to 147]	118 [90 to 147]
Total	20,416 [19,617 to 21,232]	17,376 [13,925 to 20,464]	17,375 [13,947 to 20,433]

Table S12: Projected Reported Diagnoses in 2021 by Metropolitan Statistical Area, Absent Pandemic, Prolonged Barriers to Care, and Rapid Resumption of Care Scenarios

Location	Absent Pandemic, 2021	Prolonged Barriers to Care, 2021	Rapid Resumption of Care, 2021
New York-Newark-Jersey City, NY-NJ-PA	2,308 [2,042 to 2,587]	2,213 [1,778 to 2,740]	2,340 [1,944 to 2,851]
Miami-Fort Lauderdale-Pompano Beach, FL	1,779 [1,476 to 2,076]	1,578 [1,238 to 1,933]	1,701 [1,374 to 2,038]
Los Angeles-Long Beach-Anaheim, CA	1,812 [1,590 to 2,073]	1,600 [1,265 to 1,998]	1,730 [1,433 to 2,094]
Atlanta-Sandy Springs-Alpharetta, GA	1,414 [1,260 to 1,608]	1,275 [1,017 to 1,572]	1,361 [1,126 to 1,653]
Houston-The Woodlands-Sugar Land, TX	1,215 [1,043 to 1,402]	1,078 [851 to 1,328]	1,151 [948 to 1,393]
Dallas-Fort Worth-Arlington, TX	1,129 [968 to 1,303]	1,032 [814 to 1,283]	1,096 [880 to 1,362]
Chicago-Naperville-Elgin, IL-IN-WI	1,108 [967 to 1,263]	983 [770 to 1,210]	1,046 [858 to 1,257]
Washington-Arlington-Alexandria, DC-VA-MD-WV	643 [548 to 759]	615 [481 to 783]	652 [523 to 817]
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	606 [515 to 713]	561 [445 to 703]	593 [467 to 741]
Orlando-Kissimmee-Sanford, FL	561 [473 to 675]	504 [394 to 639]	539 [430 to 683]
San Francisco-Oakland-Berkeley, CA	474 [388 to 572]	441 [327 to 572]	473 [369 to 602]
Phoenix-Mesa-Chandler, AZ	472 [382 to 584]	422 [318 to 548]	454 [348 to 573]
Tampa-St. Petersburg-Clearwater, FL	458 [376 to 573]	410 [310 to 532]	439 [347 to 559]
Riverside-San Bernardino-Ontario, CA	493 [382 to 622]	435 [317 to 575]	466 [345 to 617]
Detroit-Warren-Dearborn, MI	398 [324 to 478]	361 [276 to 465]	384 [298 to 493]
Baltimore-Columbia-Towson, MD	302 [252 to 359]	281 [216 to 353]	299 [237 to 372]
Las Vegas-Henderson-Paradise, NV	380 [320 to 449]	335 [264 to 422]	358 [292 to 441]
Boston-Cambridge-Newton, MA-NH	488 [354 to 701]	490 [338 to 695]	519 [364 to 744]
San Diego-Chula Vista-Carlsbad, CA	289 [233 to 353]	266 [200 to 341]	285 [223 to 359]
Charlotte-Concord-Gastonia, NC-SC	307 [253 to 368]	275 [211 to 352]	293 [232 to 366]
San Antonio-New Braunfels, TX	301 [255 to 352]	272 [208 to 342]	288 [224 to 360]
Jacksonville, FL	269 [217 to 339]	244 [182 to 323]	259 [200 to 336]
New Orleans-Metairie, LA	237 [200 to 281]	216 [168 to 270]	231 [187 to 284]
Memphis, TN-MS-AR	255 [210 to 302]	222 [168 to 287]	237 [185 to 301]
Seattle-Tacoma-Bellevue, WA	368 [241 to 515]	348 [220 to 529]	367 [235 to 558]
Austin-Round Rock-Georgetown, TX	210 [176 to 248]	194 [146 to 248]	206 [161 to 262]
Indianapolis-Carmel-Anderson, IN	209 [171 to 248]	190 [145 to 237]	201 [158 to 246]
Cincinnati, OH-KY-IN	271 [218 to 335]	247 [191 to 318]	263 [205 to 338]
Columbus, OH	167 [137 to 205]	152 [116 to 197]	162 [129 to 207]
Baton Rouge, LA	165 [137 to 205]	150 [117 to 190]	159 [131 to 200]
Sacramento-Roseville-Folsom, CA	177 [140 to 217]	154 [113 to 206]	166 [125 to 218]
Cleveland-Elyria, OH	121 [98 to 148]	113 [87 to 145]	119 [94 to 149]
Total	19,387 [18,135 to 20,778]	17,657 [14,525 to 21,128]	18,837 [16,194 to 22,205]

Table S13: Projected Reported Diagnoses in 2025 by Metropolitan Statistical Area, Absent Pandemic, Prolonged Barriers to Care, and Rapid Resumption of Care Scenarios

Location	Absent Pandemic, 2025	Prolonged Barriers to Care, 2025	Rapid Resumption of Care, 2025
New York-Newark-Jersey City, NY-NJ-PA	1,831 [1,511 to 2,182]	1,939 [1,566 to 2,362]	1,878 [1,535 to 2,266]
Miami-Fort Lauderdale-Pompano Beach, FL	1,424 [976 to 1,807]	1,468 [1,034 to 1,874]	1,429 [999 to 1,819]
Los Angeles-Long Beach-Anaheim, CA	1,623 [1,383 to 1,889]	1,679 [1,394 to 2,010]	1,630 [1,364 to 1,937]
Atlanta-Sandy Springs-Alpharetta, GA	1,285 [1,074 to 1,501]	1,305 [1,083 to 1,542]	1,286 [1,069 to 1,521]
Houston-The Woodlands-Sugar Land, TX	1,078 [854 to 1,313]	1,099 [866 to 1,354]	1,076 [849 to 1,325]
Dallas-Fort Worth-Arlington, TX	935 [740 to 1,142]	964 [762 to 1,201]	941 [744 to 1,170]
Chicago-Naperville-Elgin, IL-IN-WI	1,063 [879 to 1,272]	1,075 [886 to 1,300]	1,058 [872 to 1,278]
Washington-Arlington-Alexandria, DC-VA-MD-WV	449 [329 to 594]	475 [345 to 629]	460 [334 to 606]
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	485 [358 to 631]	497 [367 to 654]	487 [356 to 637]
Orlando-Kissimmee-Sanford, FL	453 [343 to 592]	467 [358 to 615]	454 [347 to 596]
San Francisco-Oakland-Berkeley, CA	363 [256 to 490]	391 [266 to 531]	373 [257 to 507]
Phoenix-Mesa-Chandler, AZ	377 [256 to 544]	388 [268 to 557]	377 [260 to 544]
Tampa-St. Petersburg-Clearwater, FL	376 [266 to 546]	387 [273 to 554]	376 [267 to 540]
Riverside-San Bernardino-Ontario, CA	425 [263 to 674]	440 [267 to 695]	422 [259 to 660]
Detroit-Warren-Dearborn, MI	346 [240 to 483]	362 [251 to 502]	348 [242 to 480]
Baltimore-Columbia-Towson, MD	214 [147 to 292]	222 [154 to 306]	217 [149 to 295]
Las Vegas-Henderson-Paradise, NV	296 [227 to 371]	301 [227 to 380]	295 [223 to 374]
Boston-Cambridge-Newton, MA-NH	431 [270 to 665]	453 [286 to 687]	443 [279 to 675]
San Diego-Chula Vista-Carlsbad, CA	216 [163 to 284]	229 [171 to 306]	221 [165 to 292]
Charlotte-Concord-Gastonia, NC-SC	280 [213 to 362]	287 [216 to 371]	280 [212 to 359]
San Antonio-New Braunfels, TX	264 [205 to 331]	270 [208 to 341]	264 [203 to 331]
Jacksonville, FL	236 [157 to 348]	241 [163 to 360]	236 [159 to 349]
New Orleans-Metairie, LA	185 [137 to 241]	192 [143 to 250]	187 [139 to 246]
Memphis, TN-MS-AR	201 [136 to 264]	207 [141 to 280]	202 [138 to 271]
Seattle-Tacoma-Bellevue, WA	327 [156 to 611]	357 [171 to 660]	333 [160 to 626]
Austin-Round Rock-Georgetown, TX	159 [124 to 202]	168 [128 to 218]	161 [123 to 207]
Indianapolis-Carmel-Anderson, IN	183 [134 to 232]	187 [138 to 243]	183 [135 to 237]
Cincinnati, OH-KY-IN	259 [187 to 345]	266 [193 to 351]	262 [190 to 346]
Columbus, OH	137 [102 to 183]	142 [105 to 192]	139 [103 to 187]
Baton Rouge, LA	132 [97 to 186]	136 [100 to 190]	134 [99 to 185]
Sacramento-Roseville-Folsom, CA	172 [120 to 235]	176 [116 to 244]	170 [115 to 237]
Cleveland-Elyria, OH	86 [60 to 118]	89 [62 to 123]	87 [61 to 121]
Total	16,290 [14,440 to 18,082]	16,859 [14,500 to 19,381]	16,409 [14,210 to 18,698]

9.3 Projected Prevalence in 2020, 2021, and 2025

Table S14: Projected Prevalence in 2020 by Metropolitan Statistical Area, Absent Pandemic, Prolonged Barriers to Care, and Rapid Resumption of Care Scenarios

New York-Newark-Jersey City, NY-NJ-PA	138,285 [133,609 to 142,783]	138,227 [133,553 to 142,751]	138,227 [133,543 to 142,793]
Miami-Fort Lauderdale-Pompano Beach, FL	65,867 [62,030 to 69,519]	65,616 [61,813 to 69,227]	65,617 [61,821 to 69,223]
Los Angeles-Long Beach-Anaheim, CA	63,738 [57,879 to 69,800]	63,479 [57,517 to 69,493]	63,477 [57,470 to 69,569]
Atlanta-Sandy Springs-Alpharetta, GA	38,805 [35,111 to 42,544]	38,635 [34,971 to 42,454]	38,635 [34,979 to 42,476]
Houston-The Woodlands-Sugar Land, TX	38,533 [35,464 to 41,621]	38,350 [35,344 to 41,374]	38,350 [35,360 to 41,375]
Dallas-Fort Worth-Arlington, TX	34,415 [31,058 to 37,742]	34,287 [30,842 to 37,735]	34,287 [30,829 to 37,753]
Chicago-Naperville-Elgin, IL-IN-WI	33,711 [31,234 to 36,419]	33,560 [31,094 to 36,159]	33,561 [31,098 to 36,169]
Washington-Arlington-Alexandria, DC-VA-MD-WV	34,951 [32,604 to 37,257]	34,923 [32,598 to 37,280]	34,923 [32,608 to 37,291]
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	26,202 [24,869 to 27,481]	26,136 [24,791 to 27,402]	26,136 [24,793 to 27,411]
Orlando-Kissimmee-Sanford, FL	15,544 [14,128 to 17,139]	15,468 [14,020 to 17,046]	15,468 [14,023 to 17,057]
San Francisco-Oakland-Berkeley, CA	26,219 [23,680 to 28,780]	26,174 [23,666 to 28,761]	26,174 [23,653 to 28,786]
Phoenix-Mesa-Chandler, AZ	14,954 [13,322 to 16,597]	14,891 [13,243 to 16,576]	14,890 [13,245 to 16,571]
Tampa-St. Petersburg-Clearwater, FL	15,468 [14,010 to 17,015]	15,398 [13,952 to 16,944]	15,398 [13,950 to 16,960]
Riverside-San Bernardino-Ontario, CA	12,519 [11,168 to 14,036]	12,442 [11,090 to 13,970]	12,442 [11,077 to 14,009]
Detroit-Warren-Dearborn, MI	12,066 [11,077 to 13,140]	12,018 [11,029 to 13,076]	12,018 [11,031 to 13,073]
Baltimore-Columbia-Towson, MD	18,337 [17,325 to 19,445]	18,303 [17,295 to 19,390]	18,302 [17,297 to 19,388]
Las Vegas-Henderson-Paradise, NV	10,250 [9,178 to 11,482]	10,190 [9,139 to 11,429]	10,190 [9,132 to 11,428]
Boston-Cambridge-Newton, MA-NH	15,512 [14,441 to 16,662]	15,521 [14,452 to 16,673]	15,520 [14,453 to 16,651]
San Diego-Chula Vista-Carlsbad, CA	14,008 [12,306 to 15,924]	13,983 [12,281 to 15,904]	13,983 [12,275 to 15,907]
Charlotte-Concord-Gastonia, NC-SC	9,777 [8,866 to 10,836]	9,735 [8,826 to 10,820]	9,735 [8,825 to 10,834]
San Antonio-New Braunfels, TX	9,034 [8,180 to 9,918]	8,992 [8,152 to 9,875]	8,992 [8,161 to 9,882]
Jacksonville, FL	8,939 [8,212 to 9,634]	8,900 [8,182 to 9,599]	8,900 [8,180 to 9,595]
New Orleans-Metairie, LA	9,516 [8,794 to 10,210]	9,486 [8,767 to 10,191]	9,486 [8,768 to 10,195]
Memphis, TN-MS-AR	8,597 [7,885 to 9,306]	8,561 [7,841 to 9,259]	8,561 [7,843 to 9,261]
Seattle-Tacoma-Bellevue, WA	10,908 [9,176 to 12,728]	10,869 [9,117 to 12,700]	10,869 [9,124 to 12,706]
Austin-Round Rock-Georgetown, TX	8,142 [7,269 to 9,093]	8,117 [7,241 to 9,075]	8,117 [7,240 to 9,073]
Indianapolis-Carmel-Anderson, IN	6,727 [5,928 to 7,622]	6,701 [5,895 to 7,585]	6,701 [5,895 to 7,586]
Cincinnati, OH-KY-IN	5,242 [4,619 to 5,942]	5,220 [4,581 to 5,906]	5,219 [4,577 to 5,911]
Columbus, OH	6,571 [5,740 to 7,393]	6,553 [5,726 to 7,385]	6,553 [5,724 to 7,380]
Baton Rouge, LA	6,313 [5,908 to 6,760]	6,293 [5,890 to 6,723]	6,293 [5,895 to 6,724]
Sacramento-Roseville-Folsom, CA	5,309 [4,646 to 6,033]	5,275 [4,610 to 6,017]	5,275 [4,603 to 6,013]
Cleveland-Elyria, OH	5,617 [5,130 to 6,159]	5,605 [5,113 to 6,142]	5,605 [5,112 to 6,142]
Total	730,077 [716,924 to 742,418]	727,910 [714,162 to 741,552]	727,905 [713,971 to 741,473]

Table S15: Projected Prevalence in 2021 by Metropolitan Statistical Area, Absent Pandemic, Prolonged Barriers to Care, and Rapid Resumption of Care Scenarios

Location	Absent Pandemic, 2021	Prolonged Barriers to Care, 2021	Rapid Resumption of Care, 2021
New York-Newark-Jersey City, NY-NJ-PA	138,460 [133,712 to 143,085]	138,666 [133,879 to 143,490]	138,438 [133,720 to 143,206]
Miami-Fort Lauderdale-Pompano Beach, FL	66,421 [62,444 to 70,305]	66,138 [61,972 to 70,013]	66,058 [61,984 to 69,933]
Los Angeles-Long Beach-Anaheim, CA	64,555 [58,629 to 70,663]	64,282 [58,198 to 70,446]	64,182 [58,035 to 70,271]
Atlanta-Sandy Springs-Alpharetta, GA	39,592 [35,824 to 43,282]	39,417 [35,718 to 43,348]	39,345 [35,664 to 43,303]
Houston-The Woodlands-Sugar Land, TX	39,166 [36,021 to 42,319]	38,942 [35,752 to 42,094]	38,892 [35,712 to 42,056]
Dallas-Fort Worth-Arlington, TX	34,939 [31,568 to 38,278]	34,828 [31,257 to 38,340]	34,763 [31,210 to 38,303]
Chicago-Naperville-Elgin, IL-IN-WI	34,320 [31,821 to 37,096]	34,133 [31,542 to 36,839]	34,088 [31,516 to 36,785]
Washington-Arlington-Alexandria, DC-VA-MD-WV	35,004 [32,651 to 37,315]	35,039 [32,623 to 37,518]	34,979 [32,608 to 37,460]
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	26,261 [24,900 to 27,566]	26,198 [24,777 to 27,542]	26,169 [24,758 to 27,542]
Orlando-Kissimmee-Sanford, FL	15,796 [14,352 to 17,443]	15,714 [14,220 to 17,319]	15,689 [14,193 to 17,287]
San Francisco-Oakland-Berkeley, CA	26,228 [23,669 to 28,880]	26,218 [23,683 to 28,857]	26,175 [23,628 to 28,823]
Phoenix-Mesa-Chandler, AZ	15,148 [13,471 to 16,877]	15,083 [13,485 to 16,864]	15,057 [13,468 to 16,815]
Tampa-St. Petersburg-Clearwater, FL	15,599 [14,114 to 17,217]	15,518 [13,994 to 17,133]	15,499 [13,973 to 17,101]
Riverside-San Bernardino-Ontario, CA	12,786 [11,379 to 14,455]	12,696 [11,295 to 14,332]	12,667 [11,271 to 14,312]
Detroit-Warren-Dearborn, MI	12,248 [11,258 to 13,335]	12,208 [11,169 to 13,263]	12,180 [11,159 to 13,246]
Baltimore-Columbia-Towson, MD	18,270 [17,242 to 19,359]	18,240 [17,198 to 19,336]	18,225 [17,191 to 19,324]
Las Vegas-Henderson-Paradise, NV	10,410 [9,314 to 11,675]	10,333 [9,258 to 11,619]	10,321 [9,253 to 11,604]
Boston-Cambridge-Newton, MA-NH	15,787 [14,597 to 17,038]	15,877 [14,676 to 17,172]	15,841 [14,641 to 17,111]
San Diego-Chula Vista-Carlsbad, CA	14,051 [12,325 to 15,975]	14,044 [12,295 to 16,039]	14,021 [12,287 to 15,964]
Charlotte-Concord-Gastonia, NC-SC	9,929 [8,989 to 11,049]	9,881 [8,942 to 10,983]	9,867 [8,925 to 10,972]
San Antonio-New Braunfels, TX	9,181 [8,311 to 10,112]	9,136 [8,258 to 10,067]	9,119 [8,250 to 10,053]
Jacksonville, FL	9,039 [8,298 to 9,762]	8,993 [8,227 to 9,713]	8,982 [8,230 to 9,701]
New Orleans-Metairie, LA	9,554 [8,833 to 10,271]	9,527 [8,790 to 10,251]	9,515 [8,782 to 10,238]
Memphis, TN-MS-AR	8,670 [7,957 to 9,381]	8,621 [7,904 to 9,325]	8,610 [7,896 to 9,316]
Seattle-Tacoma-Bellevue, WA	11,104 [9,239 to 12,997]	11,099 [9,175 to 12,960]	11,058 [9,193 to 12,945]
Austin-Round Rock-Georgetown, TX	8,208 [7,331 to 9,181]	8,192 [7,320 to 9,129]	8,177 [7,312 to 9,113]
Indianapolis-Carmel-Anderson, IN	6,818 [5,976 to 7,756]	6,792 [5,951 to 7,694]	6,781 [5,943 to 7,677]
Cincinnati, OH-KY-IN	5,447 [4,775 to 6,240]	5,431 [4,760 to 6,171]	5,420 [4,746 to 6,161]
Columbus, OH	6,612 [5,773 to 7,440]	6,596 [5,768 to 7,432]	6,588 [5,766 to 7,422]
Baton Rouge, LA	6,344 [5,926 to 6,813]	6,321 [5,902 to 6,779]	6,317 [5,901 to 6,777]
Sacramento-Roseville-Folsom, CA	5,397 [4,703 to 6,113]	5,350 [4,655 to 6,102]	5,343 [4,631 to 6,089]
Cleveland-Elyria, OH	5,610 [5,127 to 6,154]	5,602 [5,104 to 6,141]	5,596 [5,099 to 6,128]
Total	736,954 [723,454 to 749,563]	735,113 [719,310 to 751,424]	733,962 [717,987 to 749,840]

Table S16: Projected Prevalence in 2025 by Metropolitan Statistical Area, Absent Pandemic, Prolonged Barriers to Care, and Rapid Resumption of Care Scenarios

Location	Absent Pandemic, 2025	Prolonged Barriers to Care, 2025	Rapid Resumption of Care, 2025
New York-Newark-Jersey City, NY-NJ-PA	137,977 [132,816 to 143,172]	138,452 [133,246 to 143,907]	138,053 [132,969 to 143,571]
Miami-Fort Lauderdale-Pompano Beach, FL	67,751 [62,495 to 72,728]	67,604 [62,245 to 72,763]	67,398 [62,172 to 72,415]
Los Angeles-Long Beach-Anaheim, CA	67,244 [60,600 to 73,543]	67,129 [60,672 to 73,450]	66,879 [60,367 to 73,218]
Atlanta-Sandy Springs-Alpharetta, GA	42,373 [38,541 to 46,568]	42,238 [38,366 to 46,590]	42,121 [38,232 to 46,532]
Houston-The Woodlands-Sugar Land, TX	41,297 [37,814 to 44,882]	41,138 [37,585 to 44,714]	41,010 [37,502 to 44,609]
Dallas-Fort Worth-Arlington, TX	36,576 [33,038 to 40,257]	36,551 [32,951 to 40,580]	36,412 [32,833 to 40,426]
Chicago-Naperville-Elgin, IL-IN-WI	36,543 [33,729 to 39,599]	36,383 [33,332 to 39,578]	36,285 [33,272 to 39,404]
Washington-Arlington-Alexandria, DC-VA-MD-WV	34,796 [32,301 to 37,436]	34,897 [32,439 to 37,516]	34,793 [32,341 to 37,332]
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	26,219 [24,648 to 27,882]	26,191 [24,563 to 27,849]	26,129 [24,531 to 27,732]
Orlando-Kissimmee-Sanford, FL	16,545 [14,967 to 18,449]	16,505 [14,907 to 18,398]	16,439 [14,855 to 18,341]
San Francisco-Oakland-Berkeley, CA	25,993 [23,442 to 28,831]	26,069 [23,550 to 28,912]	25,966 [23,399 to 28,815]
Phoenix-Mesa-Chandler, AZ	15,711 [13,824 to 17,874]	15,683 [13,815 to 17,881]	15,617 [13,781 to 17,767]
Tampa-St. Petersburg-Clearwater, FL	15,934 [14,302 to 17,996]	15,888 [14,175 to 18,012]	15,831 [14,129 to 17,931]
Riverside-San Bernardino-Ontario, CA	13,689 [11,879 to 16,016]	13,656 [11,823 to 16,034]	13,553 [11,777 to 15,867]
Detroit-Warren-Dearborn, MI	12,821 [11,567 to 14,140]	12,839 [11,525 to 14,155]	12,759 [11,465 to 14,019]
Baltimore-Columbia-Towson, MD	17,836 [16,714 to 18,997]	17,828 [16,697 to 18,978]	17,798 [16,677 to 18,950]
Las Vegas-Henderson-Paradise, NV	10,859 [9,653 to 12,205]	10,800 [9,621 to 12,175]	10,766 [9,586 to 12,140]
Boston-Cambridge-Newton, MA-NH	16,636 [15,000 to 18,579]	16,802 [15,143 to 18,735]	16,726 [15,063 to 18,644]
San Diego-Chula Vista-Carlsbad, CA	14,055 [12,265 to 16,061]	14,090 [12,269 to 16,118]	14,038 [12,223 to 16,045]
Charlotte-Concord-Gastonia, NC-SC	10,451 [9,354 to 11,747]	10,422 [9,313 to 11,768]	10,385 [9,270 to 11,736]
San Antonio-New Braunfels, TX	9,675 [8,694 to 10,769]	9,651 [8,655 to 10,730]	9,612 [8,630 to 10,703]
Jacksonville, FL	9,364 [8,435 to 10,405]	9,334 [8,421 to 10,424]	9,303 [8,397 to 10,361]
New Orleans-Metairie, LA	9,586 [8,802 to 10,433]	9,583 [8,795 to 10,422]	9,553 [8,774 to 10,377]
Memphis, TN-MS-AR	8,843 [8,034 to 9,659]	8,813 [7,993 to 9,648]	8,788 [7,973 to 9,626]
Seattle-Tacoma-Bellevue, WA	11,773 [9,514 to 14,290]	11,889 [9,557 to 14,535]	11,749 [9,457 to 14,219]
Austin-Round Rock-Georgetown, TX	8,352 [7,470 to 9,348]	8,369 [7,465 to 9,375]	8,330 [7,431 to 9,310]
Indianapolis-Carmel-Anderson, IN	7,105 [6,179 to 8,107]	7,095 [6,157 to 8,091]	7,070 [6,134 to 8,072]
Cincinnati, OH-KY-IN	6,175 [5,325 to 7,250]	6,190 [5,346 to 7,264]	6,160 [5,320 to 7,235]
Columbus, OH	6,697 [5,835 to 7,576]	6,698 [5,809 to 7,598]	6,678 [5,804 to 7,594]
Baton Rouge, LA	6,404 [5,917 to 7,071]	6,393 [5,905 to 7,047]	6,382 [5,898 to 7,028]
Sacramento-Roseville-Folsom, CA	5,732 [4,930 to 6,616]	5,698 [4,880 to 6,606]	5,666 [4,872 to 6,567]
Cleveland-Elyria, OH	5,517 [5,010 to 6,071]	5,517 [5,002 to 6,047]	5,505 [4,994 to 6,041]
Total	756,529 [738,705 to 773,547]	756,394 [734,259 to 778,110]	753,755 [732,847 to 774,473]

9.4 Projected Prevalence in 2020, 2021, and 2025

Table S17: Projected Prevalence of Acute HIV in 2020 by Metropolitan Statistical Area, Absent Pandemic, Prolonged Barriers to Care, and Rapid Resumption of Care Scenarios

Location	Absent Pandemic, 2021	Prolonged Barriers to Care, 2021	Rapid Resumption of Care, 2021
New York-Newark-Jersey City, NY-NJ-PA	512 [443 to 583]	524 [332 to 781]	524 [333 to 780]
Miami-Fort Lauderdale-Pompano Beach, FL	398 [294 to 494]	341 [205 to 506]	341 [205 to 509]
Los Angeles-Long Beach-Anaheim, CA	440 [383 to 498]	387 [251 to 556]	387 [252 to 559]
Atlanta-Sandy Springs-Alpharetta, GA	338 [297 to 387]	299 [200 to 425]	299 [199 to 425]
Houston-The Woodlands-Sugar Land, TX	297 [243 to 352]	255 [163 to 365]	255 [164 to 369]
Dallas-Fort Worth-Arlington, TX	263 [221 to 309]	239 [152 to 354]	239 [152 to 354]
Chicago-Naperville-Elgin, IL-IN-WI	270 [231 to 314]	230 [150 to 320]	230 [151 to 320]
Washington-Arlington-Alexandria, DC-VA-MD-WV	132 [110 to 163]	131 [81 to 199]	131 [80 to 200]
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	134 [109 to 162]	121 [78 to 177]	121 [78 to 177]
Orlando-Kissimmee-Sanford, FL	127 [102 to 160]	111 [69 to 165]	111 [69 to 166]
San Francisco-Oakland-Berkeley, CA	105 [81 to 136]	103 [58 to 162]	103 [58 to 162]
Phoenix-Mesa-Chandler, AZ	105 [81 to 140]	91 [54 to 145]	91 [54 to 143]
Tampa-St. Petersburg-Clearwater, FL	107 [81 to 147]	93 [57 to 141]	93 [57 to 142]
Riverside-San Bernardino-Ontario, CA	118 [83 to 164]	100 [54 to 163]	100 [54 to 164]
Detroit-Warren-Dearborn, MI	99 [75 to 127]	90 [52 to 137]	90 [53 to 137]
Baltimore-Columbia-Towson, MD	62 [47 to 78]	58 [36 to 87]	58 [36 to 86]
Las Vegas-Henderson-Paradise, NV	86 [70 to 104]	71 [45 to 103]	71 [45 to 103]
Boston-Cambridge-Newton, MA-NH	124 [79 to 192]	133 [78 to 211]	133 [78 to 211]
San Diego-Chula Vista-Carlsbad, CA	62 [50 to 77]	59 [35 to 92]	59 [35 to 92]
Charlotte-Concord-Gastonia, NC-SC	75 [60 to 92]	65 [40 to 97]	65 [41 to 97]
San Antonio-New Braunfels, TX	74 [60 to 91]	65 [41 to 97]	65 [41 to 98]
Jacksonville, FL	64 [46 to 89]	57 [33 to 91]	57 [33 to 90]
New Orleans-Metairie, LA	55 [43 to 70]	51 [31 to 76]	51 [31 to 76]
Memphis, TN-MS-AR	56 [41 to 71]	46 [24 to 77]	46 [24 to 77]
Seattle-Tacoma-Bellevue, WA	86 [50 to 130]	83 [39 to 151]	83 [40 to 150]
Austin-Round Rock-Georgetown, TX	49 [39 to 61]	46 [26 to 71]	45 [26 to 71]
Indianapolis-Carmel-Anderson, IN	54 [43 to 67]	49 [31 to 69]	49 [31 to 70]
Cincinnati, OH-KY-IN	77 [57 to 106]	72 [46 to 105]	72 [46 to 105]
Columbus, OH	40 [30 to 54]	37 [22 to 55]	37 [22 to 56]
Baton Rouge, LA	38 [28 to 53]	34 [22 to 52]	34 [22 to 52]
Sacramento-Roseville-Folsom, CA	45 [34 to 58]	38 [21 to 59]	38 [21 to 59]
Cleveland-Elyria, OH	26 [19 to 34]	24 [15 to 37]	24 [15 to 37]
Total	4,516 [4,294 to 4,785]	4,101 [2,749 to 5,835]	4,101 [2,739 to 5,831]

Table S18: Projected Prevalence of Acute HIV in 2021 by Metropolitan Statistical Area, Absent Pandemic, Prolonged Barriers to Care, and Rapid Resumption of Care Scenarios

Location	Absent Pandemic, 2021	Prolonged Barriers to Care, 2021	Rapid Resumption of Care, 2021
New York-Newark-Jersey City, NY-NJ-PA	478 [405 to 557]	569 [434 to 744]	492 [401 to 602]
Miami-Fort Lauderdale-Pompano Beach, FL	375 [267 to 477]	398 [286 to 522]	366 [259 to 477]
Los Angeles-Long Beach-Anaheim, CA	426 [368 to 492]	463 [368 to 575]	421 [349 to 507]
Atlanta-Sandy Springs-Alpharetta, GA	329 [282 to 381]	350 [287 to 426]	324 [272 to 386]
Houston-The Woodlands-Sugar Land, TX	287 [229 to 347]	300 [232 to 384]	279 [218 to 351]
Dallas-Fort Worth-Arlington, TX	250 [204 to 298]	275 [213 to 352]	249 [197 to 312]
Chicago-Naperville-Elgin, IL-IN-WI	266 [225 to 315]	275 [221 to 338]	259 [213 to 315]
Washington-Arlington-Alexandria, DC-VA-MD-WV	119 [95 to 149]	142 [105 to 193]	122 [95 to 156]
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	126 [100 to 157]	136 [104 to 179]	125 [95 to 161]
Orlando-Kissimmee-Sanford, FL	120 [93 to 154]	129 [96 to 171]	118 [89 to 159]
San Francisco-Oakland-Berkeley, CA	98 [72 to 130]	118 [78 to 165]	100 [71 to 135]
Phoenix-Mesa-Chandler, AZ	98 [72 to 137]	107 [74 to 152]	97 [68 to 136]
Tampa-St. Petersburg-Clearwater, FL	101 [74 to 147]	109 [77 to 154]	99 [72 to 141]
Riverside-San Bernardino-Ontario, CA	113 [76 to 169]	122 [77 to 187]	109 [69 to 167]
Detroit-Warren-Dearborn, MI	94 [68 to 125]	105 [71 to 145]	93 [65 to 129]
Baltimore-Columbia-Towson, MD	56 [40 to 74]	64 [45 to 87]	56 [41 to 76]
Las Vegas-Henderson-Paradise, NV	80 [62 to 99]	82 [61 to 106]	78 [59 to 100]
Boston-Cambridge-Newton, MA-NH	119 [74 to 190]	144 [88 to 220]	130 [80 to 202]
San Diego-Chula Vista-Carlsbad, CA	57 [44 to 73]	67 [47 to 93]	58 [43 to 78]
Charlotte-Concord-Gastonia, NC-SC	72 [56 to 93]	77 [56 to 102]	71 [52 to 91]
San Antonio-New Braunfels, TX	71 [56 to 90]	77 [57 to 102]	70 [53 to 90]
Jacksonville, FL	62 [42 to 91]	66 [45 to 99]	61 [42 to 90]
New Orleans-Metairie, LA	51 [38 to 67]	57 [41 to 76]	51 [37 to 69]
Memphis, TN-MS-AR	52 [36 to 69]	55 [38 to 78]	51 [35 to 71]
Seattle-Tacoma-Bellevue, WA	84 [44 to 138]	104 [51 to 181]	86 [46 to 143]
Austin-Round Rock-Georgetown, TX	45 [35 to 58]	52 [36 to 74]	45 [33 to 62]
Indianapolis-Carmel-Anderson, IN	52 [39 to 66]	56 [41 to 73]	51 [38 to 67]
Cincinnati, OH-KY-IN	75 [55 to 105]	80 [57 to 113]	76 [54 to 108]
Columbus, OH	38 [28 to 53]	41 [29 to 58]	38 [27 to 53]
Baton Rouge, LA	36 [25 to 52]	38 [27 to 56]	36 [25 to 52]
Sacramento-Roseville-Folsom, CA	44 [32 to 59]	46 [31 to 66]	42 [29 to 59]
Cleveland-Elyria, OH	23 [17 to 31]	26 [18 to 36]	23 [17 to 32]
Total	4,298 [3,968 to 4,676]	4,732 [3,881 to 5,874]	4,275 [3,659 to 5,039]

Table S19: Projected Prevalence of Acute HIV in 2025 by Metropolitan Statistical Area, Absent Pandemic, Prolonged Barriers to Care, and Rapid Resumption of Care Scenarios

Location	Absent Pandemic, 2025	Prolonged Barriers to Care, 2025	Rapid Resumption of Care, 2025
New York-Newark-Jersey City, NY-NJ-PA	412 [308 to 519]	422 [315 to 535]	416 [311 to 527]
Miami-Fort Lauderdale-Pompano Beach, FL	316 [195 to 448]	321 [196 to 453]	316 [193 to 448]
Los Angeles-Long Beach-Anaheim, CA	397 [310 to 496]	403 [315 to 504]	396 [312 to 498]
Atlanta-Sandy Springs-Alpharetta, GA	316 [252 to 382]	317 [253 to 386]	315 [252 to 382]
Houston-The Woodlands-Sugar Land, TX	267 [191 to 354]	269 [190 to 356]	266 [188 to 351]
Dallas-Fort Worth-Arlington, TX	224 [167 to 287]	227 [168 to 291]	224 [166 to 288]
Chicago-Naperville-Elgin, IL-IN-WI	264 [207 to 333]	263 [207 to 334]	261 [204 to 330]
Washington-Arlington-Alexandria, DC-VA-MD-WV	95 [63 to 137]	97 [64 to 138]	96 [63 to 137]
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	110 [74 to 153]	110 [75 to 154]	109 [74 to 152]
Orlando-Kissimmee-Sanford, FL	103 [70 to 143]	104 [71 to 143]	103 [70 to 142]
San Francisco-Oakland-Berkeley, CA	80 [51 to 120]	84 [53 to 125]	81 [52 to 120]
Phoenix-Mesa-Chandler, AZ	85 [50 to 138]	86 [51 to 140]	85 [50 to 138]
Tampa-St. Petersburg-Clearwater, FL	89 [54 to 147]	90 [56 to 149]	88 [54 to 146]
Riverside-San Bernardino-Ontario, CA	104 [55 to 192]	105 [56 to 197]	102 [54 to 189]
Detroit-Warren-Dearborn, MI	86 [52 to 132]	88 [54 to 134]	86 [53 to 131]
Baltimore-Columbia-Towson, MD	45 [27 to 68]	46 [28 to 68]	45 [27 to 67]
Las Vegas-Henderson-Paradise, NV	67 [45 to 92]	68 [45 to 93]	67 [44 to 92]
Boston-Cambridge-Newton, MA-NH	102 [61 to 162]	103 [61 to 161]	102 [61 to 160]
San Diego-Chula Vista-Carlsbad, CA	46 [32 to 67]	48 [33 to 69]	47 [32 to 68]
Charlotte-Concord-Gastonia, NC-SC	69 [47 to 98]	70 [48 to 98]	69 [47 to 97]
San Antonio-New Braunfels, TX	66 [46 to 90]	67 [47 to 90]	66 [46 to 88]
Jacksonville, FL	59 [33 to 99]	59 [34 to 98]	58 [34 to 99]
New Orleans-Metairie, LA	43 [28 to 63]	44 [28 to 64]	43 [27 to 63]
Memphis, TN-MS-AR	45 [27 to 66]	46 [27 to 67]	45 [27 to 66]
Seattle-Tacoma-Bellevue, WA	78 [32 to 160]	82 [34 to 170]	78 [32 to 166]
Austin-Round Rock-Georgetown, TX	37 [25 to 51]	38 [26 to 53]	37 [25 to 52]
Indianapolis-Carmel-Anderson, IN	48 [32 to 66]	48 [32 to 66]	47 [32 to 66]
Cincinnati, OH-KY-IN	71 [45 to 105]	72 [47 to 105]	72 [46 to 105]
Columbus, OH	33 [22 to 51]	34 [22 to 51]	33 [22 to 50]
Baton Rouge, LA	32 [20 to 50]	32 [20 to 51]	32 [20 to 50]
Sacramento-Roseville-Folsom, CA	45 [27 to 69]	45 [27 to 69]	44 [26 to 67]
Cleveland-Elyria, OH	19 [11 to 28]	19 [11 to 28]	19 [11 to 28]
Total	3,854 [3,152 to 4,580]	3,907 [3,180 to 4,686]	3,851 [3,146 to 4,614]

9.5 Projected Knowledge of Status in 2020, 2021, and 2025

Table S20: Projected Knowledge of Status in 2020 by Metropolitan Statistical Area, Absent Pandemic, Prolonged Barriers to Care, and Rapid Resumption of Care Scenarios

Location	Absent Pandemic, 2020	Prolonged Barriers to Care, 2020	Rapid Resumption of Care, 2020
New York-Newark-Jersey City, NY-NJ-PA	95% [95 to 96%]	95% [94 to 96%]	95% [94 to 96%]
Miami-Fort Lauderdale-Pompano Beach, FL	91% [88 to 94%]	91% [88 to 94%]	91% [88 to 94%]
Los Angeles-Long Beach-Anaheim, CA	91% [90 to 93%]	91% [90 to 93%]	91% [89 to 93%]
Atlanta-Sandy Springs-Alpharetta, GA	92% [88 to 94%]	91% [88 to 94%]	91% [88 to 94%]
Houston-The Woodlands-Sugar Land, TX	88% [86 to 90%]	88% [86 to 90%]	88% [86 to 90%]
Dallas-Fort Worth-Arlington, TX	89% [87 to 92%]	89% [86 to 91%]	89% [86 to 91%]
Chicago-Naperville-Elgin, IL-IN-WI	93% [91 to 95%]	93% [91 to 95%]	93% [91 to 95%]
Washington-Arlington-Alexandria, DC-VA-MD-WV	96% [95 to 97%]	96% [94 to 97%]	96% [94 to 97%]
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	95% [93 to 96%]	95% [93 to 96%]	95% [93 to 96%]
Orlando-Kissimmee-Sanford, FL	90% [87 to 92%]	90% [87 to 92%]	90% [87 to 92%]
San Francisco-Oakland-Berkeley, CA	95% [93 to 97%]	95% [92 to 97%]	95% [92 to 97%]
Phoenix-Mesa-Chandler, AZ	88% [85 to 91%]	88% [84 to 91%]	88% [84 to 91%]
Tampa-St. Petersburg-Clearwater, FL	89% [86 to 92%]	89% [86 to 92%]	89% [86 to 92%]
Riverside-San Bernardino-Ontario, CA	89% [85 to 92%]	89% [85 to 92%]	89% [85 to 92%]
Detroit-Warren-Dearborn, MI	90% [87 to 93%]	90% [87 to 93%]	90% [87 to 93%]
Baltimore-Columbia-Towson, MD	95% [93 to 97%]	95% [93 to 97%]	95% [93 to 97%]
Las Vegas-Henderson-Paradise, NV	83% [80 to 86%]	83% [80 to 86%]	83% [80 to 86%]
Boston-Cambridge-Newton, MA-NH	94% [91 to 96%]	93% [90 to 96%]	93% [90 to 96%]
San Diego-Chula Vista-Carlsbad, CA	92% [89 to 95%]	92% [89 to 95%]	92% [89 to 95%]
Charlotte-Concord-Gastonia, NC-SC	90% [86 to 92%]	89% [86 to 92%]	89% [86 to 92%]
San Antonio-New Braunfels, TX	85% [81 to 88%]	85% [81 to 88%]	85% [81 to 88%]
Jacksonville, FL	90% [87 to 93%]	90% [87 to 93%]	90% [87 to 92%]
New Orleans-Metairie, LA	88% [85 to 91%]	88% [84 to 91%]	88% [84 to 91%]
Memphis, TN-MS-AR	90% [88 to 92%]	90% [87 to 92%]	90% [87 to 92%]
Seattle-Tacoma-Bellevue, WA	93% [91 to 95%]	92% [90 to 94%]	92% [90 to 94%]
Austin-Round Rock-Georgetown, TX	87% [84 to 90%]	87% [84 to 90%]	87% [84 to 90%]
Indianapolis-Carmel-Anderson, IN	86% [82 to 89%]	85% [82 to 89%]	85% [82 to 89%]
Cincinnati, OH-KY-IN	83% [77 to 87%]	82% [77 to 87%]	82% [77 to 87%]
Columbus, OH	88% [84 to 91%]	87% [84 to 91%]	87% [84 to 91%]
Baton Rouge, LA	87% [83 to 90%]	87% [83 to 90%]	87% [83 to 90%]
Sacramento-Roseville-Folsom, CA	90% [87 to 93%]	90% [87 to 92%]	90% [87 to 92%]
Cleveland-Elyria, OH	89% [86 to 92%]	89% [86 to 92%]	89% [86 to 92%]
Total	92% [91 to 92%]	92% [91 to 92%]	92% [91 to 92%]

Table S21: Projected Knowledge of Status in 2021 by Metropolitan Statistical Area, Absent Pandemic, Prolonged Barriers to Care, and Rapid Resumption of Care Scenarios

Location	Absent Pandemic, 2021	Prolonged Barriers to Care, 2021	Rapid Resumption of Care, 2021
New York-Newark-Jersey City, NY-NJ-PA	96% [95 to 97%]	95% [94 to 96%]	95% [94 to 97%]
Miami-Fort Lauderdale-Pompano Beach, FL	91% [88 to 95%]	91% [88 to 94%]	91% [88 to 95%]
Los Angeles-Long Beach-Anaheim, CA	92% [90 to 93%]	91% [89 to 93%]	91% [90 to 93%]
Atlanta-Sandy Springs-Alpharetta, GA	92% [89 to 94%]	91% [88 to 94%]	92% [88 to 94%]
Houston-The Woodlands-Sugar Land, TX	88% [86 to 91%]	88% [85 to 90%]	88% [86 to 91%]
Dallas-Fort Worth-Arlington, TX	90% [88 to 92%]	89% [87 to 92%]	90% [87 to 92%]
Chicago-Naperville-Elgin, IL-IN-WI	93% [91 to 95%]	93% [90 to 95%]	93% [91 to 95%]
Washington-Arlington-Alexandria, DC-VA-MD-WV	96% [95 to 97%]	96% [94 to 97%]	96% [95 to 97%]
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	95% [93 to 97%]	95% [93 to 96%]	95% [93 to 97%]
Orlando-Kissimmee-Sanford, FL	91% [88 to 93%]	90% [87 to 93%]	90% [87 to 93%]
San Francisco-Oakland-Berkeley, CA	95% [93 to 97%]	95% [92 to 97%]	95% [93 to 97%]
Phoenix-Mesa-Chandler, AZ	89% [85 to 92%]	88% [84 to 92%]	89% [85 to 92%]
Tampa-St. Petersburg-Clearwater, FL	90% [86 to 93%]	90% [86 to 93%]	90% [86 to 93%]
Riverside-San Bernardino-Ontario, CA	90% [85 to 93%]	89% [84 to 92%]	90% [85 to 93%]
Detroit-Warren-Dearborn, MI	90% [87 to 93%]	90% [86 to 93%]	90% [87 to 93%]
Baltimore-Columbia-Towson, MD	96% [94 to 97%]	95% [93 to 97%]	96% [94 to 97%]
Las Vegas-Henderson-Paradise, NV	84% [81 to 87%]	84% [80 to 87%]	84% [81 to 87%]
Boston-Cambridge-Newton, MA-NH	94% [91 to 96%]	93% [89 to 96%]	93% [90 to 96%]
San Diego-Chula Vista-Carlsbad, CA	93% [89 to 95%]	92% [89 to 95%]	92% [89 to 95%]
Charlotte-Concord-Gastonia, NC-SC	90% [87 to 93%]	90% [86 to 92%]	90% [86 to 93%]
San Antonio-New Braunfels, TX	86% [82 to 89%]	85% [81 to 88%]	85% [81 to 89%]
Jacksonville, FL	90% [87 to 93%]	90% [86 to 93%]	90% [87 to 93%]
New Orleans-Metairie, LA	88% [85 to 92%]	88% [84 to 91%]	88% [85 to 91%]
Memphis, TN-MS-AR	91% [88 to 93%]	90% [87 to 93%]	90% [88 to 93%]
Seattle-Tacoma-Bellevue, WA	93% [91 to 95%]	92% [89 to 95%]	93% [90 to 95%]
Austin-Round Rock-Georgetown, TX	88% [85 to 91%]	87% [84 to 91%]	88% [85 to 91%]
Indianapolis-Carmel-Anderson, IN	86% [82 to 89%]	85% [82 to 89%]	86% [82 to 89%]
Cincinnati, OH-KY-IN	83% [77 to 88%]	82% [76 to 87%]	83% [77 to 87%]
Columbus, OH	88% [84 to 92%]	88% [84 to 91%]	88% [84 to 91%]
Baton Rouge, LA	87% [84 to 91%]	87% [83 to 90%]	87% [83 to 91%]
Sacramento-Roseville-Folsom, CA	90% [87 to 93%]	90% [86 to 93%]	90% [87 to 93%]
Cleveland-Elyria, OH	90% [87 to 93%]	89% [86 to 92%]	90% [86 to 92%]
Total	92% [92 to 93%]	92% [90 to 93%]	92% [91 to 93%]

Table S22: Projected Knowledge of Status in 2025 by Metropolitan Statistical Area, Absent Pandemic, Prolonged Barriers to Care, and Rapid Resumption of Care Scenarios

Location	Absent Pandemic, 2025	Prolonged Barriers to Care, 2025	Rapid Resumption of Care, 2025
New York-Newark-Jersey City, NY-NJ-PA	96% [95 to 97%]	96% [95 to 97%]	96% [95 to 97%]
Miami-Fort Lauderdale-Pompano Beach, FL	93% [90 to 97%]	93% [89 to 97%]	93% [90 to 97%]
Los Angeles-Long Beach-Anaheim, CA	93% [90 to 94%]	92% [90 to 94%]	92% [90 to 94%]
Atlanta-Sandy Springs-Alpharetta, GA	93% [90 to 96%]	93% [90 to 96%]	93% [90 to 96%]
Houston-The Woodlands-Sugar Land, TX	90% [87 to 93%]	90% [86 to 93%]	90% [87 to 93%]
Dallas-Fort Worth-Arlington, TX	92% [89 to 94%]	92% [89 to 94%]	92% [89 to 94%]
Chicago-Naperville-Elgin, IL-IN-WI	94% [91 to 96%]	94% [91 to 96%]	94% [91 to 96%]
Washington-Arlington-Alexandria, DC-VA-MD-WV	97% [96 to 98%]	97% [96 to 98%]	97% [96 to 98%]
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	96% [94 to 98%]	96% [94 to 98%]	96% [94 to 98%]
Orlando-Kissimmee-Sanford, FL	93% [90 to 95%]	92% [90 to 95%]	93% [90 to 95%]
San Francisco-Oakland-Berkeley, CA	96% [93 to 98%]	96% [93 to 98%]	96% [93 to 98%]
Phoenix-Mesa-Chandler, AZ	91% [87 to 94%]	91% [87 to 94%]	91% [87 to 94%]
Tampa-St. Petersburg-Clearwater, FL	92% [87 to 95%]	92% [87 to 95%]	92% [87 to 95%]
Riverside-San Bernardino-Ontario, CA	91% [85 to 95%]	91% [85 to 95%]	91% [85 to 95%]
Detroit-Warren-Dearborn, MI	92% [88 to 95%]	91% [87 to 95%]	92% [88 to 95%]
Baltimore-Columbia-Towson, MD	97% [95 to 98%]	97% [95 to 98%]	97% [95 to 98%]
Las Vegas-Henderson-Paradise, NV	87% [84 to 91%]	87% [83 to 91%]	87% [84 to 91%]
Boston-Cambridge-Newton, MA-NH	95% [91 to 97%]	95% [91 to 97%]	95% [91 to 97%]
San Diego-Chula Vista-Carlsbad, CA	94% [91 to 97%]	94% [91 to 96%]	94% [91 to 96%]
Charlotte-Concord-Gastonia, NC-SC	91% [87 to 94%]	91% [87 to 94%]	91% [87 to 94%]
San Antonio-New Braunfels, TX	88% [83 to 91%]	87% [83 to 91%]	87% [83 to 91%]
Jacksonville, FL	92% [87 to 95%]	92% [87 to 95%]	92% [87 to 95%]
New Orleans-Metairie, LA	90% [87 to 94%]	90% [86 to 94%]	90% [86 to 94%]
Memphis, TN-MS-AR	93% [90 to 96%]	93% [89 to 95%]	93% [89 to 95%]
Seattle-Tacoma-Bellevue, WA	95% [91 to 97%]	94% [90 to 97%]	95% [91 to 97%]
Austin-Round Rock-Georgetown, TX	90% [87 to 93%]	90% [87 to 93%]	90% [87 to 93%]
Indianapolis-Carmel-Anderson, IN	88% [83 to 91%]	87% [83 to 91%]	87% [83 to 91%]
Cincinnati, OH-KY-IN	85% [78 to 90%]	84% [78 to 90%]	84% [78 to 90%]
Columbus, OH	90% [85 to 93%]	89% [85 to 93%]	90% [85 to 93%]
Baton Rouge, LA	89% [85 to 93%]	89% [85 to 93%]	89% [85 to 93%]
Sacramento-Roseville-Folsom, CA	91% [87 to 94%]	91% [87 to 94%]	91% [87 to 94%]
Cleveland-Elyria, OH	92% [89 to 95%]	92% [89 to 94%]	92% [89 to 95%]
Total	93% [92 to 95%]	93% [92 to 95%]	93% [92 to 95%]

9.6 Projected Viral Suppression in 2020, 2021, and 2025

Table S23: Projected Viral Suppression in 2020 by Metropolitan Statistical Area, Absent Pandemic, Prolonged Barriers to Care, and Rapid Resumption of Care Scenarios

Location	Absent Pandemic, 2020	Prolonged Barriers to Care, 2020	Rapid Resumption of Care, 2020
New York-Newark-Jersey City, NY-NJ-PA	80% [79 to 81%]	75% [67 to 80%]	75% [67 to 80%]
Miami-Fort Lauderdale-Pompano Beach, FL	65% [62 to 68%]	61% [54 to 66%]	61% [54 to 66%]
Los Angeles-Long Beach-Anaheim, CA	66% [64 to 68%]	62% [55 to 67%]	62% [55 to 67%]
Atlanta-Sandy Springs-Alpharetta, GA	56% [52 to 59%]	52% [46 to 58%]	52% [46 to 58%]
Houston-The Woodlands-Sugar Land, TX	67% [65 to 69%]	62% [55 to 67%]	62% [55 to 67%]
Dallas-Fort Worth-Arlington, TX	70% [68 to 74%]	66% [58 to 72%]	66% [58 to 72%]
Chicago-Naperville-Elgin, IL-IN-WI	52% [50 to 54%]	48% [43 to 53%]	48% [43 to 53%]
Washington-Arlington-Alexandria, DC-VA-MD-WV	76% [73 to 79%]	71% [63 to 77%]	71% [63 to 77%]
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	62% [58 to 65%]	58% [51 to 63%]	58% [51 to 63%]
Orlando-Kissimmee-Sanford, FL	68% [64 to 72%]	64% [56 to 71%]	64% [56 to 71%]
San Francisco-Oakland-Berkeley, CA	80% [78 to 82%]	75% [66 to 81%]	75% [66 to 81%]
Phoenix-Mesa-Chandler, AZ	69% [64 to 74%]	64% [56 to 72%]	64% [56 to 72%]
Tampa-St. Petersburg-Clearwater, FL	71% [67 to 75%]	67% [59 to 73%]	67% [59 to 73%]
Riverside-San Bernardino-Ontario, CA	73% [71 to 76%]	68% [60 to 75%]	68% [60 to 75%]
Detroit-Warren-Dearborn, MI	80% [77 to 82%]	75% [66 to 81%]	75% [66 to 81%]
Baltimore-Columbia-Towson, MD	73% [70 to 77%]	68% [60 to 75%]	68% [60 to 75%]
Las Vegas-Henderson-Paradise, NV	55% [51 to 58%]	51% [45 to 56%]	51% [45 to 56%]
Boston-Cambridge-Newton, MA-NH	75% [72 to 79%]	70% [62 to 77%]	70% [62 to 77%]
San Diego-Chula Vista-Carlsbad, CA	77% [74 to 79%]	71% [63 to 77%]	71% [63 to 77%]
Charlotte-Concord-Gastonia, NC-SC	69% [65 to 74%]	65% [56 to 72%]	65% [56 to 72%]
San Antonio-New Braunfels, TX	68% [65 to 71%]	63% [56 to 69%]	63% [56 to 69%]
Jacksonville, FL	70% [66 to 75%]	66% [58 to 73%]	66% [58 to 73%]
New Orleans-Metairie, LA	73% [66 to 78%]	68% [59 to 75%]	68% [59 to 75%]
Memphis, TN-MS-AR	69% [63 to 76%]	61% [46 to 73%]	61% [46 to 73%]
Seattle-Tacoma-Bellevue, WA	87% [86 to 88%]	81% [72 to 87%]	81% [72 to 87%]
Austin-Round Rock-Georgetown, TX	80% [77 to 83%]	75% [66 to 81%]	75% [66 to 81%]
Indianapolis-Carmel-Anderson, IN	71% [67 to 75%]	66% [58 to 73%]	66% [58 to 73%]
Cincinnati, OH-KY-IN	54% [49 to 60%]	50% [43 to 58%]	50% [43 to 58%]
Columbus, OH	70% [65 to 75%]	65% [57 to 73%]	65% [57 to 73%]
Baton Rouge, LA	70% [65 to 75%]	66% [57 to 73%]	66% [57 to 73%]
Sacramento-Roseville-Folsom, CA	75% [72 to 78%]	70% [61 to 77%]	70% [61 to 77%]
Cleveland-Elyria, OH	70% [64 to 76%]	66% [57 to 74%]	66% [57 to 74%]
Total	70% [69 to 71%]	66% [59 to 70%]	66% [59 to 70%]

Table S24: Projected Viral Suppression in 2021 by Metropolitan Statistical Area, Absent Pandemic, Prolonged Barriers to Care, and Rapid Resumption of Care Scenarios

Location	Absent Pandemic, 2021	Prolonged Barriers to Care, 2021	Rapid Resumption of Care, 2021
New York-Newark-Jersey City, NY-NJ-PA	81% [79 to 83%]	75% [58 to 81%]	75% [58 to 81%]
Miami-Fort Lauderdale-Pompano Beach, FL	66% [63 to 70%]	61% [47 to 68%]	61% [47 to 68%]
Los Angeles-Long Beach-Anaheim, CA	67% [64 to 70%]	61% [46 to 68%]	61% [46 to 68%]
Atlanta-Sandy Springs-Alpharetta, GA	57% [52 to 62%]	52% [39 to 59%]	52% [39 to 59%]
Houston-The Woodlands-Sugar Land, TX	68% [65 to 71%]	63% [48 to 69%]	63% [48 to 69%]
Dallas-Fort Worth-Arlington, TX	71% [68 to 75%]	65% [50 to 73%]	66% [50 to 73%]
Chicago-Naperville-Elgin, IL-IN-WI	52% [49 to 55%]	47% [36 to 53%]	47% [36 to 53%]
Washington-Arlington-Alexandria, DC-VA-MD-WV	78% [74 to 81%]	71% [53 to 79%]	71% [53 to 79%]
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	63% [58 to 67%]	58% [43 to 65%]	58% [43 to 65%]
Orlando-Kissimmee-Sanford, FL	70% [64 to 75%]	64% [50 to 72%]	65% [50 to 72%]
San Francisco-Oakland-Berkeley, CA	81% [78 to 84%]	74% [55 to 82%]	74% [55 to 82%]
Phoenix-Mesa-Chandler, AZ	71% [64 to 76%]	65% [49 to 74%]	65% [49 to 74%]
Tampa-St. Petersburg-Clearwater, FL	73% [68 to 77%]	67% [52 to 75%]	67% [52 to 75%]
Riverside-San Bernardino-Ontario, CA	75% [71 to 78%]	68% [51 to 76%]	68% [51 to 76%]
Detroit-Warren-Dearborn, MI	81% [77 to 84%]	75% [57 to 82%]	75% [57 to 82%]
Baltimore-Columbia-Towson, MD	75% [71 to 80%]	69% [52 to 77%]	69% [52 to 77%]
Las Vegas-Henderson-Paradise, NV	58% [51 to 63%]	53% [39 to 61%]	53% [39 to 61%]
Boston-Cambridge-Newton, MA-NH	76% [72 to 80%]	70% [53 to 78%]	70% [53 to 78%]
San Diego-Chula Vista-Carlsbad, CA	79% [74 to 82%]	72% [54 to 79%]	72% [54 to 79%]
Charlotte-Concord-Gastonia, NC-SC	71% [66 to 76%]	65% [50 to 73%]	65% [50 to 73%]
San Antonio-New Braunfels, TX	69% [65 to 72%]	63% [48 to 70%]	63% [48 to 70%]
Jacksonville, FL	71% [66 to 77%]	66% [51 to 74%]	66% [51 to 74%]
New Orleans-Metairie, LA	74% [67 to 80%]	68% [53 to 77%]	68% [53 to 77%]
Memphis, TN-MS-AR	71% [63 to 78%]	61% [34 to 74%]	61% [34 to 74%]
Seattle-Tacoma-Bellevue, WA	87% [86 to 88%]	80% [60 to 87%]	80% [60 to 87%]
Austin-Round Rock-Georgetown, TX	81% [77 to 84%]	74% [57 to 82%]	74% [57 to 82%]
Indianapolis-Carmel-Anderson, IN	72% [68 to 77%]	66% [51 to 74%]	66% [51 to 74%]
Cincinnati, OH-KY-IN	56% [49 to 63%]	51% [38 to 61%]	51% [38 to 61%]
Columbus, OH	72% [66 to 77%]	66% [50 to 74%]	66% [50 to 74%]
Baton Rouge, LA	72% [66 to 77%]	66% [50 to 74%]	66% [50 to 74%]
Sacramento-Roseville-Folsom, CA	76% [73 to 80%]	69% [51 to 77%]	69% [51 to 77%]
Cleveland-Elyria, OH	73% [65 to 79%]	67% [50 to 76%]	67% [50 to 76%]
Total	72% [69 to 74%]	66% [50 to 72%]	66% [50 to 72%]

Table S25: Projected Viral Suppression in 2025 by Metropolitan Statistical Area, Absent Pandemic, Prolonged Barriers to Care, and Rapid Resumption of Care Scenarios

Location	Absent Pandemic, 2025	Prolonged Barriers to Care, 2025	Rapid Resumption of Care, 2025
New York-Newark-Jersey City, NY-NJ-PA	83% [80 to 86%]	80% [58 to 86%]	80% [58 to 86%]
Miami-Fort Lauderdale-Pompano Beach, FL	68% [63 to 74%]	66% [47 to 74%]	66% [47 to 74%]
Los Angeles-Long Beach-Anaheim, CA	68% [64 to 74%]	66% [46 to 74%]	66% [46 to 74%]
Atlanta-Sandy Springs-Alpharetta, GA	58% [52 to 66%]	56% [39 to 66%]	56% [39 to 66%]
Houston-The Woodlands-Sugar Land, TX	69% [65 to 76%]	67% [48 to 76%]	67% [48 to 76%]
Dallas-Fort Worth-Arlington, TX	73% [68 to 78%]	70% [50 to 78%]	70% [50 to 78%]
Chicago-Naperville-Elgin, IL-IN-WI	51% [46 to 56%]	49% [35 to 56%]	49% [35 to 56%]
Washington-Arlington-Alexandria, DC-VA-MD-WV	80% [74 to 85%]	77% [53 to 85%]	77% [53 to 85%]
Philadelphia-Camden-Wilmington, PA-NJ-DE-MD	64% [57 to 72%]	62% [43 to 72%]	62% [43 to 72%]
Orlando-Kissimmee-Sanford, FL	71% [64 to 79%]	69% [50 to 79%]	69% [50 to 79%]
San Francisco-Oakland-Berkeley, CA	82% [79 to 86%]	79% [55 to 86%]	79% [55 to 86%]
Phoenix-Mesa-Chandler, AZ	73% [64 to 82%]	71% [49 to 82%]	71% [49 to 82%]
Tampa-St. Petersburg-Clearwater, FL	74% [68 to 81%]	72% [52 to 81%]	72% [52 to 81%]
Riverside-San Bernardino-Ontario, CA	76% [71 to 82%]	74% [51 to 82%]	74% [51 to 82%]
Detroit-Warren-Dearborn, MI	83% [78 to 87%]	80% [57 to 87%]	80% [57 to 87%]
Baltimore-Columbia-Towson, MD	77% [71 to 84%]	75% [52 to 84%]	75% [52 to 84%]
Las Vegas-Henderson-Paradise, NV	61% [51 to 73%]	59% [39 to 73%]	59% [39 to 73%]
Boston-Cambridge-Newton, MA-NH	77% [72 to 82%]	75% [53 to 82%]	75% [53 to 82%]
San Diego-Chula Vista-Carlsbad, CA	80% [74 to 86%]	78% [54 to 86%]	78% [54 to 86%]
Charlotte-Concord-Gastonia, NC-SC	72% [66 to 80%]	70% [50 to 80%]	70% [50 to 80%]
San Antonio-New Braunfels, TX	70% [65 to 76%]	68% [49 to 76%]	68% [49 to 76%]
Jacksonville, FL	73% [66 to 81%]	71% [51 to 81%]	71% [51 to 81%]
New Orleans-Metairie, LA	76% [68 to 83%]	73% [53 to 83%]	73% [53 to 83%]
Memphis, TN-MS-AR	73% [64 to 82%]	69% [34 to 82%]	69% [34 to 82%]
Seattle-Tacoma-Bellevue, WA	88% [87 to 89%]	85% [60 to 89%]	85% [60 to 89%]
Austin-Round Rock-Georgetown, TX	82% [78 to 86%]	79% [58 to 86%]	79% [58 to 86%]
Indianapolis-Carmel-Anderson, IN	74% [68 to 81%]	71% [51 to 81%]	72% [51 to 81%]
Cincinnati, OH-KY-IN	58% [49 to 70%]	56% [38 to 70%]	56% [38 to 70%]
Columbus, OH	73% [66 to 81%]	71% [50 to 81%]	71% [50 to 81%]
Baton Rouge, LA	74% [67 to 81%]	71% [50 to 81%]	71% [50 to 81%]
Sacramento-Roseville-Folsom, CA	77% [73 to 83%]	75% [52 to 83%]	75% [52 to 83%]
Cleveland-Elyria, OH	76% [65 to 85%]	73% [51 to 85%]	73% [51 to 85%]
Total	73% [69 to 78%]	70% [50 to 78%]	71% [50 to 78%]

10 Functional Forms for Parameters

Some of the parameters in the differential equations given in Section 6 are simple scalar quantities, but many are either time-varying or composed of two or more other parameters. We describe the functional forms of these more complex parameters here.

10.1 Some General Structural Forms

Most of our time-varying parameters follow one of three forms:

- **Linear Interpolation** between two or more knots
- **A Logistic Model** with an intercept and linear slope on the log odds scale (Section 10.1.1)
- **Interpolated using a logistic curve** between two or more knots (Section 10.1.2)

10.1.1 Logistic Model for Time-Varying Probabilities

For time varying parameters which are probabilities, we formulated a logistic model which had an intercept and a slope (relative to time), as well as coefficients for each age bracket, race, and combinations of sex/sexual behavior with drug use, plus their interactions with time. We also allowed for there to be a maximum achievable probability absent intervention:

$$
\begin{aligned}
logit\Big(\frac{p_{a,r,s,k}(t)}{p_{max}}\Big) &= \beta_0 + \beta_1 \times t \\
&+ \beta_{0,a1} \times \mathbb{1}_{a=1} + \beta_{1,a1} \times \mathbb{1}_{a=1} \times t \\
&+ \beta_{0,a2} \times \mathbb{1}_{a=2} + \beta_{1,a2} \times \mathbb{1}_{a=2} \times t \\
&+ \beta_{0,a3} \times \mathbb{1}_{a=3} + \beta_{1,a3} \times \mathbb{1}_{a=3} \times t \\
&+ \beta_{0,a4} \times \mathbb{1}_{a=4} + \beta_{1,a4} \times \mathbb{1}_{a=4} \times t \\
&+ \beta_{0,a5} \times \mathbb{1}_{a=5} + \beta_{1,a5} \times \mathbb{1}_{a=5} \times t \\
&+ \beta_{0,r1} \times \mathbb{1}_{r=Black} + \beta_{1,r1} \times \mathbb{1}_{r=Black} \times t \\
&+ \beta_{0,r2} \times \mathbb{1}_{r=Hispanic} + \beta_{1,r2} \times \mathbb{1}_{r=Hispanic} \times t \\
&+ \beta_{0,r3} \times \mathbb{1}_{r=Other} + \beta_{1,r3} \times \mathbb{1}_{r=Other} \times t \\
&+ \beta_{0,sk1} \times \mathbb{1}_{s=MSM,k=never\_use} + \beta_{1,sk1} \times \mathbb{1}_{s=MSM,k=never\_use} \times t \\
&+ \beta_{0,sk2} \times \mathbb{1}_{s=MSM,k\neq never\_use} + \beta_{1,sk2} \times \mathbb{1}_{s=MSM,k\neq never\_use} \times t \\
&+ \beta_{0,sk3} \times \mathbb{1}_{s=heterosexual\_male,k=never\_use} + \beta_{1,sk3} \times \mathbb{1}_{s=heterosexual\_male,k=never\_use} \times t \\
&+ \beta_{0,sk4} \times \mathbb{1}_{s=heterosexual\_male,k\neq never\_use} + \beta_{1,sk4} \times \mathbb{1}_{s=heterosexual\_male,k\neq never\_use} \times t \\
&+ \beta_{0,sk5} \times \mathbb{1}_{s=female,k=never\_use} + \beta_{1,sk5} \times \mathbb{1}_{s=female,k=never\_use} \times t \\
&+ \beta_{0,sk6} \times \mathbb{1}_{s=female,k\neq never\_use} + \beta_{1,sk6} \times \mathbb{1}_{s=female,k\neq never\_use} \times t
\end{aligned}
$$

10.1.2 Logistic Splines for Time-Varying Rates

Many of our time-varying parameters which are not proportions were formulated as splines with two or three knots. For most of these, we interpolated such that values between the knots follow a logistic curve.

10.1.2.1 Two-Point Spline For the case where our time-varying parameter hasdtwo knots y_0 and y_1 at times t_0 and t_1, and where we wanedt p_0 to be the proportion of the total span (difference between asymptotes) of the curve that would be traversed before t_0, and p_1 to be the proportion of the total span of the curve that would be traversed after t_1, we used the following function:

$$y(t) = f_l(t, y_0, y_1, t_0, t_1, p_0, p_1) = A + \frac{(K - A)}{1 + Q \cdot e^{-B\cdot(t-t_0)}} \tag{73}$$

where:

$$A = y_0 - p_0 \times \frac{y_1 - y_0}{1 - p_0 - p_1} \tag{74}$$

$$K = y_1 + p_0 \times \frac{y_1 - y_0}{1 - p_0 - p_1} \tag{75}$$

$$Q = \frac{K - y_0}{y_0 - A} \tag{76}$$

$$B = \frac{log(y_1 - A) - log(K - y_1)}{t_1 - t_0} \tag{77}$$

$$\tag{78}$$

10.1.2.2 Three-Point Splines For the cases where our time-varying parameter had three knots y_0, y_1, and y_2 at times t_0, t_1, and t_2, we split the spline into two logistic curves (before and after t_1). We defined p_0 to be the proportion of the total span (difference between asymptotes) of the curve from t_0 to t_1 that would be traversed before t_0, and p_2 to be the proportion of the total span of the curve from $t_1 tot_2$ that would be traversed after t_2. We took one of two approaches, depending on whether or not the curves changed direction at t_1.

10.1.2.3 Three-Point Spline that changes direction For a spline with three knots where the change from y_0 to y_1 was in the opposite direction to the change from $y_1 toy_2$, we fit one two-point spline for before y_1 and one for after:

$$y(t) = \begin{cases} f_l(t, y_0, y_1, t_0, t_1, p_0, 0.025) & t < t_1 \\ f_l(t, y_1, y_2, t_1, t_2, 0.025, p_2) & t \geq t_1 \end{cases} \tag{79}$$

10.1.2.4 Three-Point Spline that is monotonically increasing or decreasing For a spline with three knots where the change from y_0 to y_1 was in the same direction as the change from $y_1 to y_2$, we fit one two-point spline for before t_1 and one for after, such that the slopes of the two splines are the same at $t1$.

10.2 Rate of Transmission Between Strata $\left(\Gamma_{i,j,m}(t)\right)$

For shorthand, we use i to denote the stratum where age = a, race = r sex/sexual behavior = s and IV drug use state = k and j to denote stratum a', r', s', k'.

The rate of transmission from stratum j to stratum i via mode m at time t, denoted $\Gamma_{i,j,m}(t)$, follows a smooth function from initiation in 1970 through the run period (2030 for this work). Prior to the year 2000, this is a linear spline; after 2000 it follows a logistic spline (Section 10.1.2).

10.2.1 Transmission Rate After 2000

Following the year 2000, we use a logistic spline (Section 10.1.2), with knots at 2000, 2010, and 2020. These knots are decomposed into a global transmission rate, multipliers for the mode of transmission (MSM, IDU, or heterosexual) interacted with race/ethnicity, multipliers for age, and multipliers for female sex (for heterosexual transmission) or MSM-IDU (for IV transmission).

The knots for 2000 ($C_{2000,i,j,m}$) are given by:

$$C_{2000,i,j,m} = \begin{cases} \gamma \cdot \omega_{r,2000}^{(IDU)} \cdot \omega_a^{(A)} & \text{if } m = IV \text{and } s \neq MSM \\ \gamma \cdot \omega_{r,2000}^{(IDU)} \cdot \omega_a^{(A)} \cdot \omega_{2000}^{(MSM\text{-}IDU)} & \text{if } m = IV \text{and } s = MSM \\ \gamma \cdot \omega_{r,2000}^{(MSM)} \cdot \omega_a^{(A)} & \text{if } m = sexual \text{ and } s \neq female \text{ and } s' \neq female \\ 0 & \text{if } m = sexual \text{ and } s = female \text{ and } s' = female \\ \gamma \cdot \omega_{r,2000}^{(het)} \cdot \omega_a^{(A)} & \text{if } m = sexual \text{ and } s \neq female \text{ and } s' = female \\ \gamma \cdot \omega_{r,2000}^{(het)} \cdot \omega_a^{(A)} \cdot \omega^{(female)} & \text{if } m = sexual \text{ and } s = female \text{ and } s' \neq female \end{cases} \tag{80}$$

where

- γ is the global transmission rate (irrespective of time)
- $\omega_{r,2000}^{(IDU)}$ is a transmission multiplier for IV transmission in 2000, specific to the race of the at-risk partner (r)
- $\omega_a^{(A)}$ is a transmission multiplier for age (irrespective of time) specific to the age of the at-risk partner (a)
- $\omega_{2000}^{(MSM\text{-}IDU)}$ is a relative risk for IV transmission in 2000 for PWID who are MSM, as compared to female or heterosexual male PWID
- $\omega_{r,2000}^{(MSM)}$ is a transmission multiplier for male-to-male sexual transmission in 2000, specific to the race of the at-risk partner (r)
- $\omega_{r,2000}^{(het)}$ is a transmission multiplier for heterosexual transmission in 2000, specific to the race of the at-risk partner (r)
- $\omega^{(female)}$ is the relative risk (irrespective of time) for male-to-female sexual transmission, as compared to female-to-male

The knots for 2010 ($C_{2010,i,j,m}$) are analagous, with the exception that the age-specific transmission multipliers are different for MSM. This allows for greater flexibility in reproducing age trends for MSM, where transmission among younger individuals is particularly dynamic.

$$C_{2010,i,j,m} = \begin{cases} \gamma \cdot \omega_{r,2010}^{(IDU)} \cdot \omega_a^{(A)} & \text{if } m = IV \text{and } s \neq MSM \\ \gamma \cdot \omega_{r,2010}^{(IDU)} \cdot \omega_a^{(A)} \cdot \omega_{2010}^{(MSM\text{-}IDU)} & \text{if } m = IV \text{and } s = MSM \\ \gamma \cdot \omega_{r,2010}^{(MSM)} \cdot \omega_{a,2010}^{(A,MSM)} & \text{if } m = sexual \text{ and } s \neq female \text{ and } s' \neq female \\ 0 & \text{if } m = sexual \text{ and } s = female \text{ and } s' = female \\ \gamma \cdot \omega_{r,2010}^{(het)} \cdot \omega_a^{(A)} & \text{if } m = sexual \text{ and } s \neq female \text{ and } s' = female \\ \gamma \cdot \omega_{r,2010}^{(het)} \cdot \omega_a^{(A)} \cdot \omega^{(female)} & \text{if } m = sexual \text{ and } s = female \text{ and } s' \neq female \end{cases} \tag{81}$$

where $\omega_{a,2010}^{(A,MSM)}$ is an age-specific transmission multiplier that applies only to MSM for sexual transmission at the 2010 knot

The 2020 knots ($C_{2020,i,j,m}$) are analagous to the 2010 knots:

$$C_{2020,i,j,m} = \begin{cases} \gamma \cdot \omega^{(IDU)}_{r,2020} \cdot \omega^{(A)}_{a} & \text{if } m = IV \text{and } s \neq MSM \\ \gamma \cdot \omega^{(IDU)}_{r,2020} \cdot \omega^{(A)}_{a} \cdot \omega^{(MSM\text{-}IDU)}_{2020} & \text{if } m = IV \text{and } s = MSM \\ \gamma \cdot \omega^{(MSM)}_{r,2020} \cdot \omega^{(A,MSM)}_{a,2020} & \text{if } m = sexual \text{ and } s \neq female \text{ and } s' \neq female \\ 0 & \text{if } m = sexual \text{ and } s = female \text{ and } s' = female \\ \gamma \cdot \omega^{(het)}_{r,2020} \cdot \omega^{(A)}_{a} & \text{if } m = sexual \text{ and } s \neq female \text{ and } s' = female \\ \gamma \cdot \omega^{(het)}_{r,2020} \cdot \omega^{(A)}_{a} \cdot \omega^{(female)} & \text{if } m = sexual \text{ and } s = female \text{ and } s' \neq female \end{cases} \tag{82}$$

10.2.2 Transmission Rate Before 2000

Prior to 2000, the transmission rate follows a linear spline with two levels - a "base rate" and a "peak rate". In order to reproduce historical trends where cases among MSM rose first, followed later by cases among heterosexuals and PWID, rates for male-to-male sexual transmission start at the peak rate from 1970 to 1980, decrease from 1980 to the base rate at 1990, and remain flat until 2000. Rates for heterosexual and IV transmission begin at the base rate in 1970, increase to the peak rate by 1980 and continue there until 1990, and decrease back to the base rate by 2000.

The knot for the base rate is taken to be the same as the 2000 knot defined above:

$$C_{base,i,j,m} = C_{2000,i,j,m}) \tag{83}$$

The knot for the peak rate is calculated as the base rate times a multiplier specific to the mode of transmission (MSM, IDU, or heterosexual). In addition, IV transmission among PWID who are MSM factors in a relative risk ($\omega^{(MSM\text{-}IDU)}_{peak}$) that differs from the 2000 relative risk:

$$C_{peak,i,j,m} = \begin{cases} C_{base_i,j,m} \cdot \Omega^{(IDU)} & \text{if } m = IV \text{and } s \neq MSM \\ C_{base_i,j,m} \cdot \Omega^{(IDU)} \cdot \frac{\omega^{(MSM\text{-}IDU)}_{peak}}{\omega^{(MSM\text{-}IDU)}_{2000}} & \text{if } m = IV \text{and } s = MSM \\ C_{base_i,j,m} \cdot \Omega^{(MSM)} & \text{if } m = sexual \text{ and } s \neq female \text{ and } s' \neq female \\ C_{base_i,j,m} \cdot \Omega^{(het)} & \text{otherwise} \end{cases} \tag{84}$$

where $\Omega^{(IDU)}$, $\Omega^{(MSM)}$, and $\Omega^{(het)}$ are the peak transmission multipliers for IV, MSM, and heterosexual transmission respectively.

10.3 Proportion of Partners from Strata $(\Phi_{i,j,m})$

For each pair of strata i and j, and mode of transmission m, we define $\Phi_{i,j,m}$ to be the proportion of partners for those in stratum i who come from stratum j, such that $\sum_{j=1}^{N} \Phi_{i,j,m} = 1$

We decompose $\Phi_{i,j,m}$ into marginal probabilities of pairing by age, race, sex/sexual behavior, and drug use status:

$$\Phi_{i,j,m} = \phi^{(A)}_{a,a',m} \times \phi^{(R)}_{r,r',m} \times \phi^{(S)}_{s,s',m} \times \phi^{(K)}_{k,k',m} \tag{85}$$

where

- $\phi^{(A)}_{a,a',m}$ is the proportion of partners (for mode of transmission m) of those in age bracket a who come from age bracket a'. $\sum_{a^*=1}^{R} \phi^{(A)}_{a,a^*,m} = 1$
- $\phi^{(R)}_{r,r',m}$ is the proportion of partners (for mode of transmission m) of those of race r who come from race r'. $\sum_{r^*=1}^{R} \phi^{(R)}_{r,r^*,m} = 1$
- $\phi^{(S)}_{s,s',m}$ is the proportion of partners (for mode of transmission m) of those in sex/sexual behavior category s who come from sex/sexual behavior category s'. $\sum_{s^*=1}^{S} \phi^{(S)}_{s,s^*,m} = 1$
- $\phi^{(K)}_{k,k',m}$ is the proportion of partners (for mode of transmission m) of those in IV drug use state k who come from state k'. $\sum_{k^*=1}^{K} \phi^{(K)}_{k,k^*,m} = 1$

Because different locations have different population proportions of age, race, sex/sexual behavior, and IV drug use, we derive $\phi^{(A)}$, $\phi^{(R)}$, $\phi^{(S)}$, and $\phi^{(K)}$ from observed-to-expected ratios. For age pairings, we define the observed-to-expected ratio, $\chi^{(A)}_{a,a',m}$, for every pair of age brackets a and a', which represents the proportion of partners for those in age bracket a who come from age bracket a', relative to the proportion of the general population that is in age bracket a'. We derive $\phi^{(A)}_{a,a',m}$ from $\chi^{(A)}_{a,a',m}$ as follows:

$$\phi^{(A)}_{a,a',m} = \frac{\chi^{(A)}_{a,a',m} \times \frac{P_{a'}}{P}}{\sum_{a^*=1}^{A} \chi^{(A)}_{a,a^*,m} \times \frac{P_{a^*}}{P}} \tag{86}$$

where P_a is the population of individuals in age bracket a and P is the total population size (we used 2012 census estimates for population sizes). We define observed-to-expected ratios for race $\left(\chi^{(R)}_{r,r',m}\right)$, sex/sexual behavior $\left(\chi^{(S)}_{s,s',m}\right)$, and IV drug use $\left(\chi^{(K)}_{k,k',m}\right)$, and calculate the pairing proportions ($\phi^{(R)}_{r,r',m}$, $\phi^{(S)}_{s,s',m}$, and $\phi^{(K)}_{k,k',m}$) in an analagous manner.

Note that when m denotes IV transmission, the observed-to-expected ratios (and therefore pairing probabilities) are zero when either s or s' are not active use strata.

10.4 Proportion of PWH Suppressed $\left(\rho_{a,r,s,k}(t)\right)$

After 2010, the proportion suppressed in stratum a, r, s, k follows a logistic model as described in Section 10.1.1, with a maximum achievable proportion of 0.9 absent intervention. Suppression is presumed to be zero in all strata prior to 1996 (the advent of ART), and scales linearly from 1996 to the 2010-level.

10.5 Rate of HIV Diagnosis $\left(\beta_{a,r,s,k}(t)\right)$

We modeled the time-varying proportion of undiagnosed PWH who receive an HIV test within a given year using a logistic model as described in Section 10.1.1, with a maximum achievable proportion of 0.9 absent intervention. Assuming that this proportion, which we denote $p_{a,r,s,k}(t)$ is the result of a Poisson process with rate $\beta_{a,r,s,k}(t)$, can back-calculate the rate of diagnosis as:

$$\beta_{a,r,s,k}(t) = -Ln\left[1 - p_{a,r,s,k}(t)\right] \tag{87}$$

10.6 Proportion on PrEP $\left(\pi_{a,r,s,k}\right)$

We assume that the maximum proportion, p_{max} of those in each stratum a, r, s, k who are at risk for HIV and can become enrolled in a PrEP program on current trends (ie, absent intervention) is 50%.

Our model sets the proportion of those in each stratum a, r, s, k at risk for HIV infection who are on PrEP to zero in 2011. The proportion rises linearly to an intercept, which we denote $b_{a,r,s,k}$ in 2014. After 2014, the proportion increases linearly with slope $m_{a,r,s,k}$ until reaching 25%. From 25% to 50%, the proportion on PrEP follows the second half of a logistic curve, with a logistic slope and intercept chosen such that the slope of the logistic curve equals $m_{a,r,s,k}$ at the value of 25%:

$$\pi_{a,r,s,k} = \begin{cases} m_{a,r,s,k} \cdot (t - 2014) + b_{a,r,s,k} & \text{if } m_{a,r,s,k} \cdot (t - 2014) + b_{a,r,s,k} \ < 0.5 \cdot p_{max} \\ p_{max} \cdot \left[1 + e^{-(m'_{a,r,s,k} \cdot t + b'_{a,r,s,k})}\right]^{-1} & \text{otherwise} \end{cases} \tag{88}$$

where $m'_{a,r,s,k}$ and $b'_{a,r,s,k}$ are the slope and intercept on the logistic scale, and are calculated from $m_{a,r,s,k}$ and $b_{a,r,s,k}$:

$$m'_{a,r,s,k} = \frac{m_{a,r,s,k}}{0.5 \cdot (1 - 0.5) \cdot p_{max}} \tag{89}$$

$$t^* = 2014 + \frac{0.5 \cdot p_{max} - b_{a,r,s,k}}{m_{a,r,s,k}} \tag{90}$$

$$b'_{a,r,s,k} = -m'_{a,r,s,k} \cdot (t^* - 2014) \tag{91}$$

where t^* represents the year at which the proportion on PrEP reaches 25%.

10.7 IV Drug Use Initiation, Remission, and Relapse Rates $\left(\zeta_{a,r,s}(t)\right.$, $\xi_{a,r,s}(t)$, and $\left.\psi_{a,r,s}(t)\right)$

For each stratum a, r, s of age, race, and sex/sexual behavior, the rate of IV drug use initiation follows a logistic spline (Section 10.1.2) with knots at 2000 and 2020. The rates of remission and relapse do not vary with time.

We estimated "best-guess" rates for initiation, remission, and relapse from NSDUH 2014-2016 national data[36] as detailed below. In MCMC sampling, we sampled multipliers for each race for 2000 and 2020 for how much our initiation rates in each race differed from our best guess. We also sampled one multiplier for remission and one multiplier for relapse for how these parameters (across all strata) differed from our best guess.

10.7.1 IV Drug Use Initiation Rates

For each age bracket, we took the proportion of individuals at that age who have ever injected any drug and whose first use of heroin was when they were one year younger, and calculated the constant rate that yielded that proportion ($r = -log(1-p)$). For age groupings that spanned multiple years, we assumed ages are distributed uniformly. For each stratum of age x race x sex/sexual behavior we multiplied this rate by the national ratio of prevalent IV drug use in the stratum divided by IV drug use in the age group

10.7.2 IV Drug Use Remission Rates

For each stratum, we took the ratio of (used in past 30d) / (used in past year), and calculated the (constant) rate that yields that proportion at one year, ignoring mortality, new users, etc.

10.7.3 IV Drug Use Relapse Rates

We assumed that the proportion of active users is in steady state, ignoring contributions from mortality and new users as trivial, and solved: $n_{active\ users} \times r_{remission} = n_{in\ remission} \times r_{relapse}$

10.8 Aging Rates for PWH $\left(\alpha^{(H)}_{a,r,s,k}\right)$

Aging rates for those who are HIV-negative are taken to be the inverse of the number of years in the age bracket (eg, for the 25-34 age bracket, the aging rate is $\frac{1}{10}$).

However, we allowed aging rates among some brackets of PWH to deviate from this for two reasons:

1. HIV infections are not distributed uniformly across the 13-24 age bracket; they are concentrated among the older end of the bracket
2. In order to reproduce the age distribution among PWH with a compartmental model, we had to vary aging rates to "push" the large number of people infected at the height of the epidemic in the 1980s and 1990s along the age spectrum. For example, as those individuals reach their 50s, more will be leaving the 45-54 age bracket than entering it, and thus the aging rate will be greater than $\frac{1}{10}$.

To simplify the parameter space, we set aging rates to be the same within each risk group (MSM, PWID, and heterosexuals). The 13-24 aging rate was held fixed through time at a sampled rate. Other age brackets followed a logistic spline (Section 10.1.2) with knots at 2000, 2010, and 2020.

We estimated rates by calculating the proportion of PWH within an age bracket who were in the last year of that age bracket using CDC data.

10.9 HIV Mortality $\left(\theta^{HIV}(t)\right)$

Since our model does not represent CD4 strata, we allowed the excess mortality for unsuppressed HIV to vary over time to reproduce the much higher mortality in the early phases of the epidemic. We kept HIV mortality the same for all strata. From 2000 onwards, it followed a logistic spline (Section 10.1.2) with knots at 2000 and 2010. Prior to 2000, it rose linearly from the base (2000) level in 1970 to a sampled peak level in 1980, continued at the peak level until 1996 (the advent of ART), and fell linearly from 1996 to the base level in 2000.

The mortality rate of unsuppressed HIV was multiplied by the proportion unsuppressed in each compartment of PWH to give the mortality rate for that compartment.

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