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Assessing the Impact of COVID-19-Related Behavioral Changes and Clinical Service Disruptions on the HIV Epidemic in the United States

By

Laura M. Mann
Doctor of Philosophy

Epidemiology

Samuel M. Jenness, PhD, MPH
Advisor

Patrick S. Sullivan, PhD, DVM
Co-Advisor

Travis Sanchez, DVM, MPH
Committee Member

Accepted:

Kimberly Jacob Arriola, PhD, MPH
Dean of the James T. Laney School of Graduate Studies

Date

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By

Laura M. Mann
MPH, Columbia University, 2015
BS, University of Maryland, 2012

Advisor: Samuel M. Jenness, PhD, MPH

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Abstract

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HIV is a major public health challenge that has become more complex because of the COVID-19 pandemic. Economic and social disruptions from the pandemic have created new challenges in the control of HIV, prompting major behavioral changes and disrupting access to HIV screening, prevention, and clinical care services. This dissertation aimed to assess the impact of these COVID-related changes on the US HIV epidemic and to identify how potential home-based HIV prevention interventions that provide an alternative to clinic-based HIV services could have offset some of the COVID pandemic's epidemiologic impact on HIV.

In **Aim 1**, we described the magnitude, timing, and variation of sexual distancing and HIV service utilization changes among MSM in the US during the COVID-19 pandemic. Our results were consistent with prior studies demonstrating population-level decreases in sexual behavior, interruptions to use of HIV prevention services, but limited changes to HIV medical care for persons living with HIV. We newly identified the persistence these changes through the end of 2020 into 2021, demonstrating the durable impact of the COVID pandemic on HIV-related behavior and services.

In **Aim 2**, we used a dynamic network-based HIV transmission model of US MSM to estimate the incidence of HIV during the COVID-19 pandemic. We found that HIV transmission among US MSM decreased during 2020, but that temporary decreases in HIV incidence during the pandemic did not lead to long-term decreases in HIV transmission.

In **Aim 3**, we used a dynamic network-based HIV transmission model of Atlanta MSM to assess the potential impact that home-based HIV prevention interventions could have had during the COVID pandemic. We demonstrated that although home-based PrEP retention and HIV testing interventions could be effective at increasing PrEP use and HIV testing, in isolation they would have minimal impact on pandemic-era population-level HIV incidence. Scaling up interventions in terms of coverage, length, post-intervention persistence, increasing their efficacy, or combining them with other home-based HIV prevention interventions could aid in increasing their impact on HIV transmission in a pandemic context.

The findings of this dissertation contribute to the overall understanding of how the COVID pandemic has impacted the US HIV epidemic. We found that though the pandemic affected sexual behavior and HIV prevention service use of US MSM, the combined effects of these changes were likely not significant enough to cause long-term effects to the US HIV epidemic's trajectory. While home-based HIV prevention interventions could play a role in increasing PrEP use and HIV testing among MSM, these interventions by themselves may not have substantial impacts on HIV transmission in a pandemic context.

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Chapter 1. Background and Significance

HIV Prevention in the US

The prevention of HIV remains a major public health challenge in the US. There are approximately 1.2 million people in the US living with HIV,[1] and approximately 40 thousand new diagnoses occur every year.[2,3] Despite recent strides in HIV prevention, the rate of new HIV diagnoses has remained persistently high over the past decade.[4]

The risk of HIV is not uniform across the US population. Gay, bisexual, and other men who have sex with men (MSM) are at increased risk for HIV: despite representing less than 5% of the US population,[5,6] MSM account for nearly 70% of all HIV diagnoses.[3] Furthermore, certain subgroups of MSM are at higher HIV risk. For example, since the beginning of the HIV epidemic, Black/African American MSM have experienced disproportionate HIV prevalence and incidence.[7,8] In 2019, Black MSM represented more than 36% of all new HIV diagnoses among US MSM, despite Black individuals representing only 13% of the US population.[3,9] Studies have demonstrated that the increased risk among Black MSM is not attributable to higher risk behaviors but rather network factors and socioeconomic and treatment disparities.[10–12] In addition, Hispanic or Latino MSM also experience disproportionate HIV risk: while HIV diagnoses have decreased among white MSM and remained stable in Black MSM over the past decade, HIV diagnoses have increased among Hispanic or Latino MSM.[13]

Most HIV infections in MSM are transmitted through sexual contact.[14] In particular, unprotected receptive anal sex carries the highest risk for HIV acquisition.[15] Historically, consistent condom use has been promoted as an effective way to prevent HIV transmission among sexually active MSM, and as a result, public health efforts to reduce HIV have focused on promotion of condom use.[16] However, over the past decade, strides in HIV prophylaxis and

treatment have shifted HIV prevention efforts towards biomedical solutions that require minimal or no behavioral modification.

In July 2012, the US Food and Drug administration approved the first label indication for emtricitabine/tenofovir disoproxil fumarate (Truvada) for use as HIV pre-exposure prophylaxis (PrEP) for patients at high risk of HIV acquisition.[17] When taken consistently, PrEP has been shown to reduce the risk of HIV acquisition among MSM not known to be living with HIV by 99%.[18] However, effectiveness of PrEP is highly dependent on adherence and retention in PrEP care.[19,20] Research has therefore been focused on implementing programs to increase PrEP initiation, adherence, and retention, especially among groups that have been underserved by PrEP delivery.[12,21–23]

Initiation of and adherence to PrEP requires ongoing access to health care services. The PrEP care system/continuum has many steps. To begin PrEP, an individual must first attend an initial clinical visit. At this visit, a medical provider will perform an clinical evaluation that includes assessing indications for PrEP, taking a medical history, and performing various lab tests (including an HIV blood test and screening for sexually transmitted infections (STIs) and Hepatitis B and C viruses).[24] After evaluating for indications for PrEP (in the US, the CDC indicates PrEP for MSM who are HIV-negative, are sexually active and not in a monogamous partnership with a recently tested HIV-negative man, and have had unprotected anal sex in the past six months or a bacterial STI in the past six months),[18] PrEP medication may be prescribed. If laboratory testing results are available on the same day as the initial clinical visit, this can be on the same day, otherwise obtaining a prescription may take longer.[24] Once a prescription is obtained, the individual must fill it at a pharmacy, unless the medication is offered at their clinic.[24] As per current clinical recommendations, in order to stay on PrEP, indicated individuals must return for follow-up visits every three months (at which time an HIV risk behavior assessment, HIV blood test, and STI screening will take place) in order to maintain

their prescription.[24] Partially as a result of this cascade, PrEP uptake has been slow and gaps exist between recommended and actual levels of PrEP use. Estimates of coverage levels vary: according to the American Men's Internet Survey (AMIS), an estimated 20% of PrEP-eligible MSM in the US were on PrEP in 2017;[25] compared to an estimated 35% of MSM who were at risk for HIV infection and likely to meet clinical indications for PrEP from National HIV Behavioral Surveillance System data;[26] compared to 32% of MSM meeting PrEP indications during 2017-2019 according to ARTnet.[27] PrEP use also varies by demographics and geographic area: use of PrEP may be lower for men who are younger, living outside of urban areas, and lacking health insurance.[25–27] Furthermore, PrEP adherence is dependent on ongoing access to medical care.[24] Recent HIV prevention interventions have been focused on getting men into PrEP care and retaining access to care.

Treatment of HIV infection requires ongoing access to antiretroviral therapy (ART). When taken consistently as prescribed, ART can suppress viral load, maintain high CD4 cell counts and prevent AIDS, and reduce HIV/AIDS morbidity and mortality.[28,29] In addition, ART use can reduce the risk of transmitting HIV to others due to decreased or undetectable viral load (referred to as "treatment as prevention")—there is effectively no risk of sexual transmission of HIV from a person living with HIV that has an undetectable viral load.[30]

However, similar to the PrEP cascade, the HIV care continuum also requires ongoing access to health care services. The HIV care continuum begins with HIV testing and diagnosis of HIV infection.[31] Regular testing is needed to diagnose individuals with undiagnosed HIV and get them into HIV clinical care.[31] Then, individuals need to be linked to care (i.e., have one or more documented CD4 or viral load tests within 30 days of HIV diagnosis; however, this is only one metric to evaluate care linkage and care linkage should be done as fast as possible).[32] Once in care, people living with HIV be prescribed ART, fill their prescription, and start ART.[31] After ART initiation, individuals need routine HIV viral load and CD4 testing and medical care to

be retained in care.[31] The recommended testing schedule is testing at entry into care, on initiation of ART, at any time of treatment regimen modification, two to eight weeks after ART initiation or modification, every four to eight weeks until viral suppression is achieved, and then every three or four months.[31] This requires ongoing and frequent access to clinical care.

Through ongoing use of ART, individuals can achieve HIV viral suppression. However, viral suppression is not widespread. According to the CDC, in 2018, approximately 35% of individuals diagnosed with HIV in the US were not virally suppressed at their last test.[33] However, this may be an underestimate, as it is derived from reported viral load data from a subset of jurisdictions that vary yearly.[34] The prevalence of not being virally suppressed among individuals living with diagnosed HIV in the US may be closer to 50%.[34,35] In addition, 25% of individuals living with HIV did not have any viral load test in 2018.[14] One major factor associated with the lack of viral load testing, ART adherence, and viral suppression is lack of accessibility of quality health care. In addition, regular testing is needed to diagnose individuals with undiagnosed HIV and get them into HIV clinical care.[31] Approximately 14% of people with HIV in the US are not diagnosed.[36] These gaps in HIV testing and clinical care drive HIV transmission in the US and impact the quality of life of individuals living with HIV.[37]

To address these issues, in 2019 the US Department of Health and Human Services (HHS) announced the Ending the HIV Epidemic in the US (EHE) plan, which aims to eliminate HIV in the US by 2030.[38] EHE has four key strategies. The first strategy is to diagnose individuals with HIV as early as possible after infection. The second is to treat individuals with HIV rapidly and effectively to reach sustained viral suppression. This strategy includes promptly linking individuals newly diagnosed with HIV to care as well as finding innovative and effective ways to reengage individuals who are aware of their infection but not receiving HIV care and treatment. The third strategy is to use interventions, including pre-exposure prophylaxis (PrEP) and syringe services programs, to prevent new HIV transmissions. The last EHE strategy is to

respond quickly to potential HIV outbreaks to get needed prevention and treatment services to people who need them. The EHE initiative focuses its efforts on geographic areas with a high burden of HIV, many of which are in the southeast US (the Atlanta metropolitan area, Alabama, Mississippi, South Carolina, among other areas).

The goal of EHE is to reduce new HIV infections in the US by at least 75% in 2025 and at least 90% by 2030. Modeling studies have predicted that in order for these goals to be achieved, HIV testing, PrEP initiation, and HIV care retention would need to increase dramatically (approximately ten-fold, if screening and retention were improved jointly and key subpopulations were targeted). However, these estimates assume continuity of prevention and clinical care services. Major disruptions to HIV prevention and clinical care services may instead move the US further from EHE targets.

COVID-19 Pandemic and HIV

Severe acute respiratory syndrome coronavirus-2 (SARS-CoV-2), the virus that causes coronavirus disease 2019 (COVID-19), was first identified in January 2020 in Wuhan, China following a December 2019 outbreak of pneumonia.[39] International spread of COVID-19 occurred during the following months and on 11 March 2020 the World Health Organization (WHO) officially characterized the global COVID-19 outbreak as a pandemic.[40] International "lockdown" orders soon after went into effect, with many countries requiring individuals to limit social contact and activity with those outside of their household ("social distance") or quarantine to prevent potential spread of SARS-CoV-2. In the US, COVID-19 was declared a national emergency on 13 March 2020 and many states thereafter issued statewide stay-at-home orders. Aside from businesses and services deemed essential, many workplaces, schools, restaurants, and other venues were closed. Restrictions have varied over time and by state and

municipality but decreases in mobility and social contact have been observed through the pandemic.[41]

The Impact of COVID-19 on Sexual Activity. In addition to social distancing and decreased mobility, COVID-19 has also prompted reductions in sexual activity ("sexual distancing"). Reports of sexual distancing have varied but most studies have suggested an initial overall decrease in sexual behavior among US adults, especially with partners outside of one's household. A cross-sectional study of US adults by Hensel et al. demonstrated that nearly half of adults reported some kind of change in sexual behavior during March–April 2020, with most reporting a decrease in partnered sex.[42] Another survey of US adults found that half of study participants reported a decline in their sex life during April–May 2020, but many incorporated various other sexual activities such as sexting or having cybersex.[43]

Sexual distancing has also been observed among US MSM. Using data from a cohort of PrEP-using MSM in the southern US, Pampati et al. demonstrated a decrease in sexual partners, anal sex acts, condomless sex, and oral sex during February–March followed by an increase in April–June.[44] A study by Sanchez et al. that used data from the AMIS COVID Impact Survey (which will be used in this dissertation) found that approximately half of US MSM reported fewer sexual partners during April 2020.[45] Similarly, a study by McKay et al. demonstrated that many US MSM reported a substantial decrease in the amount of sex had and the number sexual partners during April–May (compared to February–early March), and also reported changes to the type of sex had (e.g., more virtual sex) and less sex with casual partners.[46] International reports have noted similar trends in sexual distancing among MSM. In London, 75% of surveyed MSM reported fewer partners during March–June 2020 COVID-19 lockdown.[47] In Melbourne, Australia, MSM reported experiencing a decrease in sexual activities and sex partners during certain periods of lockdown.[48]

In contrast to these reports, Stephenson et al. found that there was an average increase in anal sex partners among US MSM during April–May 2020 compared to February of that year; however, reported changes in sex partners were variable (and ranged from 19 fewer to 38 more partners among study participants).[49] Stephenson et al. used data from the first cycle of the Love & Sex in the Time of COVID survey (which was used in this dissertation). Despite these early reports, more research is needed that examines the magnitude and variation of sexual distancing among US MSM, especially among key subpopulations. While most of these studies collected data on age, race, and geographic region, they did not present stratified estimates of sexual distancing measures.[44–46] This approach is needed given that sexual distancing is likely to vary within and between demographic groups and change over time.

A lack of published evidence about sexual distancing after March–June 2020 exists. Because social distancing practices were maintained for much of the US through 2020 and into 2021, studies are needed that assess the longitudinal patterns of sexual distancing through the COVID-19 pandemic. Rebounding sexual behavior has been hypothesized, in which sexual behavior may have substantially increased after the first US "wave" of COVID infections (i.e., after March–June 2020) (perhaps even above pre-pandemic levels), but empirical evidence is needed to determine if this occurred (or is occurring) among US MSM.

The Impact of COVID-19 on Clinical Services. The COVID-19 pandemic has prompted clinical service disruptions alongside decreased mobility and social contact.[50] In addition to health care systems being overburden by COVID-19 treatment, diverting resources away from prevention and treatment of non-respiratory diseases, non-emergency medical services were disrupted as social distancing measures were enacted.[51–55] Beginning in March 2020, some US medical practices were temporarily closed in order to reduce possible transmission of SARS-CoV-2.[55] For example, many sexually transmitted disease (STD) clinics in New York were either closed or experienced a dramatic reduction in services during April 2020.[56] Nationally, over 80%

of STD programs deferred STD services beginning in March 2020 and 62% reported being unable to maintain their HIV and syphilis caseloads.[57] In South Carolina, 56% of HIV clinics funded by the Ryan White HIV/AIDS Program were partially interrupted and 26% were completely closed during March 2020 (the Ryan White HIV/AIDS Program is the largest federal program designed specifically for people with HIV in the US and provides outpatient care and support services to individuals living with HIV).[58] In the months following March–April 2020, the financial strain resulting from COVID-19 (e.g., reduced revenues due to cancellation of certain services) caused some US hospitals and clinics to close.[59,60] In addition to clinical disruptions, COVID-19-related surges in unemployment (approximately 20 million workers) have caused many to lose employer-sponsored health insurance, leading to further reduction in health care access.[61] Thus, the COVID-19 pandemic has posed significant challenges in access to and delivery of health care.

HIV programs have attempted to adapt to COVID-19-related challenges but evidence of decreased access to HIV care still exists. In a survey of Ryan White HIV/AIDS Program medical provider grantees during the pandemic, 99% reported offering telehealth visits, 89% reported providing multi-month prescriptions for ART, 56% reported providing home HIV tests for patients and their partners, and 34% reported reducing frequency of laboratory visits.[62] However, 28% of providers reported seeing a decrease in retention of patients in HIV care, 61% reported a decrease in their ability to provide HIV testing, and 25% reported a decrease in the ability to provide PrEP services.[62] Similarly, surveys of MSM from April 2020 have demonstrated reduced access to HIV testing, HIV care visits, and viral load testing.[44,45,49] Further, there is evidence that HIV infection rates have increased during 2020, but these infections are not being diagnosed. In a Chicago emergency department that incorporated HIV testing alongside COVID testing, the resulting observed number of acute HIV diagnoses was significantly higher than in prior years, whereas other local hospitals (that did not incorporate HIV screening into COVID testing) observed a decline in HIV screenings and a 25% decrease in HIV diagnoses.[63]

The Centers for Disease Control and Prevention (CDC) have released guidance encouraging health facilities to optimize telehealth and home care during the pandemic to reduce the impact of COVID-19 on other diseases,[52] but gaps in care still remain. Further, disparities exist in accessing telehealth services. In a study using electronic healthcare record data at a large hospital in New York City, even after adjusting for individual and community-level attributes, Black patients had a significantly lower odds of accessing medical care through telemedicine during March–April 2020 compared to white patients.[64] Similar race/ethnic disparities have been noted across various disease-specific telehealth services.[65,66]

Sexual distancing may counterbalance the effects of clinical interruptions on HIV dynamics: reductions in sexual activity may decrease the rate of HIV acquisition and transmission while clinical interruptions increase it. Recent modeling studies have found that the impact of this balance on the HIV epidemic depends on the relative extent and timing of these changes.[67–69] Jenness et al. found that among MSM in Atlanta, if sexual behavior rebounds while service interruptions persist, an excess of hundreds of HIV cases in this target population will be expected over the next five years (Dr. Jenness is the chair of this dissertation and I was a coauthor of this study).[67] Research examining the timing of these changes is lacking, but is needed to be able to elucidate the full expected impact of the COVID-19 pandemic on HIV in the US.

HIV Prevention and Care Retention Approaches. Home-based HIV prevention and HIV care initiation and retention approaches may offset some of the epidemiologic impact of COVID-19 on the HIV epidemic in the US. These approaches may include telehealth services, at-home HIV testing, at-home PrEP care, multi-month ART prescriptions, at-home HIV testing, and potential at-home HIV viral load tests.

Telehealth, or the delivery and facilitation of health and health-related services including medical care, provider and patient education, health information services, and self-care via

telecommunications and digital communication technologies,[70] has become an important component of the US health care system in recent years.[71] It has been demonstrated to increase access to health care and potentially reduce health care costs,[72] and can be particularly useful to reach geographically remote or otherwise less accessible populations (e.g., currently incarcerated individuals).[73,74] For HIV care, studies have shown that individuals taking ART achieve similar clinical responses to therapy, adherence to treatment, and quality-of-life scores whether treated in-person or through telehealth.[75,76]

Telehealth has been used by HIV providers during the COVID-19 pandemic, alongside other interventions such as multi-month prescriptions for ART, at-home HIV testing, and reduced frequency of laboratory visits (as discussed in The Impact of COVID-19 on Clinical Services).[62,77] Multi-month prescriptions for ART work by providing patients living with diagnosed HIV with two to six months of ART medication (instead of 30-day prescriptions), therefore reducing the frequency of clinical visits.[78] A recent systematic review of eight studies showed that multi-month ART prescriptions and reduction of clinic visits led to better care retention without differences in viral failure.[79] At-home HIV testing may also be used to diagnose HIV infection and get individuals into HIV clinical care. At-home tests can be a rapid oral fluid test (which can be done entirely at home) or a mail-in finger prick blood test.[80] Clinical studies have demonstrated that the oral fluid test has sensitivity of 92% and the mail-in tests have a sensitivity of 99%.[81,82] Lastly, at-home HIV viral load testing could potentially be used as a home-based HIV care retention approach. This would allow individuals living with HIV to undergo their reoccurring viral load testing from home and therefore increase ongoing ART access and potentially adherence. However, at-home viral load testing is still being developed given that current testing of viral load relies on a blood draw and nucleic acid testing, both of which need to be conducted at a clinic or laboratory.[31,83] Therefore, research gaps exist regarding the potential impact of at-home viral tests on HIV care retention and population-level

viral suppression, both independently and alongside other telehealth and at-home HIV care approaches.

These home-based HIV prevention and HIV care approaches may curtail the impact of service disruptions such as those introduced by the COVID-19 pandemic on PrEP use and consequentially HIV acquisition risk, or ART adherence and consequentially HIV viral load. At a population-level, they may also impact HIV transmission and incidence.[84] Research is needed, however, to examine the extent of the potential epidemiologic impact of these approaches in the context of COVID-19, as well as identify the most effective scenarios for their deployment.[77] Because of the vast inequities in health and HIV care, the impact of these interventions may be greatest in certain subpopulations, such as Black MSM.[10–12] Research focused on the effect of HIV prevention and care approaches on HIV transmission is prudent.

Mathematical Models of HIV Transmission

Overview of Mathematical Modeling. Mathematical models have been used throughout the past century to investigate infectious disease dynamics and guide public health policy.[85] Their use ranges from identifying ideal public health intervention scenarios (such as optimal vaccine strategies), to predicting or forecasting the incidence of emerging diseases, to supporting surveillance-based estimates of infectious diseases.[85]

Models are a way to represent complex phenomena simply.[86] For infectious diseases, models use population parameters to simulate infection transmission in populations.[86] Mathematical models come in many forms, each of which can represent varying levels of complexity of infectious disease transmission. They may incorporate randomness into their parameters and transitions (stochastic) or use only fixed parameters and thus have stable results (deterministic).[86] Compartmental models can be either deterministic or stochastic. They

model disease dynamics by dividing individuals in a population into categories (compartments) representing various disease stages (e.g., susceptible to infection, infected, and recovered from infection) and model their collective progress through disease states.[86] Alternatively, individual- or agent-based models track the infection process for every individual in the simulated population, often incorporating stochasticity.[86]

Network Modeling. Network-based models are a type of agent-based models that explicitly incorporate partnerships. Partnerships can be defined as repeated contact (which has the possibility of disease transmission if disease were present in at least one of the partners) between two individuals; in HIV models of sexual transmission, for example, a partnership is repeated sexual contact/exposure with the same set of persons over time. Network-based transmission models model the network of contacts within a population and simulate disease transmission within that network.[86,87] Their major strengths over compartmental models are that they allow for repeated contacts with the same set of persons, and that they do not rely on the assumptions that individuals in a subpopulation mix randomly at each time step and each individual in one subpopulation has a non-zero chance of contacting every other individual in another subpopulation—this is not representative of human behavior.[86,87] Network models can explicitly model that each individual only has a finite set of contacts to whom they may transmit or acquire infection.[87]

Network-based mathematical models have played an important role in understanding the epidemiologic processes of infectious diseases, especially STIs and HIV.[87] They work by simulating individuals (nodes) and their contacts (edges) to create a network (a collection of nodes and edges). One statistical framework that is commonly used in network models to predict the network configuration of a population is exponential random graph modeling (ERGM). ERGMs use maximum likelihood estimation to fit statistical models for network structures to data.[88,89] They are somewhat analogous to logistic regression: in logistic

regression, the probability of an outcome/dependent variable is predicted based on a set of independent variables, whereas with ERGMs, the probability that two nodes will have an edge is predicted based on a set of network statistics. The general functional form for an ERGM is given in Equation 1.

Eq. 1. $P(Y = y) = \frac{e^{\theta' g(y)}}{\kappa(\theta)} = \frac{e^{\theta_1 x_1 + \theta_2 x_2 + \cdots + \theta_p x_p}}{\kappa(\theta)}$

Where y is the observed network of edges, nodes, and nodal attributes, $g(y)$ is the vector of network statistics, θ is the vector of parameters, and $\kappa(\theta)$ is a normalizing constant representing all possible network configurations.

The conditional log-odds of an edge is represented in Equation 2.

Eq. 2. $\text{logit}(\text{P}(\text{Y}_{\text{ij}} = 1 | rest\ of\ the\ network) = \log\left(\frac{P(Y_{ij} = 1 | rest\ of\ the\ network)}{P(Y_{ij} = 0 | rest\ of\ the\ network)}\right) = \theta' \partial(g(y))$

Where Y_{ij} is the edge between nodes i and j, and $\partial(g(y))$ represents the change in $g(y)$ when Y_{ij} changes from 0 to 1.

ERGMs model cross-sectional network structures, so they predict presence of an edge, but not formation and dissolution of edges over time. Temporal exponential random graph models (TERGMs) are used to model changes in a network over time. The conditional log-odds of an edge forming and persisting (i.e., the inverse of dissolving) over time are represented in Equations 3 and 4, respectively.

Eq. 3. $logit\left(P(Y_{ij,t+1} = 1 | Y_{ij,t} = 0, rest\ of\ the\ network)\right) = \theta^{+\prime} \partial(g^{+}(y))$

Eq. 4. $logit\left(P(Y_{ij,t+1} = 1 | Y_{ij,t} = 1, rest\ of\ the\ network)\right) = \theta^{-\prime} \partial(g^{-}(y))$

Where $g^{+}(y)$ is the vector of network statistics in the formation model, θ^{+} is the vector of parameters in the formation model, $g^{-}(y)$ is the vector of network statistics in the persistence model, and θ^{-} is the vector of parameters in the persistence model.

Various network sampling designs can be used to collect data for these forms of network models. These designs include adaptively sampled networks (such as snowball designs), convenience samples, or egocentrically sampled networks. The egocentrically sampled network design was used to collect the data used for the network models in this dissertation. With egocentric sampling, a population sample is enrolled into a study (nodes) and participants are asked about their partners/partnerships (edges).[90] It does not involve link or contact tracing as partners are not sampled directly. While this sampling method does not provide a network census (that is, data on the complete network including all nodes and edges), it can provide enough data to infer the complete dynamic network structure.[91]

The *EpiModel* R software package can be used to build network-based transmission models.[92] *EpiModel* uses the TERGM framework to estimate and simulate partnership processes alongside other modules that simulate infection and demographic processes in order to simulate epidemics over dynamic networks.[92] The simulation of networks in *EpiModel* use the Markov chain Monte Carlo (MCMC) algorithm functions from the *ergm* software package.[93] *EpiModelHIV* is an extension of the *EpiModel* package designed for simulating HIV and STI transmission dynamics among MSM and heterosexual populations.[94] It was used to simulate the network-based HIV transmission model used in Aims 2 and 3 of this dissertation.

Network-based models can be used to inform public health policy as they can simulate the spread of an infection within a population, estimate epidemic potential, and compare the effectiveness of various mitigation strategies. For example, they have been used to forecast SARS-CoV-2 infections and the potential impact of various control measures.[95,96] Overall,

mathematical modeling studies have contributed to the understanding of the dynamics of the spread of HIV and the theoretical assessment of intervention strategies.[97,98]

Modeling of the COVID-19 Pandemic & HIV. Modeling studies have also advanced our understanding of the potential impact of COVID-19-related changes on HIV dynamics. For example, a modeling study examining the potential COVID-related effects in sub-Saharan Africa found that interruptions to the supply of ART could significantly increase the rate of HIV transmission and the rate of HIV-related deaths.[99] Another modeling study focused on South Africa, Malawi, Zimbabwe, and Uganda, similarly found that interruptions to ART supply could substantially increase HIV deaths (and moreover, that a three-month interruption for 40% of individuals on ART could cause a similar number of additional deaths as those that might be saved from COVID-19 through social distancing).[100] In a study focused on six US cities, researchers found that COVID-19-related disruptions in HIV services and sexual behaviors may increase or decrease HIV incidence (depending on their magnitude), and that a campaign in which HIV testing is linked with SARS-CoV-2 testing could substantially reduce HIV incidence.[68]

Other modeling studies examining the impact of COVID-19 on HIV have focused on MSM populations. In China, one study found that fewer new HIV infections are projected to occur among MSM in four Chinese cities during 2020 compared to what would have occurred in the absence of the COVID-19 pandemic.[101] Similar to other studies,[67,99,100] this study also found that in China, new HIV infections would be increased most by disruptions to viral suppression, compared to disruptions in HIV testing, ART initiation, and condom use.[101] A study focused on Baltimore MSM found that sexual distancing could reduce new HIV infections but reductions in condom use, HIV testing, viral suppression, PrEP initiations, PrEP adherence, and ART initiations could increase new HIV infections.[69] This study also found that maintaining access to ART and adherence support should be the priority to minimize excess HIV-related mortality.[69] These studies complement the findings of Jenness et al. that the impact of COVID-19-related

changes on incidence of HIV among Atlanta MSM depends on the relative extent and timing of the changes, and that reductions in ART adherence may have more relative impact on HIV incidence than reductions in other HIV prevention measures.[67]

While these modeling studies have provided insights on the potential impact of the COVID-19 pandemic on HIV dynamics in various settings, research gaps remain. First, these studies did not use empirical data on sexual distancing and clinical service interruptions to estimate the actual impact on HIV incidence in a population, and consequently they did also did not distinguish diagnosed cases from actual incident infections. This was completed in Aim 2 of this dissertation. This work is important to elucidate both the actual impact of COVID-19 on HIV and the limitations of case-based surveillance estimates of HIV diagnoses this context. Some modeling studies have examined the impact the lack of HIV prevention services on HIV transmission, but did not examine the potential epidemiologic impact of at-home HIV prevention approaches at varying coverage and length scenarios (this was completed in Aim 3). This study is needed in order to identify the most effective HIV prevention interventions during periods of service disruption.

Measuring HIV Incidence in the US

HIV incidence may be the most useful metric to assess the HIV epidemic because it provides information on active HIV transmission in communities. Timely incidence information can guide development and implementation of HIV prevention interventions. However, the incidence of HIV in the US has never been directly measured.[102,103] Incidence has been measured in a number of US cohort studies representing select subpopulations,[104–108] however, these estimates are not representative of the full US population and estimates may be impacted by from selection bias or the “adherence effect” (e.g., if enrollment in a study with follow-up visits affects HIV incidence rate through recurring exposure to HIV prevention messages).[103,109]

National estimates are useful in order to assess the US HIV epidemic at a population-level.[102] Measuring national HIV incidence would require longitudinal follow-up of all individuals who do not have HIV infection with frequent testing; this is extremely difficult to apply on a large scale due to the resources it would require.[110] Instead, back-calculation models and laboratory assay data have been used to estimate HIV incidence in the US.[102]

The first estimates of HIV incidence in the US were generated from back-calculation models that used AIDS incidence data and data on the estimated median incubation period for HIV infection to AIDS diagnosis.[111,112] These estimates were unreliable, however, because incubation period can differ considerably by individual characteristics (estimates range from less than one year to over 20 years).[113–115]

The development of laboratory assays prompted new methods for incidence estimation. Laboratory assays test for biomarkers that can be used to infer the phase of HIV infection. They can differentiate recent from existing HIV infections. Using assay results and information about the duration of time spent in a phase of HIV infection, incidence can be calculated.[116] This method, originally known as serological testing algorithm for recent HIV seroconversion (STARHS), relies on the principle that HIV antibody titers evolve in a predictable fashion after initial seroconversion.[110,117] However, because there is large variation in biomarkers between individuals and because assays sometimes misclassify late-stage AIDS as recent infections, STARHS estimates are unreliable.[117,118] An additional assay approach, known as recent infection testing algorithm (RITA), integrates assay results with clinical information (such as CD4 count) to classify infections as recent or existing.[110] However, RITAs are still imperfect because there is individual variation in HIV immunological responses. The WHO has noted that misclassification of cases as recent when they are long-standing can severely bias incidence estimates.[110]

Recent national estimates generated by the CDC use a CD4 cell count data-based model to estimate annual HIV incidence.[119,120] Specifically, estimates are obtained using the following steps:[119]

(1.) The date of HIV infection is estimated for each person with a CD4 test result by using the CD4 model. The number of persons with a CD4 test result is weighted to account for those without a CD4 test result; weighting is based on the year of HIV diagnosis, sex, race/ethnicity, transmission category, age at diagnosis, disease classification, and vital status at year-end.

(2.) The distribution of delay (from HIV infection to diagnosis) is used to estimate the annual number of HIV infections, which includes diagnosed and undiagnosed infections.

(3.) The number of persons with undiagnosed HIV infection is estimated by subtracting cumulative diagnoses (reported to the National HIV Surveillance System, NHSS) from cumulative infections.

(4.) HIV prevalence, which represents counts of persons with diagnosed or undiagnosed HIV infection who were alive at the end of the year, is estimated by adding the number of persons with undiagnosed HIV infection to the number of persons living with diagnosed HIV infection (reported to NHSS).

(5.) The percentage of diagnosed (or of undiagnosed) infections is determined by dividing the number of persons living with diagnosed (or with undiagnosed) infection by the total HIV prevalence for each year.

Similar to the aforementioned estimation methods, this method is also limited given that individual CD4 counts are highly variable even over short time intervals[120] and this method assumes that population-level access to CD4 testing remains constant (i.e., there is no period of HIV service disruption). This is a major limitation to this method; in a period of widespread service disruption such as the COVID-19 pandemic,[50] this approach may not estimate valid HIV

incidence because it relies on uninterrupted CD4 testing results and diagnoses. Specifically, the CD4 distribution of individuals living with HIV and who are retained in care during a period of service disruptions will likely be different than those who were not retained in care.[121] This has the potential to bias CD4 models and therefore estimates of HIV incidence obtained from these models.

Even if the above methods were methodologically valid and produced reliable estimates of HIV incidence, they are limited in that they calculate incidence retroactively and estimates can be delayed. If estimates are not current, many of the benefits of measuring incidence instead of prevalence, such as targeting prevention efforts, are lost. New methods that can produce up-to-date incidence estimates are thus needed.

Innovative methods incorporating mathematical models may produce timelier incidence estimates. In influenza surveillance, for example, models have been used alongside surveillance data to estimate real-time and future estimates of flu activity.[122,123] Development of model-based methods to track HIV incidence may also be useful as a supplement to existing HIV surveillance methods.

Dissertation Aims

The purpose of this dissertation is to understand the epidemiologic impact of disruptions to sexual risk behavior and HIV prevention and clinical care on HIV incidence during and after the COVID-19 pandemic. This dissertation advances knowledge of how US MSM change health behaviors during pandemic restrictions, how these changes ultimately affect short- and long-term HIV transmission, and how innovations in HIV prevention interventions could reduce transmission in this context. The findings of this dissertation have implications for both HIV surveillance and the implementation of HIV prevention and treatment programs. These findings may help support the EHE goals of reducing new HIV infections in the US. The specific aims of this dissertation are:

Aim 1: Describe the magnitude, timing, and variation of sexual distancing and HIV service utilization changes among MSM in the US during the COVID-19 pandemic.
Hypotheses: We expected that sexual distancing and service interruptions will vary in magnitude and timing by demographic, clinical, and behavioral factors. We also anticipate that HIV service interruptions will outlast sexual distancing.

Aim 2: Estimate the incidence of HIV among US MSM during the COVID-19 pandemic in the presence of competing forces of sexual distancing and clinical service interruptions.
Hypotheses: We expected that sexual distancing (including reductions in sexual risk behavior) and service reductions will alter the incidence of HIV across the pandemic era. We also anticipated that changes in HIV service utilization will increase HIV incidence to such an extent that EHE goals for 2030 may be unattainable.

Aim 3: Assessing the epidemiologic impact of home-based HIV prevention interventions during the COVID-19 pandemic.
Hypotheses: We expected that because targeted home-based HIV prevention interventions may

curtail the impact of COVID-19-related service interruptions, increased coverage, length, and persistence of key HIV prevention interventions will result in reductions in HIV transmission, and thus lower HIV morbidity and mortality.

Data Sources

The data for this dissertation came from multiple sources: (1.) the American Men's Internet Survey (AMIS) COVID-19 impact survey, (2.) the Love and Sex in the Time of COVID-19 survey, (3.) the ARTnet study, and (4.) published literature and publicly available data. The AMIS COVID-19 impact survey collected data on sexual distancing and HIV service utilization/care engagement during the COVID-19 pandemic experienced by US MSM at three time points: April, July, and September–December 2020. The Love and Sex in the Time of COVID-19 survey also collected data from US MSM on sexual distancing and HIV service utilization/care engagement during the COVID-19 pandemic, but at two time points: April/May 2020 and November 2020–January 2021. The ARTnet study collected data from US MSM during 2017–2019 on HIV-related risk behaviors, testing, and use of prevention services. It implemented a population-based egocentric network study design that sampled individuals and collected data on the number, attributes, and timing of their sexual partnerships. Data from the AMIS COVID-19 impact survey and the Love and Sex in the Time of COVID-19 survey was used in Aim 1 to examine the magnitude, timing, and variation of sexual distancing and clinical service disruptions at various time points during the COVID-19 pandemic. ARTnet data will provide the foundation of the network-based HIV transmission models used in Aims 2 and 3. The results obtained from Aim 1, published literature, and publicly available data were also used to parameterize the models used in Aims 2 and 3.

AMIS COVID-19 Impact Survey

One of the two data sources that was used to assess sexual distancing and HIV service utilization changes among MSM in the US during the COVID-19 pandemic is the AMIS COVID-19 impact survey. AMIS and the AMIS COVID-19 impact survey were led by Dr. Travis Sanchez (dissertation committee member). This survey collected data from a cohort of US MSM at three

time points during the COVID-19 pandemic: April, July, and September–December 2020. Participants were recruited via participation in the August–December 2019 annual AMIS study; COVID-19 impact survey responses can be linked to 2019 AMIS responses. AMIS study participants were recruited through convenience sampling from a variety of websites and through social media applications using banner ads and email blasts to members. AMIS targets hard-to-reach subpopulations of MSM (based on age, race, and geographic areas). Participants were eligible to participate in the AMIS study if they were 15 years or older, male sex at birth, resided in the US, and reported oral or anal sex with a man at least once at any time in the past. Invited participants for the COVID-19 impact survey were those who participated in the 2019 AMIS study and provided their email address for future study invitations. These individuals were sent a link to a special COVID-19 impact survey screener where AMIS eligibility was reassessed. Those who still met AMIS eligibility and consented to participation comprised the COVID-19 impact survey participants.

The goal of the COVID-19 impact survey was to measure COVID-19 related impacts on several areas: general wellbeing, sexual and substance use behavior, HIV and STI prevention, and HIV treatment. The survey collected data on reported changes in the above categories as well as standard demographic information, self-reported HIV status, and COVID-19 mitigation measures in an individual's local area (additional information about the study's measures of interest that was used in this dissertation is included in Section D.1). Total enrollment in the first COVID-19 study was 1,051 men, but enrollment decreased over the three survey cycles (Table 1). Participants ranged in age and US region. Approximately 70% of the study sample was non-Hispanic white, and approximately 90% were not known to be living with HIV.

The September–December COVID-19 impact survey took place within the 2020 annual AMIS study. Study participants were recruited in the same manner as the 2019 annual study, as described above. The analyses in this dissertation will focus on the men from the September–

December cycle that also participated in the April and/or July survey (as described in Section D.1). However, an additional 6,549 men completed the COVID-19 impact survey in September–December and their responses was examined and compared.

***Table 1.1**. AMIS COVID Impact Survey Sample Characteristics*

	April 2020 n (%)	July 2020 n (%)	September–December 2020 n (%)
Total Sample	1,051	572	373
Race/Ethnicity			
Non-Hispanic Black	89 (8.5)	35 (6.1)	24 (6.5)
Hispanic or Latino	146 (13.9)	74 (12.9)	40 (10.8)
Non-Hispanic White	740 (70.4)	425 (74.3)	278 (75.3)
Other or multiple races	62 (6.2)	33 (5.8)	27 (7.3)
Age			
15–24	214 (20.4)	83 (14.5)	49 (13.1)
25–29	179 (17.0)	89 (15.6)	57 (15.3)
30–39	210 (20.0)	118 (20.6)	94 (25.2)
≥40	448 (42.6)	282 (49.3)	173 (46.4)
HIV Status			
Positive	122 (11.6)	59 (10.3)	32 (8.6)
Negative	809 (77.0)	466 (81.5)	327 (87.7)
Unknown	120 (11.4)	47 (8.2)	14 (3.8)
Region			
Northeast	187 (17.8)	98 (17.1)	68 (18.2)
Midwest	194 (18.5)	107 (18.7)	65 (17.4)
South	427 (40.6)	223 (39)	154 (41.3)
West	241 (22.9)	143 (25)	85 (22.8)
US Territories	2 (0.2)	1 (0.2)	1 (0.3)

Love and Sex in the Time of COVID-19 Survey

The second data source that was used to assess and parameterize sexual distancing and HIV service utilization changes among MSM in the US during the COVID-19 pandemic is the Love and Sex in the Time of COVID-19 survey. This survey collected data from US MSM at two time points during the COVID-19 pandemic: April/May 2020 and November 2020–January 2021. Participants were recruited through paid banner advertisements featured on the social networking platforms Facebook and Instagram, and on the Grindr app. Eligibility criteria

included being over the age of 18, current residency in the US and its dependent areas, assigned male sex at birth and currently identifying as a cis man, and reporting any type of sex in the past 12 months. The Love and Sex in the Time of COVID-19 survey collected data on the impact of the COVID-19 pandemic on sexual behavior, HIV prevention behaviors, substance use, and economic and structural instability (e.g., unemployment, housing instability) (additional information about the study's measures of interest that was used in this dissertation is included in Section D.1).

Approximately 700 individuals completed the survey (Table 2). Participants ranged in age and US region. Approximately 75% of the study sample was non-Hispanic white, and approximately 90% were not known to be living with HIV.

***Table 1.2**. Love and Sex in the Time of COVID-19 Survey Sample Characteristics*

	April/May 2020 n (%)	November 2020–January 2021 n (%)
Total Sample	696	279
Race/Ethnicity		
Black	35 (5.0)	11 (3.9)
White	518 (74.4)	226 (81.0)
Other	143 (20.5)	42 (15.1)
Age		
18–24	140 (20.1)	40 (14.3)
25–34	317 (45.5)	129 (46.2)
35–44	171 (24.6)	78 (28.0)
≥45	68 (9.8)	32 (11.5)
HIV Status		
Positive	56 (8.0)	23 (8.2)
Negative	550 (79.0)	238 (85.3)
Unknown	90 (12.9)	18 (6.5)
Region		
Northeast	117 (16.8)	45 (16.1)
Midwest	194 (27.9)	84 (30.1)
South	195 (28.0)	64 (22.9)
West	190 (27.3)	85 (30.5)
Puerto Rico	0 (0.0)	1 (0.4)

ARTnet Study

Data from the ARTnet study was used to create the network-based HIV transmission models used in Aims 2 and 3. ARTnet was led by Dr. Samuel Jenness (dissertation chair). ARTnet is a cross-sectional web-based study of US MSM conducted between 2017 and 2019. It collected data in two waves: during July 2017–February 2018 and September 2018–January 2019. Participants were recruited through the annual AMIS study (described in Section C.1).[124] ARTnet eligibility criteria included male sex at birth, current male cisgender identity, lifetime history of sexual activity with another man, and age between 15 and 65 years.

ARTnet collected data on demographic and clinical information (including HIV status), sexual and HIV prevention behaviors, and egocentric network structures. It had an egocentric network sampling design (described in Section B.3). Participants were asked summary questions about their overall number of partnerships within three types in the past year: main (a "boyfriend, significant other, or life partner"), casual (someone they have had sex with more than once, but not a main partner), and one-time. Persistent partnerships include both main and casual partnerships. They were then asked detailed partner-specific questions for up to their most recent five partners. These questions included attributes of the partner (e.g., demographics) and about the partnership itself (e.g., start and end dates, frequency of sexual activity).

ARTnet enrolled 4,904 men and collected data on 16,198 partnerships (Table 3, Table 4). Participants ranged in age and US region. Approximately 72% of the study sample was non-Hispanic white and approximately 90% were not known to be living with HIV.

Table 1.3*. ARTnet Study Sample Characteristics*

	n (%)
Total Sample	4,904
Race/Ethnicity	
Non-Hispanic Black	266 (5.4)

Hispanic	676 (13.8)
Non-Hispanic White	3,523 (71.8)
Non-Hispanic Other	439 (9.0)
Age	
15–24	1324 (27.0)
25–34	1,268 (25.9)
35–44	694 (14.2)
45–54	833 (17.0)
55–65	785 (16.0)
HIV Status	
Positive	428 (8.7)
Negative	3,726 (76.0)
Unknown	750 (15.3)
Region	
Northeast	882 (18)
Midwest	994 (20.3)
South	1,782 (36.3)
West	1,246 (25.4)

***Table 1.4**. ARTnet Study Partnership Characteristics*

	n (%)
Total Sexual Partnerships	16,198 (100.0)
Main Partners	2,618 (16.2)
Casual Partners	5,978 (36.9)
One-time Partnerships	7,602 (46.9)
Race/Ethnicity of Partners	
Black-Black	369 (2.4)
Black-Hispanic	308 (2.0)
Black-Other	181 (1.2)
Black-White	1,341 (8.8)
Hispanic-Hispanic	796 (5.2)
Hispanic-Other	453 (3.0)
Hispanic-White	2,792 (18.3)
Other-Other	233 (1.5)
Other-White	1,684 (11.0)
White-White	7,094 (46.5)
HIV Status of Partners	
Negative-Negative	8,752 (54.1)
Negative-Positive	1,013 (6.3)
Negative-Unknown	4,632 (28.6)
Positive-Positive	367 (2.3)
Positive-Unknown	551 (3.4)
Unknown-Unknown	863 (5.3)
Age (Both Partners)	
15–24	2,289 (14.7)
25–34	2,116 (13.6)
35–44	685 (4.4)

45–54	747 (4.8)
55–65	489 (3.1)
Different Age Groups	9,229 (59.3)

External Sources

Additional Sources for Model Parameterization. Models used in Aims 2 and 3 were additionally parameterized by estimates from external literature and publicly available data (Table 5). Parameters included population-level information about demography, HIV clinical epidemiology, HIV intrahost epidemiology, and HIV transmission probability. Reported estimates were obtained in the pre-COVID era. Where applicable, parameters were updated during the COVID-19 pandemic as indicated by Aim 1 results (e.g., clinical parameters such as HIV testing, PrEP discontinuation, etc.). We assumed that certain parameters, in particular those related to HIV intrahost epidemiology and HIV transmission probability, remained the same throughout the COVID-19 pandemic.

Table 1.5*. Key External Data Sources for Model Parameterization*

Parameter	Potential Source	Aim
Demography		
Race/ethnicity distribution (US)	US Census Bureau[9]	2
Race/ethnicity distribution (Atlanta)	US Census Bureau[9]	3
Age distribution (US)	US Census Bureau[9]	2
Age distribution (Atlanta)	US Census Bureau[9]	3
All-cause mortality	National Vital Statistics[125]	2, 3
Proportion households headed by a male who lived with a male partner	ACS[126]	2
Urbanicity distribution	NHANES[127]	2
HIV Prevention & Clinical Epidemiology (pre-COVID Era)		
HIV screening	ARTnet[91]	2, 3
ART initiation	Rosenberg[8]	2, 3
ART adherence and viral suppression	Rosenberg[8]	2, 3
Disease progression after ART initiation	Chu[128]	2, 3
PrEP coverage (US)	ARTnet[91], NHBS[26], AIDSVu[129]	2
PrEP coverage (Atlanta)	ARTnet[91], NHBS[26], AIDSVu[129]	3
PrEP adherence	Liu[130]	2, 3
PrEP discontinuation	Chan[131]	2, 3

ART initiation, adherence, viral suppression in Georgia	GA DPH[132]	3
HIV Intrahost Epidemiology		
Time to peak viremia	Little[133]	2, 3
Viral load at peak viremia	Little[133]	2, 3
Time from peak viremia to viral set point	Little[133], Leynaert[134]	2, 3
Level of set point	Little[133]	2, 3
Duration of chronic stage infection	Buchbinder[135]	2, 3
Duration of AIDS	Buchbinder[135]	2, 3
HIV Transmission Probability		
By sexual role	Vittinghoff[136]	2, 3
By viral suppression status of HIV	Wilson[137], Supervie[138]	2, 3
By acute stage	Leynaert[134]	2, 3
By condom use	Varghese[139]	2, 3
By circumcision status	Gray[140]	2, 3
By PrEP adherence	Grant[141]	2, 3

Reported HIV Diagnoses. Case-based surveillance estimates of HIV diagnoses were used to compare estimated incidence to reported diagnoses to examine the pattern between reported cases and actual HIV transmission.

Multiple jurisdictions have noted less overall HIV diagnoses than expected during 2020. For example, in North Carolina, there were 1,085 diagnoses in 2020, down from 1,379 in 2019 and 1,205 in 2018.[142] For jurisdictions releasing quarterly data, the reductions in HIV diagnoses (relative to previous quarters) appear to be more pronounced in quarter 2 or 3 (i.e., April–June or July–September 2020).[142–144] Other jurisdictions have noticed a similar drop in HIV diagnoses in early 2020: in New York City, there were 56 HIV diagnoses during March 23–June 7, 2019 but only 23 during March 23–June 7, 2020 (a 59% decrease).[145] Similar trends have also been observed in reported STI diagnoses by local jurisdictions.[145,146]

Although local data were available, we used national HIV diagnoses data of HIV infections that are attributed to male-to-male sexual contact transmission from the National HIV Surveillance System (NHSS).[147] These data were available quarterly from January 2019–December 2021. Although NHSS represents HIV diagnoses, whereas our models estimated

incidence, we used these data to understand how closely, if at all, model-based incidence may line up with real-world diagnoses.

Chapter 2. The Magnitude, Timing, and Variation of Sexual Distancing and HIV Service Utilization Changes among MSM in the US During the COVID-19 Pandemic

ABSTRACT

Early in the COVID-19 pandemic, disruptions to sexual health services and changes to sexual behavior due to the first COVID-19 lockdowns were common among US gay, bisexual, and other men who have sex with men (GBMSM). Less is known about the persistence of these changes after this initial lockdown period. These changes have long-term implications for HIV prevention for current and future pandemic periods. This study collected information on COVID-related impacts on sexual behavior and HIV-related health service disruptions from a cohort of US GBMSM at three time points during the COVID-19 pandemic. We observed that COVID-related disruptions to sexual behavior continued from early lockdown periods through December 2020. Though early interruptions to PrEP access resolved in later 2020 and interruptions to ART adherence were minimal, extended disruptions were observed in HIV testing, STI testing, HIV care clinical visits, and HIV viral load testing. Although sexual behavior did not return to pre-pandemic levels in late 2020, the reduced access to HIV prevention, testing, and treatment services during this period could result in an overall increased HIV transmission rate, with long-term impacts to the trajectory of the US HIV epidemic. Additional resources and programs are needed to address challenges created by the COVID-19 pandemic, as well as prepare for future potential pandemics and other disruptive events.

INTRODUCTION

International restrictions to social contact and mobility (“lockdowns”), spurred by the spread of SARS-CoV-2, have caused social and economic disruptions since March 2020. In the United States (US), reports from early 2020 have identified that COVID-19 has prompted major behavioral changes related to the prevention and control of HIV [44,45,49,50,148,149]. These changes include reductions in sexual activity (“sexual distancing”) as well as disruptions to patient access to HIV prevention, screening, and clinical care services [44,45,49,50,148,149].

Present-day HIV prevention efforts for gay, bisexual, and other men who have sex with men (GBMSM) focus on reducing HIV acquisition and transmission through promoting safer sexual behaviors, increasing the availability and use of preexposure prophylaxis (PrEP), and promoting the consistent and correct use of antiretroviral therapy (ART) so persons living with diagnosed HIV can maintain a suppressed HIV viral load [16,24,150]. The latter two strategies require ongoing access to clinical services [24,32]; HIV transmission remains high partly due to gaps in access to these tools [37].

COVID-related disruptions have the potential to impact the trajectory of the US HIV epidemic. For example, clinical interruptions that lead to decreased HIV and sexually transmitted infection (STI) testing, PrEP use, STI treatment, and HIV care may increase HIV incidence – decreasing the proportions of GBMSM who know their status, have access to PrEP, or are virally suppressed. Conversely, reductions in sexual risk behaviors may decrease the spread of HIV. The impact of COVID-related disruptions firstly depends on the demographic distribution of disruptions. Like HIV burden, disruptions have not been uniform across the US [3,151]. For example, Black individuals experience a higher risk of HIV and may also experience more COVID-related disruptions in HIV prevention and care (due to disproportionate impacts of COVID-19 on Black communities in addition to existent decreased access to HIV prevention and care programs) [3,151–153]. In addition to demographic variations, the impact of pandemic-related disruptions on the HIV epidemic depends on the relative extent and timing of changes in

sexual behavior and clinical interruptions. A 2021 modeling study assessing the impact of the COVID pandemic on HIV incidence identified that if sexual behavior rebounded while clinical interruptions persisted, excess HIV infections would be expected because clinical interruptions outweighed transmission-reducing impacts of sexual distancing [67].

Short-term COVID-related changes can alter the US HIV epidemic in the long term because HIV incidence and prevalence are affected by changes in HIV risk behavior and HIV care engagement. It is necessary to understand the demographic distribution, magnitude, and timing of COVID-related changes to sexual behavior and disruptions to HIV-related health services in order to predict their long-term impact on HIV dynamics. Early data have documented changes in early 2020 [44,45,50,148,149], but the persistence of these changes remains unclear. It is possible that with increased social mobility following easing of lockdown restrictions in the later months of 2020 (the "post-lockdown" period) [154], sexual behavior and access to clinical services may have returned to pre-pandemic levels. Data on sexual behavior and clinical service disruptions in the post-lockdown period are needed to inform how HIV transmission may have changed at later stages of the COVID-19 pandemic.

In this study, we present the prevalence and trends of COVID-related sexual distancing and clinical service disruptions among a cohort of US GBMSM through December 2020. Outcomes include information on how the COVID-19 pandemic has impacted sexual behavior, HIV testing, PrEP use, HIV clinical care, and ART adherence during the first year of the pandemic. Characterizing the impact of the COVID-19 pandemic on HIV-related behaviors of US GBMSM may help guide HIV prevention programs in the post-lockdown era, for example through highlighting the need for targeted HIV testing, targeted PrEP programs, and home-based HIV care approaches. Further, understanding the impact of the COVID-19 pandemic on GBMSM HIV-related behavior can provide insight on how behavior may alter in future pandemics, and thus aid in pandemic preparedness.

METHODS

Participants. This study used data from the American Men's Internet Survey (AMIS) COVID-19 impact survey, collected from a cohort of US GBMSM at three time points during the COVID-19 pandemic: April 2020, July 2020, and September–December 2020. Participants were recruited via participation in the August–December 2019 annual AMIS study [155]; COVID-19 impact survey responses were linked to 2019 AMIS responses. AMIS study participants were recruited through convenience sampling from websites and through social media applications using banner ads and email messages to members. AMIS targets subpopulations of GBMSM that are underserved (with respect to age, race, and geographic area). Participants were eligible to participate in the AMIS study if they were 15 years or older (participants 15–17 years had a waiver of parental permission), male sex at birth, resided in the US (including US territories), and reported oral or anal sex with a man at least once. For the April 2020 COVID-19 impact survey, individuals from the 2019 AMIS study were sent a link to a special COVID-19 impact survey screener where AMIS eligibility was reassessed. Those who were still eligible and consented to participation (provided online written consent) comprised the COVID-19 impact survey participants. The analyses in this study include only on the men that completed the April 2020 survey and at least one of the follow-up surveys (either the July and/or September–December follow-up surveys) (Figure 2.2). The study was conducted in compliance with federal regulations governing protection of human subjects and was reviewed and approved by Emory Univeristy's institutional review board.

Measures. The goal of the COVID-19 impact survey was to measure COVID-19 related impacts on several areas: general wellbeing, sexual and substance use behavior, HIV and STI prevention, and HIV treatment. The survey collected data on reported changes in the above categories as well as standard demographic information, self-reported HIV status, and COVID-

19 mitigation measures in an individual's local area. This analysis focuses on outcomes related to sexual behavior, HIV and STI prevention, and HIV treatment in order to assess the impact that the COVID pandemic had on HIV-related behaviors. At each time point, participants were asked if the COVID-19 pandemic has impacted various behaviors/experiences related to sexual health and substance use. Specifically, participants were asked, "compared to the time before COVID-19/Coronavirus, please tell us if COVID-19 and the plans used to manage COVID-19 have impacted these things related to related to sexual health and substance use. Please tell us only if it has changed because of COVID-19." These behaviors/items included number of sexual partners, opportunities to have sex, access to STI testing or treatment, use of condoms, getting HIV tested, access to HIV medications, taking HIV medications every day as prescribed, getting HIV care clinical visits, and getting viral loads or other labs done. Participants were asked to select if the behavior/item "has decreased/less because of COVID-19, has not changed or changed for reasons other than COVID-19, or has increased/more because of COVID-19." Participants also were asked a series of questions related to service interruptions: "Have you had trouble getting [a given service] because of COVID-19 or the public health efforts to manage it?" Clinical services included getting an HIV test, getting PrEP prescription from your doctor, and getting your PrEP prescription filled at the pharmacy.

Analyses. The prevalence of COVID-19 related impacts were calculated overall and stratified by age category and race/ethnicity category. In order to represent the full US GBMSM population, demographic standardization using 2019 US Census age and race/ethnicity distribution weights [9] was used to obtain standardized estimates with 95% confidence intervals of sexual distancing and HIV clinical care interruptions for all US GBMSM. Chi-squared tests or Fisher's exact tests, where applicable, were used to determine if differences by race/ethnicity were statistically significant (with a *p*-value of 0.05). To examine the impacts of attrition on the study results, a sensitivity analysis that examined the prevalence of COVID-19 related impacts only on the men who completed each of the three study cycles was completed.

RESULTS

Total enrollment in the first COVID-19 impact survey was 1,051 men, but enrollment decreased over the three survey cycles (Table 1). Participants ranged in age from 15–82 years, with a median age of 35 years (SD=15.7 years). Participants were from across the US, with the most represented regions being the South (n=427, 40.6%). Approximately 70% of participants (n=740) were non-Hispanic White in the first cycle, but this increased to 75% (n=278) by the third cycle. Approximately 10% (n=122) of participants self-reported as HIV-positive.

Over half of participants (n=542, 51.5%) reported a decrease in the number of sexual partners in April 2020, relative to sexual partners at any time before the pandemic (Table 2.2). This continues through 2020. Approximately 5% of participants (n=57, 5.5%) reported a decrease in condom use because of COVID-19 through December 2020. Reported decreases in the number of sexual partners did not vary by race/ethnicity at any study cycle (Figure 2.1, Supplemental Table 2.1), although change in use of condoms did vary (p=0.02, 0.01, 0.02 for April, July, September–December, respectively): at each study cycle, non-Hispanic Black participants reported both more increases in condom use (n=7, 7.8%; n=3, 9.1%; and n=3, 14.3%; respectively) and decreases in condom use (n=3, 3.3%; n=2, 6.1%; and n=3, 14.3%; respectively) (e.g., reported the least amount of no change in condom use) relative to other race/ethnicity groups.

Among men self-reporting as HIV-negative or with unknown HIV status, about 15% of participants reported a decrease in HIV testing in both early and late 2020 (n=142, n=47, respectively) (Table 2.2). In April 2020, approximately 9% of men (n=18) currently on PrEP reported trouble getting PrEP prescription from their doctor because of the COVID-19 pandemic; by the end of the year, 7% of participants (n=6) reported trouble getting a PrEP prescription. Although point estimates of the proportion of Hispanic men and non-Hispanic Black

men reporting a decrease in HIV testing were higher relative to non-Hispanic White men in the first two study cycles (n=25, 19.8%; n=8, 16.3%; and n=94, 14.7%; respectively in April 2020; n=10, 16.4%; n=3, 15.8%; and n=44, 11.9% in July 2020), differences were not statistically significantly different by race/ethnicity at any study cycle (p=0.12, 0.67, and 0.10, respectively). Differences in trouble getting an HIV test or getting a PrEP prescription also were not statistically significantly different by race/ethnicity at any study cycle.

Among men self-reporting as living with HIV, 28% of men (n=33) reported a decrease in getting HIV care clinical visits because of the COVID-19 pandemic in April 2020, decreasing to 19% (n=6) by the end of the year (Table 2.2). Few participants reported disruptions in their access to antiretroviral therapy: only 5% (n=6) of participants living with HIV reported a decrease in taking HIV medication every day as prescribed in April 2020, although this increased to 6.7% (n=2) in late 2020. Although participants reported decreases in access to HIV medication, taking HIV medication every day as prescribed, getting HIV care clinical visits, getting viral loads or other labs are higher among minority race/ethnic groups relative to non-Hispanic White men, differences were not statistically significantly different by race/ethnicity at any study cycle.

Standardization by Census-derived age and race/ethnicity weights did not greatly impact our results (Table 2.3). For example, the percent of men who reported a decrease in sexual partners in April 2020 changed from a crude percent of 52% to a standardized percent of 54%. However, the 95% confidence intervals for some standardized estimates are wide due to limited sample size within strata.

We observed similar results when restricting the study participants to only those who participated in all three study cycles (n=265) (Table 2.4). Overall, approximately 55% (n=143) of these participants reported a decrease in the number of sexual partners through the study period. Among these HIV-negative participants, approximately 14% reported a decrease in HIV

testing in both early and late 2020 (n=34 and n=39, respectively), and 9% (n=5) of these participants on PrEP reported trouble getting a PrEP prescription in late 2020. Among these HIV-positive participants, 32% of men (n=7) reported a decrease in getting HIV care clinical visits because of the COVID-19 pandemic in April 2020, decreasing to 10% (n=2) by the end of the year. Only one participant (5%) that participated in all three study cycles reported a disruption in antiretroviral therapy adherence, which occurred in April 2020 only.

DISCUSSION

In this study, we observed that COVID-related disruptions to HIV prevention and treatment services and changes in sexual behavior continued from early lockdown periods through December 2020. Extended disruptions were observed in HIV testing, STI testing, HIV care clinical visits, and HIV viral load testing, with only small improvements over time. Although sexual behaviors including number of sexual partners and opportunities to have sex remained below pre-pandemic levels in later 2020 for many GBMSM, reduced access to HIV prevention, testing, and treatment services that lasted through the year created additional challenges for the control of HIV, which could result in an overall increased HIV transmission rate.

Consistent with other studies and as previously reported,[44,148] we observed that measures of sexual behavior decreased in early 2020. In our study, GBMSM reported both a decrease in sexual partners and opportunities to have sex in April–May 2020. This aligns with the findings of Pampati et al, who observed that among a cohort of PrEP-using MSM in the southern US, MSM had a decrease in number of sexual partners during February–April 2020 [44]. A study by McKay et al of US gay and bisexual men also noted a decrease in sexual partners during April–May 2020 [148]. Our results expand upon these early findings in finding that changes in sexual behavior persisted through the end of the year: most participants reported both a

decrease in number of sexual partners and opportunities to have sex in both July 2020 and September–December 2020.

Our results additionally complement the early reports that document decreased utilization of/access to HIV prevention and treatment services in the initial stages of the COVID-19 pandemic [49,149]; our study observed that US GBMSM experienced HIV prevention and service disruptions because of the pandemic. For GBMSM not living with HIV, initial disruptions to HIV testing and PrEP prescriptions continued in late 2020 for 15% and 7% of participants, respectively. For GBMSM living with HIV, care access was reduced throughout 2020; in late 2020, approximately 19% of participants reported a decrease in HIV medical care visits, down from 28% in April 2020. As others have reported, we observed that few participants reported disruptions in their access to antiretroviral therapy in early 2020, and this continued through the year. Although interruptions to HIV clinical care were not widespread and decreased by the end of 2020, these findings highlight the opportunity for new and targeted HIV clinical care interventions, such as home-based HIV care initiation and retention approaches, including telehealth services and multi-month ART prescriptions.

We observed that most sexual behavior and clinical service disruption measures did not vary significantly by race/ethnicity. Due to the vast racial/ethnic inequities in HIV infection and HIV prevention in the US that pre-date the COVID pandemic, we would expect HIV transmission to increase most dramatically as a result of the COVID pandemic in a scenario in which clinical service disruptions are more experienced by Black and Hispanic/Latino GBMSM. Historically and in present day, Black and Hispanic/Latino GBMSM have been the most disproportionately affected populations in the US [3]. This is a result of social and structural factors, including but not limited to structural racism, lack of access to quality health care, provider bias, discrimination, and poverty, which exist in the environments in which sexual risk behaviors occur [12,156]. In our study, we observed that non-Hispanic White men reported less trouble accessing HIV testing,

PrEP, and HIV clinical care services, but these differences were not statistically significant for any measure at any study cycle. However, small population-level changes in health care access and/or behavior might still affect the HIV epidemic since HIV transmission in a community can be driven by a small number of individuals,[157] so even non-significant differences are of note. Targeted HIV prevention efforts among marginalized communities remain essential due to the historically higher burden of HIV experienced by Black and Hispanic GBMSM populations.

Data that assess the temporal changes of sexual risk behaviors and HIV prevention and treatment service utilization are necessary to determine the impact of the COVID-19 pandemic on HIV transmission. The impact of decreased HIV screening, for example, could be offset by concurrent reductions in sexual risk behavior, but the timing and demographic distribution of changes are important. If service interruptions occur in populations with the highest burden of HIV, for example, there may be greater effects on HIV transmission. Modeling studies that use demographically stratified empirical reports of sexual distancing and HIV clinical service disruptions, such as the data presented in our study, can help examine how pandemic disruptions will impact the trajectory of the US HIV epidemic.

This analysis has several limitations. First, study data were obtained from convenience sampling and may not generalizable to all US GBMSM even after demographic standardization. Study participants were more likely to be of non-Hispanic White race/ethnicity, of higher socioeconomic status, and more likely to be insured than the general US GBMSM population. This was particularly true in the later cycles of this study because there was significant loss to follow-up. Although our sensitivity analysis findings demonstrate that attrition did not affect the overall results (the prevalence of sexual behavior and clinical services disruptions experienced by the subset of men who participated in all three study cycles were similar to those experienced by the full study population), participants in the third study cycle were more likely to be non-Hispanic white, older, and not known to be living with HIV. Lack of generalizability may

be particularly important for our race/ethnicity findings, given that minority race/ethnicity participants may be more likely to be insured and of higher SES than minority race/ethnicity GBMSM populations, skewing our results to appear to have less racial/ethnic disparities.

Further, the surveys only involved self-report of COVID-related impacts. Participants might have misreported the impacts that the COVID-19 pandemic have had on their sexual behaviors or service utilization/access or misreported the timing of changes. For example, although all participants in this study participated at each study cycle, participants may have been referring to any time during the COVID-19 pandemic when they complete the impact questions (e.g., referring to a decrease in partners during August when they complete the survey in September). However, this concern is somewhat mitigated in seeing that clear temporal decreases in some outcomes are observed (e.g., trouble getting an HIV test, trouble in getting a PrEP prescription). Further, COVID-19 impact survey measures are primarily categorical (e.g., behavior increased, decreased, no change); continuous measures such as the exact number of sexual partners would be useful to identify more specific changes in sexual behavior. For example, a fraction of participants may have reduced their partners by only one partner, whereas others may have reduced their partners by several partners. The impact of these reductions on population-level transmission dynamics are difficult to predict without data on these nuances. Lastly, our findings have limited temporal generalizability, given the ongoing changing nature of the COVID-19 pandemic and local restrictions and social behavior patterns. A major strength of this study is its longitudinal nature, but even within one study cycle there could be short-term temporal fluctuations.

This study is the first to examine the impact of the COVID-19 pandemic on both sexual behavior and clinical services disruptions among US GBMSM through December 2020. Although our findings demonstrated that GBMSM had continued reductions in sexual behavior in late 2020, that access to PrEP was returned to normal in late 2020, interruptions to ART

adherence were minimal, and interruptions did not significantly vary by race/ethnicity, our findings highlight the gaps in HIV prevention and treatment that have worsened in the pandemic era. In addition to elucidating behavioral patterns that may occur during future pandemics (and thus aiding in pandemic preparedness), our findings highlight that additional resources and programs will be needed to address existing disparities in HIV prevention and treatment (such as those increasing uptake of PrEP among indicated GBMSM), in addition to solving the new challenges created by the COVID-19 pandemic (such as decreases in HIV testing).

TABLES

Table 2.1. *Characteristics of GBMSM Who Participated in All Three Cycles of the 2020 AMIS COVID-19 Impact Survey, United States, April–December 2020*

	April 2020 ***n*** **(%)**	**July 2020** ***n*** **(%)**	**September–December 2020** ***n*** **(%)**
Total Sample	1,051	572	373
Race/Ethnicity			
Non-Hispanic Black	89 (8.5)	36 (6.3)	24 (6.5)
Non-Hispanic White	740 (70.4)	428 (75.0)	278 (75.3)
Hispanic or Latino	146 (13.9)	74 (13.0)	42 (11.4)
Other or multiple races	65 (6.2)	33 (5.8)	25 (6.8)
Age (years)			
15–24	214 (20.4)	83 (14.5)	49 (13.1)
25–29	179 (17.0)	89 (15.6)	57 (15.3)
30–39	210 (20.0)	118 (20.6)	94 (25.2)
≥40	448 (42.6)	282 (49.3)	173 (46.4)
HIV Status			
Positive	122 (11.6)	59 (10.3)	32 (8.6)
Negative	809 (77.0)	466 (81.5)	327 (87.7)
Unknown	120 (11.4)	47 (8.2)	14 (3.8)
Region			
Northeast	187 (17.8)	98 (17.1)	68 (18.2)
Midwest	194 (18.5)	107 (18.7)	65 (17.4)
South	427 (40.6)	223 (39)	154 (41.3)
West	241 (22.9)	143 (25)	85 (22.8)
US Territories	2 (0.2)	1 (0.2)	1 (0.3)

Table 2.2. *Frequency of Selected AMIS COVID-19 Impact Survey Outcomes, United States, April–December 2020*

		Not Changed *n* (%)	Decreased *n* (%)	Increased *n* (%)
Number of sexual partners	**April**	501 (47.6)	542 (51.5)	9 (0.9)
	July	219 (40)	320 (58.4)	9 (1.6)
	Sept–Dec	158 (44.8)	189 (53.5)	6 (1.7)
Opportunities to have sex	**April**	283 (27.1)	718 (68.6)	45 (4.3)
	July	151 (27.6)	381 (69.5)	16 (2.9)
	Sept–Dec	104 (29.8)	237 (67.9)	8 (2.3)
Use of condoms	**April**	980 (93.8)	57 (5.5)	8 (0.8)
	July	515 (94.3)	23 (4.2)	8 (1.5)
	Sept–Dec	322 (92.3)	19 (5.4)	8 (2.3)
Getting HIV tested[a]	**April**	737 (83.4)	142 (16.1)	5 (0.6)
	July	415 (86.8)	62 (13.0)	1 (0.2)
	Sept–Dec	261 (84.5)	47 (15.2)	1 (0.3)
Access to STI testing or treatment	**April**	775 (74.2)	267 (25.6)	3 (0.3)
	July	438 (80.4)	106 (19.4)	1 (0.2)
	Sept–Dec	281 (80.5)	66 (18.9)	2 (0.6)
Access to HIV meds[b]	**April**	112 (92.6)	7 (5.8)	2 (1.7)
	July	53 (93)	3 (5.3)	1 (1.8)
	Sept–Dec	28 (90.3)	2 (6.5)	1 (3.2)
Taking HIV meds every day as prescribed[b]	**April**	111 (91.7)	6 (5)	4 (3.3)
	July	55 (96.5)	1 (1.8)	1 (1.8)
	Sept–Dec	28 (93.3)	2 (6.7)	0 (0)
Getting HIV care clinical visits[b]	**April**	86 (71.7)	33 (27.5)	1 (0.8)
	July	38 (66.7)	19 (33.3)	0 (0)
	Sept–Dec	25 (80.6)	6 (19.4)	0 (0)
Getting viral loads or other labs done[b]	**April**	88 (73.3)	29 (24.2)	3 (2.5)
	July	41 (71.9)	16 (28.1)	0 (0)

	Sept–Dec	25 (83.3)	5 (16.7)	0 (0)
		No n (%)	**Yes n (%)**	**I haven't tried to get n (%)**
Trouble getting an HIV test[a]	**April**	236 (25.8)	52 (5.7)	628 (68.6)
	July	244 (50.4)	39 (8.1)	201 (41.5)
	Sept–Dec	207 (65.1)	31 (9.7)	80 (25.2)
Trouble getting PrEP prescription from your doctor[c]	**April**	140 (68.6)	18 (8.8)	46 (22.5)
	July	84 (88.4)	8 (8.4)	3 (3.2)
	Sept–Dec	76 (92.7)	6 (7.3)	0 (0)
Trouble getting your PrEP prescription filled at the pharmacy[c]	**April**	138 (67.6)	12 (5.9)	54 (26.5)
	July	87 (91.6)	5 (5.3)	3 (3.2)
	Sept–Dec	72 (87.8)	7 (8.5)	3 (3.7)

STI, sexually transmitted infection; PrEP, pre-exposure prophylaxis
[a]For men self-reporting as HIV-negative or with unknown HIV status
[b]For men self-reporting as living with HIV
[c]For men self-reporting as HIV-negative or with unknown HIV status and currently using PrEP

Table 2.3. *Age and Race/Ethnicity Standardization of Selected AMIS COVID-19 Impact Survey Outcomes, United States, April–December 2020*

		No Change % (95% CI)	**Decreased % (95% CI)**	**Increased % (95% CI)**
Number of sexual partners	**April**	0.45 (0.4, 0.49)	0.54 (0.49, 0.59)	0.01 (0, 0.02)
	July	0.39 (0.33, 0.44)	0.6 (0.52, 0.68)	0.02 (0.01, 0.03)
	Sept–Dec	0.43 (0.35, 0.51)	0.56 (0.46, 0.65)	0.01 (0, 0.03)
Opportunities to have sex	**April**	0.27 (0.23, 0.3)	0.69 (0.64, 0.75)	0.04 (0.03, 0.05)
	July	0.25 (0.21, 0.3)	0.72 (0.63, 0.8)	0.03 (0.01, 0.04)
	Sept–Dec	0.28 (0.21, 0.34)	0.7 (0.6, 0.81)	0.02 (0.01, 0.04)
Use of condoms	**April**	0.93 (0.87, 1)	0.06 (0.04, 0.07)	0.01 (0, 0.02)
	July	0.93 (0.84, 1)	0.05 (0.03, 0.07)	0.02 (0, 0.04)
	Sept–Dec	0.91 (0.79, 1)	0.06 (0.03, 0.1)	0.03 (0.01, 0.05)
Getting HIV tested[a]	**April**	0.83 (0.76, 0.91)	0.16 (0.13, 0.19)	0.01 (0, 0.01)

	July	0.87 (0.77, 0.98)	0.13 (0.09, 0.16)	0 (0, 0.01)
	Sept–Dec	0.86 (0.73, 0.99)	0.14 (0.09, 0.2)	0 (0, 0.01)
Access to STI testing or treatment	**April**	0.74 (0.69, 0.8)	0.25 (0.22, 0.29)	0 (0, 0.01)
	July	0.81 (0.72, 0.9)	0.19 (0.15, 0.23)	0 (0, 0)
	Sept–Dec	0.8 (0.69, 0.91)	0.19 (0.14, 0.24)	0.01 (0, 0.02)
Access to HIV meds[b]	**April**	0.87 (0.67, 1)	0.07 (0.01, 0.13)	0.03 (0, 0.09)
	July	0.76 (0.53, 0.98)	0.04 (0, 0.08)	0.02 (0, 0.05)
	Sept–Dec	0.6 (0.37, 0.83)	0.04 (0, 0.09)	0.02 (0, 0.05)
Taking HIV meds every day as prescribed[b]	**April**	0.88 (0.68, 1)	0.06 (0.01, 0.11)	0.04 (0, 0.08)
	July	0.78 (0.56, 1)	0.01 (0, 0.04)	0.02 (0, 0.05)
	Sept–Dec	0.6 (0.37, 0.83)	0.06 (0, 0.14)	0 (0, 0)
Getting HIV care clinical visits[b]	**April**	0.74 (0.54, 0.93)	0.24 (0.14, 0.33)	0 (0, 0.01)
	July	0.51 (0.34, 0.68)	0.3 (0.15, 0.45)	0 (0, 0)
	Sept–Dec	0.52 (0.31, 0.74)	0.13 (0.02, 0.25)	0 (0, 0)
Getting viral loads or other labs done[b]	**April**	0.71 (0.53, 0.89)	0.25 (0.14, 0.36)	0.02 (0, 0.04)
	July	0.56 (0.38, 0.75)	0.25 (0.11, 0.39)	0 (0, 0)
	Sept–Dec	0.54 (0.32, 0.76)	0.12 (0.01, 0.23)	0 (0, 0)
		No % (95% CI)	**Yes % (95% CI)**	**I haven't tried to get % (95% CI)**
Trouble getting an HIV test[a]	**April**	0.27 (0.23, 0.31)	0.06 (0.04, 0.08)	0.67 (0.6, 0.73)
	July	0.52 (0.43, 0.6)	0.08 (0.05, 0.11)	0.4 (0.33, 0.46)
	Sept–Dec	0.64 (0.53, 0.74)	0.1 (0.05, 0.15)	0.27 (0.19, 0.34)
Trouble getting PrEP prescription from your doctor[c]	**April**	0.73 (0.59, 0.87)	0.07 (0.03, 0.1)	0.2 (0.13, 0.28)
	July	0.84 (0.61, 1)	0.1 (0.02, 0.19)	0.02 (0, 0.04)
	Sept–Dec	0.87 (0.63, 1)	0.08 (0, 0.17)	0 (0, 0)
Trouble getting your PrEP prescription filled at the pharmacy[c]	**April**	0.7 (0.56, 0.83)	0.04 (0.01, 0.06)	0.27 (0.18, 0.35)
	July	0.88 (0.64, 1)	0.05 (0, 0.11)	0.03 (0, 0.06)
	Sept–Dec	0.83 (0.59, 1)	0.09 (0, 0.17)	0.03 (0, 0.07)

Standardized by age (15–24, 25–29, 30–39, ≥40 years) and race (NH Black, NH White, Hispanic, Other).
CI: confidence interval; STI, sexually transmitted infection; PrEP, pre-exposure prophylaxis
[a]For men self-reporting as HIV-negative or with unknown HIV status

[b]For men self-reporting as living with HIV
[c]For men self-reporting as HIV-negative or with unknown HIV status and currently using PrEP

Table 2.4. *Frequency of Selected AMIS COVID Impact Survey Outcomes Where Participant Participated in All Three Survey Cycles (n=265)*

		Not Changed *n* (%)	Decreased *n* (%)	Increased *n* (%)
Number of sexual partners	**April**	120 (45.6)	143 (54.4)	0 (0.0)
	July	106 (42.7)	137 (55.2)	5 (2.0)
	Sept–Dec	107 (42.8)	137 (54.8)	6 (2.4)
Opportunities to have sex	**April**	67 (25.5)	185 (70.3)	11 (4.2)
	July	68 (27.4)	171 (69.0)	9 (3.6)
	Sept–Dec	68 (27.6)	173 (70.3)	5 (2.0)
Use of condoms	**April**	248 (94.3)	13 (4.9)	2 (0.8)
	July	232 (93.5)	11 (4.4)	5 (2.0)
	Sept–Dec	227 (91.2)	15 (6.0)	7 (2.8)
Getting HIV tested[a]	**April**	195 (84.4)	34 (14.7)	2 (0.9)
	July	195 (86.7)	30 (13.3)	0 (0.0)
	Sept–Dec	190 (86.4)	29 (13.2)	1 (0.5)
Access to STI testing or treatment	**April**	202 (76.8)	61 (23.2)	0 (0.0)
	July	201 (81.0)	46 (18.5)	1 (0.4)
	Sept–Dec	207 (83.1)	41 (16.5)	1 (0.4)
Access to HIV meds[b]	**April**	22 (100.0)	0 (0.0)	0 (0.0)
	July	15 (88.2)	1 (5.9)	1 (5.9)
	Sept–Dec	18 (90.0)	1 (5.0)	1 (5.0)
Taking HIV meds every day as prescribed[b]	**April**	21 (95.5)	1 (4.5)	0 (0.0)
	July	16 (94.1)	0 (0.0)	1 (5.9)
	Sept–Dec	20 (100.0)	0 (0.0)	0 (0.0)
Getting HIV care clinical visits[b]	**April**	15 (68.2)	7 (31.8)	0 (0.0)
	July	14 (82.4)	3 (17.6)	0 (0.0)

	Sept–Dec	18 (90.0)	2 (10.0)	0 (0.0)
Getting viral loads or other labs done[b]	**April**	17 (77.3)	5 (22.7)	0 (0.0)
	July	15 (88.2)	2 (11.8)	0 (0.0)
	Sept–Dec	16 (84.2)	3 (15.8)	0 (0.0)
		No n (%)	**Yes n (%)**	**I haven't tried to get n (%)**
Trouble getting an HIV test[a]	**April**	69 (28.9)	16 (6.7)	154 (34.4)
	July	128 (56.1)	20 (8.8)	80 (35.1)
	Sept–Dec	149 (65.6)	22 (9.7)	56 (24.7)
Trouble getting PrEP prescription from your doctor[c]	**April**	39 (69.6)	2 (3.6)	15 (26.8)
	July	52 (89.7)	5 (8.6)	1 (1.7)
	Sept–Dec	52 (91.2)	5 (8.8)	0 (0.0)
Trouble getting your PrEP prescription filled at the pharmacy[c]	**April**	39 (69.6)	3 (5.4)	14 (25.0)
	July	53 (91.4)	3 (5.2)	2 (3.4)
	Sept–Dec	50 (87.7)	5 (8.8)	2 (3.5)

STI, sexually transmitted infection; PrEP, pre-exposure prophylaxis
[a]For men self-reporting as HIV-negative or with unknown HIV status
[b]For men self-reporting as living with HIV
[c]For men self-reporting as HIV-negative or with unknown HIV status and currently using PrEP

Table 2.5. *Frequency of Selected AMIS COVID-19 Impact Survey Outcomes Stratified by Race/Ethnicity*

		Hispanic			**Non-Hispanic Black**			**Non-Hispanic White**			**Other**			***P-value***
		Decreased *n* (%)	**Increased *n* (%)**	**Not Changed *n* (%)**	**Decreased *n* (%)**	**Increased *n* (%)**	**Not Changed *n* (%)**	**Decreased *n* (%)**	**Increased *n* (%)**	**Not Changed *n* (%)**	**Decreased *n* (%)**	**Increased *n* (%)**	**Not Changed *n* (%)**	
Number of sexual partners	**April**	74 (51.0)	2 (1.4)	69 (47.6)	49 (54.4)	1 (1.1)	40 (44.4)	380 (51.3)	6 (0.8)	355 (47.9)	33 (50.8)	0 (0.0)	32 (49.2)	0.94
	July	43 (63.2)	0 (0.0)	25 (36.8)	18 (54.5)	1 (3.0)	14 (42.4)	241 (58.2)	8 (1.9)	165 (39.9)	16 (57.1)	0 (0.0)	12 (42.9)	0.86
	Sept–Dec	17 (45.9)	0 (0.0)	20 (54.1)	13 (61.9)	1 (4.8)	7 (33.3)	144 (53.9)	5 (1.9)	118 (44.2)	14 (56.0)	0 (0.0)	11 (44.0)	0.61

Use of condoms	**April**	9 (6.3)	0 (0.0)	134 (93.7)	7 (7.8)	3 (3.3)	80 (88.9)	36 (4.9)	3 (0.4)	699 (94.7)	3 (4.7)	2 (3.1)	59 (92.2)	***0.02***
	July	4 (5.9)	3 (4.4)	61 (89.7)	3 (9.1)	2 (6.1)	28 (84.8)	14 (3.4)	3 (0.7)	395 (95.9)	2 (7.1)	0 (0.0)	26 (92.9)	***0.01***
	Sept –Dec	2 (5.4)	0 (0.0)	35 (94.6)	3 (14.3)	3 (14.3)	15 (71.4)	14 (5.3)	5 (1.9)	244 (92.8)	0 (0.0)	0 (0.0)	25 (100.0)	***0.02***
Getting HIV tested[a]	**April**	25 (19.8)	2 (1.6%)	99 (78.6)	8 (16.3)	1 (2.0)	40 (81.6)	94 (14.7)	2 (0.3)	545 (85.0)	12 (21.1)	0 (0.0)	45 (78.9)	0.12
	July	10 (16.4)	0 (0.0%)	51 (83.6)	3 (15.8)	0 (0.0)	16 (84.2)	44 (11.9)	1 (0.3)	324 (87.8)	4 (16.7)	0 (0.0)	20 (83.3)	0.67
	Sept –Dec	4 (12.1)	0 (0.0%)	29 (87.9)	4 (26.7)	1 (6.7)	10 (66.7)	37 (15.6)	0 (0.0)	200 (84.4)	2 (9.5)	0 (0.0)	19 (90.5)	0.10
Access to HIV meds[b]	**April**	1 (7.7)	0 (0.0)	12 (92.3)	2 (5.3)	1 (2.6)	35 (92.1)	4 (6.2)	1 (1.5)	60 (92.3)	0 (0.0)	0 (0.0)	5 (100.0)	1.00
	July	0 (0.0)	0 (0.0)	7 (100.0)	1 (9.1)	0 (0.0)	10 (90.9)	2 (5.6)	1 (2.8)	33 (91.7)	0 (0.0)	0 (0.0)	3 (100.0)	1.00
	Sept –Dec	0 (0.0)	0 (0.0)	2 (100.0)	0 (0.0)	0 (0.0)	6 (100.0)	2 (9.5)	1 (4.8)	18 (85.7)	0 (0.0)	0 (0.0)	2 (100.0)	1.00
Taking HIV meds every day as prescribed [b]	**April**	2 (15.4)	1 (7.7)	10 (76.9)	1 (2.6)	3 (7.9)	34 (89.5)	3 (4.6)	0 (0.0)	62 (95.4)	0 (0.0)	0 (0.0)	5 (100.0)	0.08
	July	0 (0.0)	0 (0.0)	7 (100.0)	1 (9.1)	0 (0.0)	10 (90.9)	0 (0.0)	1 (2.8)	35 (97.2)	0 (0.0)	0 (0.0)	3 (100.0)	0.61
	Sept –Dec	1 (50.0)	0 (0.0)	1 (50.0)	0 (0.0)	0 (0.0)	5 (100.0)	1 (4.8)	0 (0.0)	20 (95.2)	0 (0.0)	0 (0.0)	2 (100.0)	0.28
Getting HIV care clinical visits[b]	**April**	4 (30.8)	0 (0.0)	9 (69.2)	14 (36.8)	1 (2.6)	23 (60.5)	15 (23.4)	0 (0.0)	49 (76.6)	0 (0.0)	0 (0.0)	5 (100.0)	0.26
	July	4 (57.1)	0 (0.0)	3 (42.9)	6 (54.5)	0 (0.0)	5 (45.5)	8 (22.2)	0 (0.0)	28 (77.8)	1 (33.3)	0 (0.0)	2 (66.7)	0.09
	Sept –Dec	1 (50.0)	0 (0.0)	1 (50.0)	1 (16.7)	0 (0.0)	5 (83.3)	4 (19.0)	0 (0.0)	17 (81.0)	0 (0.0)	0 (0.0)	2 (100.0)	0.71
Getting viral loads or other labs done[b]	**April**	4 (30.8)	1 (7.7)	8 (61.5)	10 (26.3)	2 (5.3)	26 (68.4)	15 (23.4)	0 (0.0)	49 (76.6)	0 (0.0)	0 (0.0)	5 (100.0)	0.25
	July	2 (28.6)	0 (0.0)	5 (71.4)	6 (54.5)	0 (0.0)	5 (45.5)	7 (19.4)	0 (0.0)	29 (80.6)	1 (33.3)	0 (0.0)	2 (66.7)	0.11
	Sept –Dec	1 (50.0)	0 (0.0)	1 (50.0)	0 (0.0)	0 (0.0)	6 (100.0)	4 (20.0)	0 (0.0)	16 (80.0)	0 (0.0)	0 (0.0)	2 (100.0)	0.38
		I haven't tried to get n (%)	**No n (%)**	**Yes n (%)**	**I haven't tried to get n (%)**	**No n (%)**	**Yes n (%)**	**I haven't tried to get n (%)**	**No n (%)**	**Yes n (%)**	**I haven't tried to get n (%)**	**No n (%)**	**Yes n (%)**	
Had trouble getting an HIV test[a]	**April**	83 (63.4)	38 (29.0)	10 (7.6)	34 (68.0)	13 (26.0)	3 (6.0)	466 (70.1)	167 (25.1)	32 (4.8)	38 (64.4)	16 (27.1)	5 (8.5)	0.56
	July	25 (41.0)	29 (47.5)	7 (11.5)	4 (20.0)	12 (60.0)	4 (20.0)	159 (42.6)	189 (50.7)	25 (6.7)	10 (40.0)	12 (48.0)	3 (12.0)	0.15
	Sept –Dec	8 (22.9)	25 (71.4)	2 (5.7)	5 (33.3)	7 (46.7)	3 (20.0)	62 (25.6)	157 (64.9)	23 (9.5)	5 (21.7)	15 (65.2)	3 (13.0)	0.62
	April	4 (14.3)	20 (71.4)	4 (14.3)	4 (25.0)	12 (75.0)	0 (0.0)	34 (23.3)	98 (67.1)	14 (9.6)	3 (25.0)	9 (75.0)	0 (0.0)	0.69

Had trouble getting PrEP prescription from doctor[c]	**July**	1 (7.1)	11 (78.6)	2 (14.3)	0 (0.0)	6 (100.0)	0 (0.0)	2 (2.9)	62 (89.9)	5 (7.2)	0 (0.0)	5 (83.3)	1 (16.7)	0.56
	Sept –Dec	0 (0.0)	11 (91.7)	1 (8.3)	0 (0.0)	4 (100.0)	0 (0.0)	0 (0.0)	57 (91.9)	5 (8.1)	0 (0.0)	4 (100.0)	0 (0.0)	1.00

PrEP, pre-exposure prophylaxis

[a]For men self-reporting as HIV-negative or with unknown HIV status

[b]For men self-reporting as living with HIV

[c]For men self-reporting as HIV-negative or with unknown HIV status and currently using PrEP

FIGURES

Figure 2.1. *Prevalence of Selected AMIS COVID-19 Impact Survey Outcomes Stratified by Race/Ethnicity during April–December 2020*

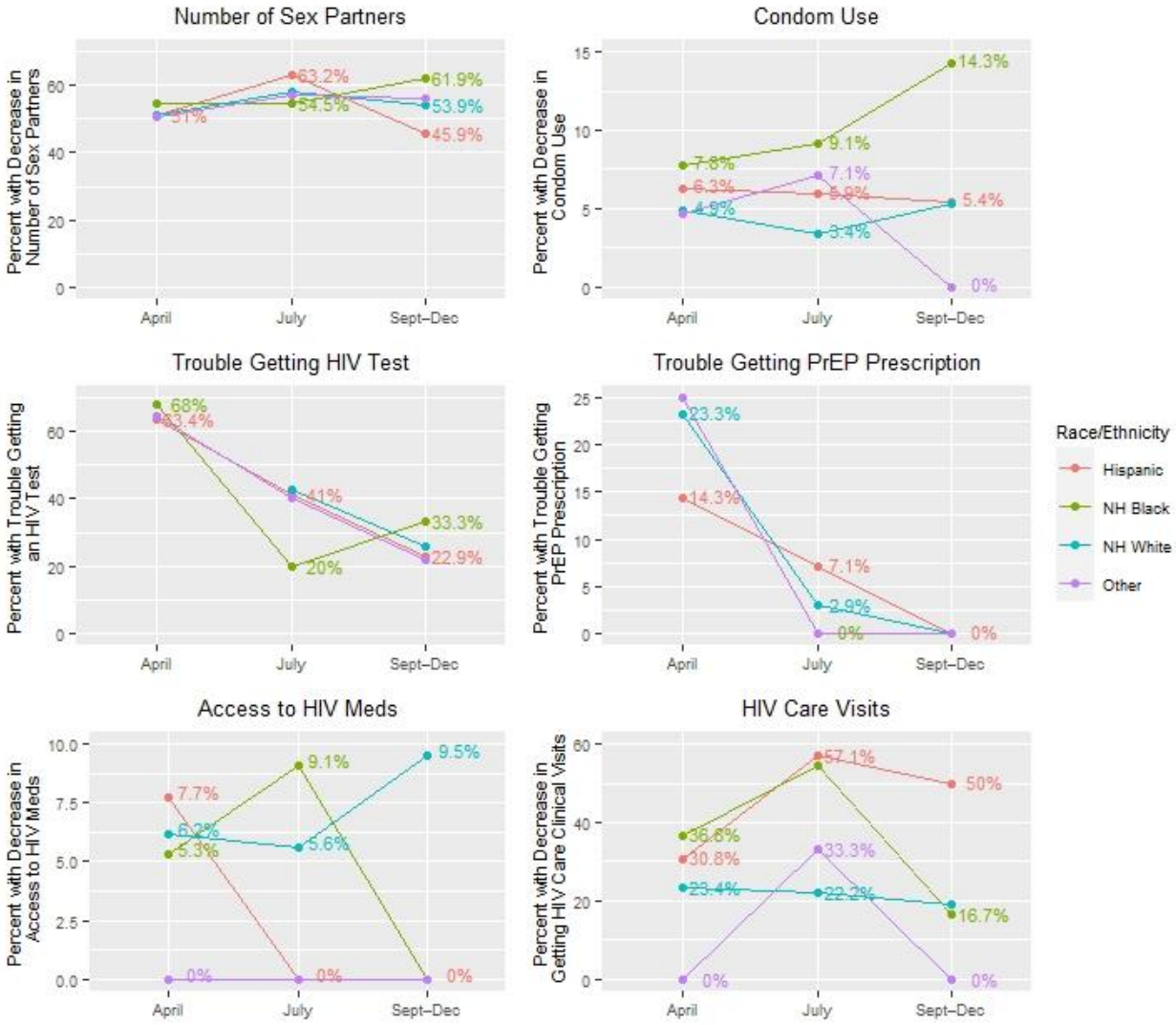
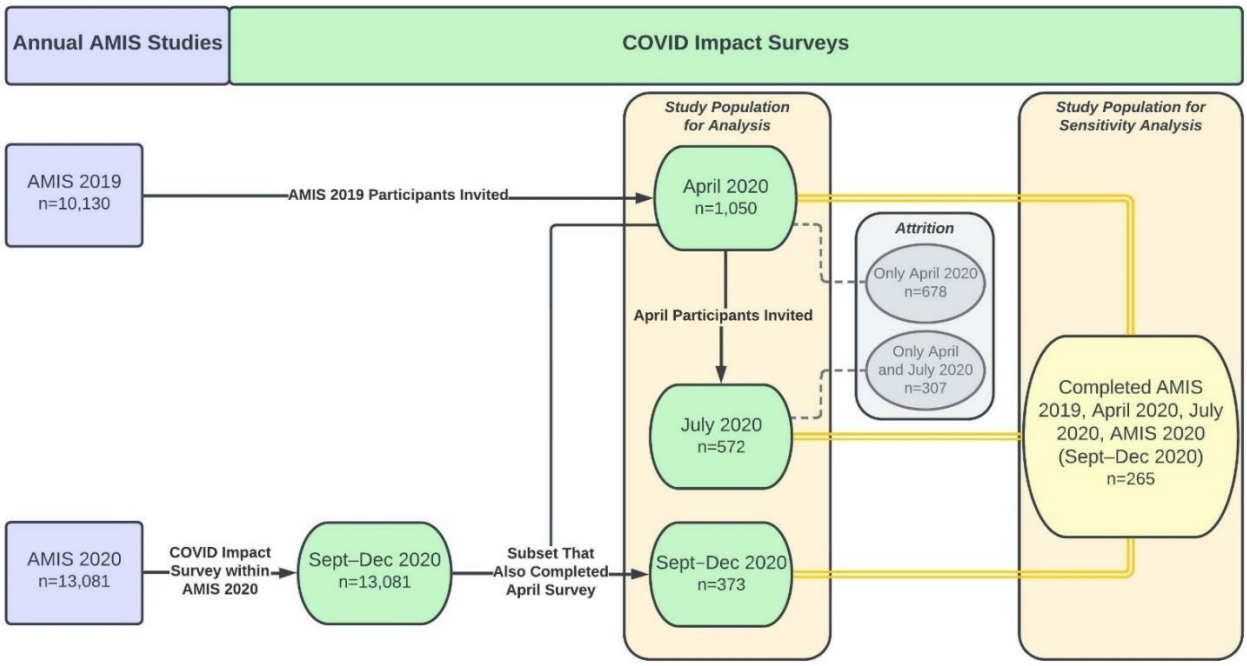


Figure 2.2. *Flow Diagram Linking AMIS 2019, AMIS 2020, AMIS COVID-19 Impact Survey Cycles, and Study Population*



Chapter 3. Estimation of the Incidence of HIV among US MSM During the COVID-19 Pandemic in the Presence of Competing Forces of Sexual Distancing and Clinical Service Interruptions

ABSTRACT

BACKGROUND

HIV is a major public health challenge that has become more complex because of the COVID-19 pandemic. It is unclear what the long-term impacts of temporary COVID-19-related social distancing and clinical service disruptions will be on HIV transmission and dynamics. This study uses empirical behavioral data in a mathematical model to estimate the incidence of HIV among US MSM during the COVID-19 pandemic up to mid-2021.

METHODS

Parameterized by multiple nationally representative data sources of COVID-era sexual behavior, HIV prevention services, and/or HIV clinical service disruptions, we used a network-based model of HIV transmission dynamics to estimate HIV incidence during the COVID pandemic among all US MSM. Model scenarios were used to simulate the combined effect of COVID-era changes in sexual behavior, condom use, HIV testing, and PrEP use; the individual isolated effects of these changes; and to represent a counterfactual scenario in which the COVID pandemic did not take place and affect HIV-related behaviors and services.

RESULTS

When incorporating reported sexual behavior and service disruption changes through the Spring of 2021, a decrease in HIV incidence was observed from March 2020 and is sustained until mid-2021. The largest decrease in incidence occurred in May 2020, representing a 36% decrease in

HIV incidence compared to the base (no pandemic) scenario. Driven mainly by reductions in sexual behavior, the COVID pandemic is projected to have prevented 2,227 new HIV infections among all US MSM over a five year period. Despite the temporary reductions in HIV transmission, by 2022, HIV incidence returned to the counterfactual HIV incidence of our base (no pandemic) scenario.

CONCLUSIONS

Although temporary decreases in HIV transmission may have occurred during the COVID pandemic, they were not sufficient to alter the long-term trajectory of the US HIV epidemic. HIV prevention efforts remain important, both in and out of a pandemic context.

INTRODUCTION

Human immunodeficiency virus (HIV) remains a major public health challenge in the United States (US) and has become more complex because of the COVID-19 pandemic. Current public health efforts to prevent HIV among gay, bisexual, and other men who have sex with men (MSM) focus on reducing HIV acquisition and transmission by promoting safer sexual behaviors,[16] increasing the availability and use of pre-exposure prophylaxis (PrEP),[24] and increasing the consistent use of antiretroviral therapy (ART).[150] These strategies are a part of the US Ending the HIV Epidemic: A Plan for America (EHE) initiative.[38] Announced in early 2019, EHE aims to reduce new HIV infections in the US by 75% by 2025 and 90% by 2030 by expanding HIV prevention and treatment efforts.[38] EHE was developed and initiated in the pre-COVID era, however, and did not anticipate mass pandemic-related impacts. But since its inception, economic and social disruptions in response to the COVID-19 global pandemic have interrupted HIV prevention and treatment services, reducing access to HIV testing, PrEP visits, and HIV care retention.[44,45,49,50,158,159]

These COVID-19-related interruptions to HIV prevention and clinical care may increase the rate of HIV acquisition and transmission. For example, reduced access to PrEP for indicated persons can lead to additional risk of HIV acquisition, and reduced HIV testing can lead to more undiagnosed HIV, and therefore more population-level risk of HIV transmission as newly infected individuals do not know their HIV status (but may not take precautions to prevent transmitting it to others). Reduced access to HIV care retention can lead to less viral suppression, and a higher risk for HIV transmission. At a population level, these factors can increase HIV transmission and alter the trajectory of the HIV epidemic.

COVID-19 disruptions have also prompted major behavioral changes to social interaction, including reductions in sexual activity ("sexual distancing") and reductions in number of sexual partners.[41,160] Such reductions in sexual activity may counterbalance the effects of clinical service interruptions with respect to HIV transmission. Disruptions to HIV prevention and clinical care can increase the rate of HIV acquisition and transmission, while reductions in sexual risk activity can decrease it. The impact of this balance depends on the relative extent and timing of such changes.[67,69] Studies of the magnitude of clinical interruptions and sexual behavior changes among US MSM[44,45,49,158,161–168] suggest that COVID impacts may be detrimental to HIV prevention efforts. For example, in a cohort of PrEP-using MSM in the south, Pampati et al. found that a quarter of the cohort documented challenges when attempting to access PrEP, HIV testing, or STI testing.[44] Using data from 60 state and local health departments, Patel et al. found that there was a 46.0% reduction in the number of HIV tests conducted in 2020 compared to 2019.[167] On the other hand, in a study of US MSM, McKay et al. found that there were decreases to number of reported sexual partners in April and May 2020 compared to before the pandemic.[158]

However, the actual combined effect of these changes (based on empirical data, not theoretical data) on HIV transmission among US MSM during the COVID-19 pandemic has not

yet been quantified. Some modeling studies have examined how certain theoretical levels of COVID-related changes may potentially impact HIV transmission,[67,69] but to our knowledge none have examined actual HIV transmission using empirical data. The Centers for Disease Control and Prevention (CDC) has released HIV incidence estimates during the pandemic period, but have noted that these data are not reliable due to pandemic impacts to HIV services.[169,170] Studies which determine the actual impact of COVID-related disruptions to clinical care services and sexual behavior on HIV transmission among US MSM are needed. These studies can help fill the gap in the literature regarding unknown COVID-era HIV transmission (caused both by theoretical COVID impact studies, and by the unreliability of case-based HIV surveillance-based incidence estimates during the COVID pandemic).

This study uses empirical data to parameterize a network-based mathematical model in order to estimate the incidence of HIV among US MSM during the COVID-19 pandemic. We hypothesized that sexual distancing and service reductions would alter the incidence of HIV across the pandemic era, with long-term effects/consequences on control of HIV transmission. We also hypothesized that changes in HIV service utilization would increase HIV incidence to such an extent that EHE goals for 2030 would be unattainable. This study represents a novel approach to estimating the actual impact of COVID-19 on HIV transmission among US MSM.

METHODS

Study Design. This model of HIV transmission dynamics for US MSM was built on the *EpiModel* software platform.[171] *EpiModel* simulates HIV epidemics over dynamic contact networks of US MSM using temporal exponential random graph models (TERGMs).[172] Specific model extensions were built to simulate HIV transmission among US MSM from 2018 to 2030 to estimate the impact of reported COVID-related changes in sexual behavior and HIV clinical

services on HIV transmission during the COVID pandemic period. Our goal was to project the long-term impact of these pandemic changes on HIV incidence.

Network Model. Components of the model representing sexual network structure were fit using data from ARTnet, a cross-sectional web-based study of US MSM conducted between 2017 and 2019.[91] ARTnet participants were recruited through the annual American Men's Internet Survey (AMIS) study.[124] ARTnet eligibility criteria included male sex at birth, current male cisgender identity, lifetime history of sexual activity with another man, and age between 15 and 65 years. The use of ARTnet data in *EpiModel* network models has been described previously.[67,173]

Our model represented main, casual, and one-time sexual partnerships. Age and race/ethnicity mixing, the formation and dissolution of persistent partnerships, and the rate of one-time partnership formation were represented as estimated from ARTnet data. Behavior within sexual partnerships, including the rate of intercourse per partnership per time step, condom use per sexual act, and sexual role were modeled based on individual and partnership characteristics, with probabilities estimated from ARTnet data.

The model also represented demography of the population, HIV interhost epidemiology (disease transmission), HIV intrahost epidemiology (disease progression), and HIV clinical epidemiology.[91] Demography included aging, entries, and exits. HIV interhost epidemiology included HIV transmission (per-act transmission probability). HIV intrahost epidemiology represented HIV disease progression, including viral load progression, within HIV-positive individuals. HIV clinical epidemiology included disease diagnosis, ART initiation, ART adherence and viral load suppression, and AIDS disease progression and mortality.

The HIV prevention care cascade and HIV care continuum were both represented in the model. The HIV prevention continuum consisted of HIV testing, PrEP initiation, PrEP

adherence, and persistence in PrEP care for daily oral tenofovir/emtricitabine.[23] Weekly pre-COVID HIV testing rates were race-stratified and determined by ARTnet HIV testing rates, surveillance data on diagnosed fraction of HIV-infected MSM, and model calibration.[33,91] After testing negative for HIV, MSM who met indications for PrEP based on CDC guidelines were eligible to start PrEP.[18] They then started PrEP based on an initiation probability generating a coverage level of approximately 30%, which approximates US estimates of PrEP coverage.[33] Heterogeneous PrEP adherence was modeled, with 78% of PrEP users reaching a high-adherence level that resulted in a 99% relative reduction in HIV acquisition risk. Pre-COVID PrEP discontinuation was based on estimates of the proportion of MSM who were retained in PrEP care at 6 months,[141] and weekly pre-COVID PrEP discontinuation rates were 0.021, 0.012, and 0.012, for Black, Hispanic, and White/other MSM, respectively. COVID and post-COVID PrEP discontinuation was based on the number of PrEP prescriptions over time in a national pharmacy database (IQVIA Real World Data—Longitudinal Prescriptions Database).[174] PrEP care consisted of routine HIV and STI screening. For the HIV care continuum, MSM initiated ART after testing positive for HIV. ART lowered their HIV viral load and increased their longevity. MSM progressed through HIV disease with viral loads represented continuously. Lower viral load with sustained ART use was associated with a reduced probability of HIV transmission per act. HIV transmission probability was also modified by PrEP use, condom use, sexual position, and circumcision. Additional full methodological details of HIV interhost, intrahost, and clinical epidemiology; network generation; parameter selection; calibration; and modeling are provided in the Supplemental Appendix.

Modeling COVID-19-Related Impacts. Changes in sexual behavior and condom use representing from March 2020–January 2021 were included in the model. These changes were parameterized based on behavioral data from the AMIS COVID Impact Survey and the Love and Sex in the Time of COVID studies. The AMIS COVID-19 Impact Survey collected data on

sexual distancing and HIV service utilization/care engagement from 1,051 US MSM at three time points during the COVID-19 pandemic: April, July, and September–December 2020.[45] The Love and Sex in the Time of COVID-19 survey also collected data from 696 US MSM on sexual distancing and HIV service utilization/care engagement during the COVID-19 pandemic, at two time points: April–May 2020 and November 2020–January 2021.[49] Where applicable, such as for sexual behavior by partnership type, sexual behavior parameters were standardized using the proportions of partnership types obtained from the ARTnet study. This approach allowed us to stratify COVID-era sexual behavior results to best map to *EpiModelHIV* partnership-stratified parameters. Because these surveys did not collect data in all months of the COVID pandemic (e.g., in August 2020, between July 2020 and September 2020 AMIS COVID-19 Impact Survey time points), we assumed that during these periods, changes in outcomes were steady and continuous. Therefore, where applicable between survey points, we implemented weekly gradual changes in model parameters (e.g., to fill the gap in COVID-19 Impact Survey data, outcomes steadily changed in magnitude by week in August 2020). Full details on all parameter estimates, ranges, sources, and calculations (where applicable) are included in the Supplemental Appendix.

Before implementing COVID-related changes, we first ran a base scenario in which we assumed model parameters remained at their 2019 levels for the full model simulation. Changes in HIV prevention and clinical care services, including race-stratified HIV testing and PrEP use rates, were incorporated from March 2020–April 2021 as indicated by national estimates of HIV screening tests from three overlapping data sources (Health Resources and Services Administration's Uniform Data System, CDC's National HIV Prevention Program Monitoring and Evaluation system, National Syndromic Surveillance Program's commercial laboratory data)[175] and PrEP prescriptions and new PrEP users in national pharmacy database (IQVIA Real World Data—Longitudinal Prescriptions Database).[174] Changes in ART initiation, ART adherence and

viral load suppression, and AIDS disease progression were not incorporated during the pandemic, since meaningful changes in ART use among men living with diagnosed HIV were not observed in either the AMIS COVID Impact Survey nor the Love and Sex in the Time of COVID study, nor in external reports examining ART prescriptions during the COVID pandemic.[176–178]

Because we found that in a subset of individuals (in both the AMIS COVID Impact Survey and the Love and Sex in the Time of COVID study) decreases in sexual behavior occurred alongside decreases in HIV testing and/or PrEP use, we introduced a behavior changer feature/attribute into our model. This feature allowed us to modify persistent partnership act rates and one-time partnership formation rates alongside HIV testing and PrEP use in the same group of individuals. Modification rates were set as determined from our primary data sources.

Because our primary data sources and other studies[161,176,177,179] did not observe significant decreases in ART use or viral load suppression, we did not incorporate these changes into our models and examine their isolated impact.

Sexual distancing and clinical care interruptions were integrated into the model by changing the appropriate parameters for behavior and HIV prevention and clinical services use. Because at the time of this study, data on the sexual behavior and HIV testing of US MSM was not available after April 2021, we assumed parameters reverted to their pre-pandemic value in the latter half of 2021 and did not change after 2021 (though for PrEP and HIV testing, data has shown that PrEP use and HIV testing have returned to and/or exceeded pre-pandemic levels).[180] Full details of parameter selection and source are available in the Supplemental Technical Appendix. Sensitivity analyses regarding the magnitude and timing of sexual behavior and clinical care changes were additionally completed (Supplementary Figure 1) to explore the impact of some of the uncertainty in our parameterization. Our modeling and analytic code is

available in a git repository at https://github.com/EpiModel/COVIDHIVAim2 *[to be renamed/made public]*.

Calibration and Simulation. The model spanned 2018 to 2030. This timespan was chosen to demonstrate HIV incidence before, during, and after the COVID-19 pandemic, and up to the EHE target of 2030.

The model was calibrated with a Bayesian approach that defined prior distributions for parameters and fit the model to empirical surveillance-based estimates of diagnosed HIV for all US MSM in 2019. After calibration, we simulated the model 500 times and summarized the distribution of results with medians and 95% simulation intervals. COVID-related model scenarios were compared to the baseline (no COVID) scenario in order to assess how the COVID pandemic affected HIV transmission, relative to a no pandemic state.

The primary outcomes were HIV incidence per 100 person-years at risk (PYAR), five-year cumulative incidence during March 2020–March 2025, and population impact. Population impact was calculated in two steps: first, we adjusted the 5-year cumulative incidence to represent the full US MSM population (approximately 4,503,080 MSM),[181] then we subtracted this total US MSM population cumulative incidence for each scenario from the value of the base scenario to obtain the difference. Because of the stochastic framework of our model, 95% simulation intervals were calculated for all primary outcome measures along with simulation medians.

Comparison to Surveillance-Based Diagnoses. In order to determine how closely our model-based estimates of HIV incidence and HIV positive tests track with case-based surveillance estimates, we used HIV diagnoses data that are attributed to male-to-male sexual contact transmission from the National HIV Surveillance System (NHSS).[147] These data were available quarterly from January 2019–December 2021. Although NHSS represents HIV diagnoses,

whereas our model estimates incidence, we wanted to track how closely model-based incidence may line up with real world diagnoses data.

RESULTS

Figure 3.1 depicts HIV incidence among US MSM from 2019 to 2022. A decrease in HIV incidence was observed from March 2020 and was sustained through March 2021. At its lowest point in May 2020, simulated HIV incidence was 0.25 per 100 person-years at risk (PYAR) (95% simulation interval (SI): 0.05, 0.49), 36% lower than the base (no COVID pandemic) scenario (HIV incidence of 0.39 per 100 PYAR; 95% SI: 0.15, 0.64) (Table 3.1). Slight increases in HIV incidence are noted in mid-2021, but they neither persist nor affect the trajectory of the epidemic later in the year. In a sensitivity analysis with more conservative estimates of behavior changes, the overall decrease in HIV incidence during 2020 is still observed (Figure 3.6). From the period of March 2020 to March 2025, the simulated 5-year cumulative incidence was 1,661.5 (95% SI: 1,547.4, 1,773.4) per 100,000 MSM. Compared to the base scenario, this represents a 3% reduction in 5-year cumulative incidence (cumulative incidence of 1,710.9; 95% SI: 1,600.3, 1,820.5), but for all US MSM, represents a five-year population impact of 2,227 (95% SI: -2,382.5, -2,121.4) less HIV infections.

When the effects of reported changes in sexual behavior, condom use, HIV testing, and PrEP use are isolated (Figure 3.2), the decrease in HIV incidence observed in the pandemic period is most attributable to changes in sexual behavior: over five years and in isolation, the decreases in sexual behavior during 2020–2021 would have prevented -4,341.8 (95% SI: -4,192.8, -4,345.0) HIV infections among US MSM compared to the base scenario. In isolation, the 2020–2021 changes in condom use, HIV testing, and PrEP use, would have increased new

HIV infections by 186.2 (95% SI: 184.5, 523.6), 475.2 (95% SI: 564.7, 599.4), and 2,360.3 (95% SI: 2,683.2, 2,794.6), respectively.

When compared to NHSS-sourced quarterly HIV diagnoses (attributed to male-to-male sexual contact transmission) data,[147] although comparing two separate things (diagnoses vs. incidence) our model-based estimates of HIV incidence and HIV positive tests follow a similar trend, with the largest decreases occurring in the second quarter of 2020 (Figure 3.3). In our model, HIV test positivity (the proportion of all HIV tests that are positive) dips during the pandemic period, from 0.0036 before March 2020 to 0.0017 at its lowest point in 2020 (Figure 4). Our model-based PrEP coverage estimate decreases from 32% in January 2020 to 22% in March 2021, and only reverts to 27% by December 2021, nine months after COVID-era PrEP changes are discontinued (Figure 3.7). By 2030, PrEP coverage returns to 31%, aligning with the base (no COVID) scenario of a PrEP coverage of 31% in 2030 (Figure 3.8).

Figure 3.5 visualizes the long-term trajectory of the HIV epidemic in our model-based population, assuming parameters remain stable and no other HIV prevention or treatment interventions or disruptions occur between 2022 and 2030. Between 2022 and 2030, the median HIV incidence from our simulations decreased by 14%, from 0.389 to 0.336 per 100 PYAR, though with a wide simulation interval (Figure 3.5). In the base (no COVID) scenario, HIV incidence was similarly 0.388 in 2022 and 0.336 per 100 PYAR in 2030; we did not observe long-term effects of the COVID pandemic on HIV incidence.

DISCUSSION

This study represents a novel approach that uses empirical data within a network-based mathematical model to estimate HIV incidence among US MSM in a period of both HIV-related behavior changes and clinical service disruptions. Using multiple nationally representative data

sources on pandemic-era sexual behavior, HIV prevention, and HIV clinical care services, we found that HIV incidence among US MSM decreased during 2020, and that COVID-related impacts did not generate long-term increases in HIV transmission in the post-pandemic period. Although we observed temporary decreases in HIV incidence compared to a no pandemic scenario, these reductions were not significant enough to sustain lasting decreases to HIV transmission that will affect the trajectory of the US HIV epidemic. Our results draw attention to the ongoing need for HIV prevention programs for MSM at risk of HIV infection, HIV testing for those with newly acquired HIV, and for HIV treatment services for men living with diagnosed HIV, both within and outside of a pandemic context.

Consistent with prior studies,[67,69] we found that the magnitude and timing of pandemic-related changes drives changes in HIV transmission. We also found that the widespread changes in sexual behavior can be a significant driver of changes in HIV transmission.[67] However, unlike other US-based modeling studies that found that changes in sexual behavior would effectively offset changes in HIV services, resulting in minimal differences compared to a no COVID scenario,[67,69] we found that the combined effects of COVID-related behavior changes resulted in an overall decrease in HIV transmission. Our findings likely diverge from previous studies because we used actual reported data from US MSM to parameterize our models, whereas previous studies relied only on predicted or hypothetical patterns of pandemic-era HIV-related behavior.[67,69]

When comparing our results to nationally available estimates of quarterly HIV diagnoses,[147] our observed changes in HIV incidence and positive HIV tests closely follows the trend of new HIV cases. This is a notable finding, because US HIV diagnosis data in 2020 have been largely considered to be unreliable and recommended to be interpreted with caution.[169] Although it is important to interpret diagnostic data during 2020 in the context of widespread decreases in HIV testing with appropriate skepticism, our findings suggest that decreasing new

cases of HIV in 2020 may reflect an overall trend of decreased incidence during this period. However, because it can take weeks to months for antibodies to become detectable[182] and the average time from HIV infection to HIV diagnosis may be several years,[183] immediate decreases in diagnoses following the onset of the COVID pandemic might be a result of decreased testing and not simply changes in underlying transmission. Yet, because an increase in HIV diagnoses in 2021 (compared to 2019) was not observed[170,184] even after testing returned to pre-pandemic levels in 2021,[147] the decrease in incidence that our model estimated in 2020 seems to accurately reflect the overall trend. Even with a lag between infection and diagnosis, if there were many undiagnosed HIV cases in 2020, then 2021 data should have reflected a sharp increase in new diagnoses—which it does not.[170,184] In our model, we found that decreases in HIV testing (and other HIV services) during the COVID pandemic were not severe enough to overcome the decreased risk of HIV transmission resulting from population-level decreases in sexual risk behaviors.

Our findings demonstrate that although we may expect long-term marginal/slight decreases in HIV incidence, the trajectory of the US HIV epidemic is still far from the EHE goal of reducing new HIV infections in the US by 90% by 2030.[38] In our model, we noted a decrease in HIV incidence from 2019 to 2030 by only 14%. Similarly, in a no COVID scenario, HIV incidence also decreased from 2019 to 2030 only by 14%. However, these base scenario and projected results should be interpreted with caution because they do not include counterfactual increases in HIV prevention and care services that may have occurred in the absence of COVID, nor those that may occur between now and 2030. However, our findings support that targeted and immediate HIV prevention services are needed in high burden areas to better approach EHE goals.[173,185] Even without pandemic disruptions, significant investments are required to scale up EHE's core strategies, particularly because approved federal funding for EHE during fiscal year (FY) 2019–FY 2023 has fell short of proposed funding.[186]

Beyond overall HIV prevention needs, our results demonstrate some key weaknesses in HIV testing provisioning. Our model found decreases in HIV test positivity during the COVID period, suggesting that provision of HIV testing could be improved; in the context of less HIV testing, we would expect positivity to increase if testing was targeted to those most likely to test positive. However, a limitation of our positivity results is that we did not model changes related to testing behaviors during the pandemic; in our model, we are still using the same criteria to drive/predict testing behavior in the model before and after the onset of the COVID pandemic. Because we only modeled decreases in the rate of HIV testing, but not changes in the processes that drive HIV testing in a pandemic context (such as testing only if one had a recent high risk behavior), our positivity results may not be appropriate to use as a guideline of positivity during the pandemic. Real-world data on the positivity of HIV tests administered to MSM during the COVID pandemic are needed to support our findings and their interpretations.

For PrEP, although many reductions in PrEP during the COVID pandemic might correspond to reductions in sexual risk behavior (and, therefore loss of PrEP indication), decreases in PrEP coverage from pre-pandemic limits still remained at the onset of 2022, and the overall PrEP coverage levels before and after the pandemic remained lower than ideal targets.[187] PrEP coverage varies significantly between US cities and communities,[26] and resulting risk behavior[188,189] and HIV risk[190] can lead to disparities in HIV transmission between US communities. Additionally, during the pandemic, MSM who reported pandemic-related changes to PrEP access had significantly higher odds of HIV seroconversion.[191] Increased provision of HIV testing and PrEP to those at highest risk of HIV infection, and who have challenges with access to HIV prevention services, should be prioritized regardless of pandemic context.

A major limitation of this study is the uncertainty surrounding our model parameters, particularly those that control the magnitude and timing of COVID-era HIV-related behavior

changes. A strength of our approach is that we triangulated data from multiple primary data sources to parameterize these processes; however, many of the data sources did not include granular information that would allow for better accuracy and precision of model estimates. For example, HIV testing and PrEP use data were available by week through December 2020 and by month through March 2021, respectively.[174,175] These data allowed for stratification by race or age, but not transmission category. Ideally, we would have had access to data available by week for MSM only and available through present day, by both race and age sub-strata. For sexual behavior parameters, our data spanned only through January 2021, and these data were grouped into multi-month time periods (though we implemented weekly gradual changes where possible). A previous study found that many of the key patterns in sexual behavior, such as change in the number of sexual partners during various stages of the pandemic, did not significantly vary by age, race, or US geography,[161] However, the most accurate models would represent variations in changes at the most granular scale, because small but well-linked sub-networks can drive epidemics.[192] Further, like all modeling studies, our results are subject to limitations of the studies from which model parameters were sourced (e.g., limited generalizability or selection biases). For example, there could be selection bias present in our sexual behavior data sources if MSM with less risky sexual behavior may be more likely to participate in the survey. The purpose of our sensitivity analyses assuming the most conservative decreases in sexual behavior changes was to explore the effect of this potential bias; even with smaller decreases in sexual risk behavior, an overall trend of decreases HIV incidence during COVID was observed. Therefore, this bias is unlikely to affect our overall study conclusions.

There are several other limitations to this study. First, this study is focused on all US MSM, and does not represent city or regional variations. Therefore, this study does not capture city- or community-level differences in HIV-related behavior, nor differences in COVID

responses (and ensuing changes to social and health behaviors) among different geographic areas. Additionally, although many of the model parameters were race-stratified (capturing differences in HIV prevention services, HIV treatment, and behavior by race/ethnic group), this model does not explore how the COVID pandemic affected different racial/ethnic groups. Future studies should explore how the pandemic affected HIV sub-epidemics in specific racial/ethnic populations, particularly because certain groups, such as Black MSM, are at disproportionately high risk of contracting HIV and may be less likely to have access to or receive key HIV prevention services like PrEP.[169,193,194] This additionally model also fails to represent network structure related to geographic clustering, which can play a role in the dynamics of local HIV epidemics. However, by using a target population of all US MSM, we are able to draw inferences on a wider population, and also compare our results to estimates of HIV diagnoses that are only available on the national scale.

This is the first study to use empirical sexual behavior and clinical data to estimate the impact of the COVID pandemic on the HIV epidemic among US MSM. Using a network-based transmission model, we provide evidence that HIV incidence among US MSM temporarily decreased during 2020, and did not generate long-term increases in HIV transmission in the post-pandemic period. Ongoing assessment of the effect of COVID-related changes on HIV transmission are needed at the local, state, and national level to guide effective post-pandemic HIV mitigation recommendations, and to contribute to the development of future pandemic preparedness strategies.

TABLES

Table 3.1*. Effect of COVID-Related Sexual Behavior and Service Utilization Changes on Incidence Rate, Cumulative Incidence, and Population Impact, over 500 Simulations*

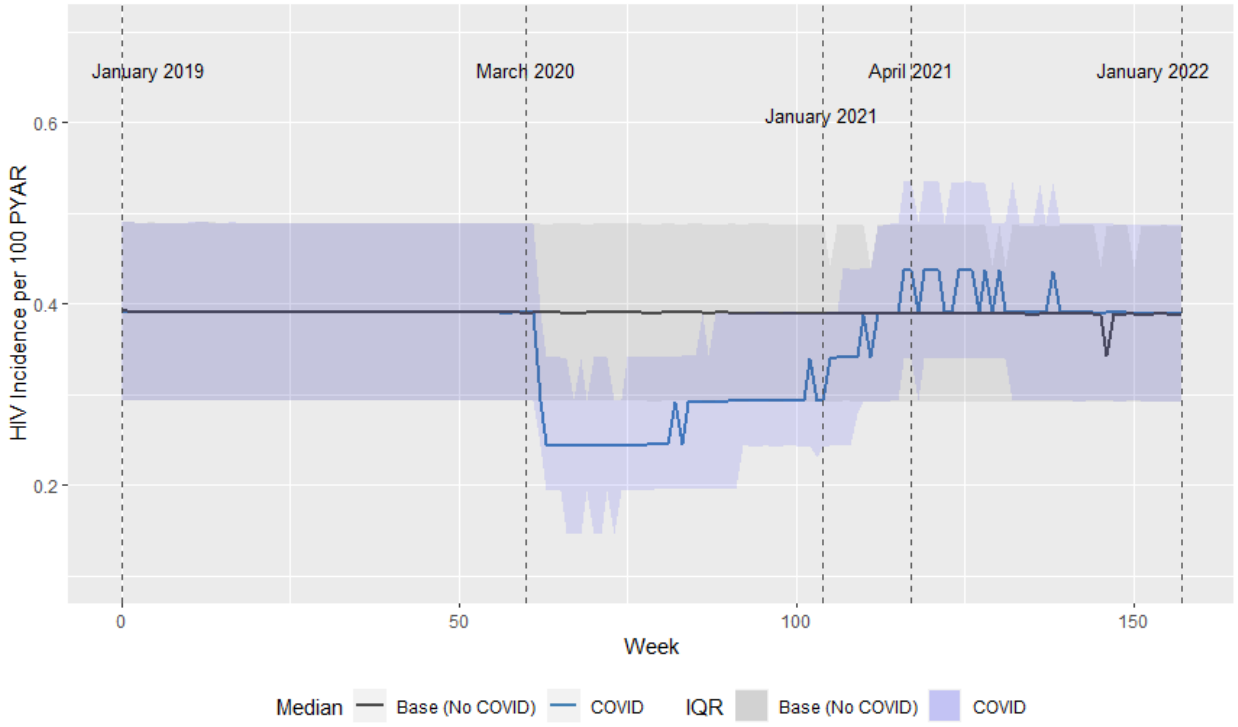
Scenario	Incidence Rate, May 2020 (95% SI)*	Cumulative Incidence (95% SI)**	Population Impact (95% SI)†
Base Scenario (No COVID)	0.39 (0.15, 0.64)	1710.9 (1600.3, 1820.5)	—
Combined Impact of COVID-Related Changes			
Lower Estimate	0.13 (0, 0.29)	1634.5 (1533.8, 1743.9)	-3438.9 (-3452.0, 2994.5)
Estimate	0.25 (0.05, 0.49)	1661.5 (1547.4, 1773.4)	-2226.5 (-2382.5, -2121.4)
Upper Estimate	0.33 (0.10, 0.59)	1717.4 (1608, 1823.9)	292.7 (344.5, 152.2)
Isolated Impact of COVID-Related Changes			
Sexual Acts	0.24 (0.05, 0.49)	1614.5 (1507.2, 1724)	-4341.8 (-4192.8, -4345.0)
Condom Use	0.4 (0.15, 0.69)	1715 (1604.4, 1832.1)	186.2 (184.5, 523.6)
HIV Testing	0.39 (0.15, 0.68)	1721.5 (1612.9, 1833.8)	475.2 (564.7, 599.4)
PrEP Use	0.4 (0.15, 0.69)	1763.3 (1659.9, 1882.6)	2360.3 (2683.2, 2794.6)

*Rate per 100 person-years at risk during May 2020.

**Cumulative incidence over 5 year period (from March 2020–March 2025) per 100,000 MSM.

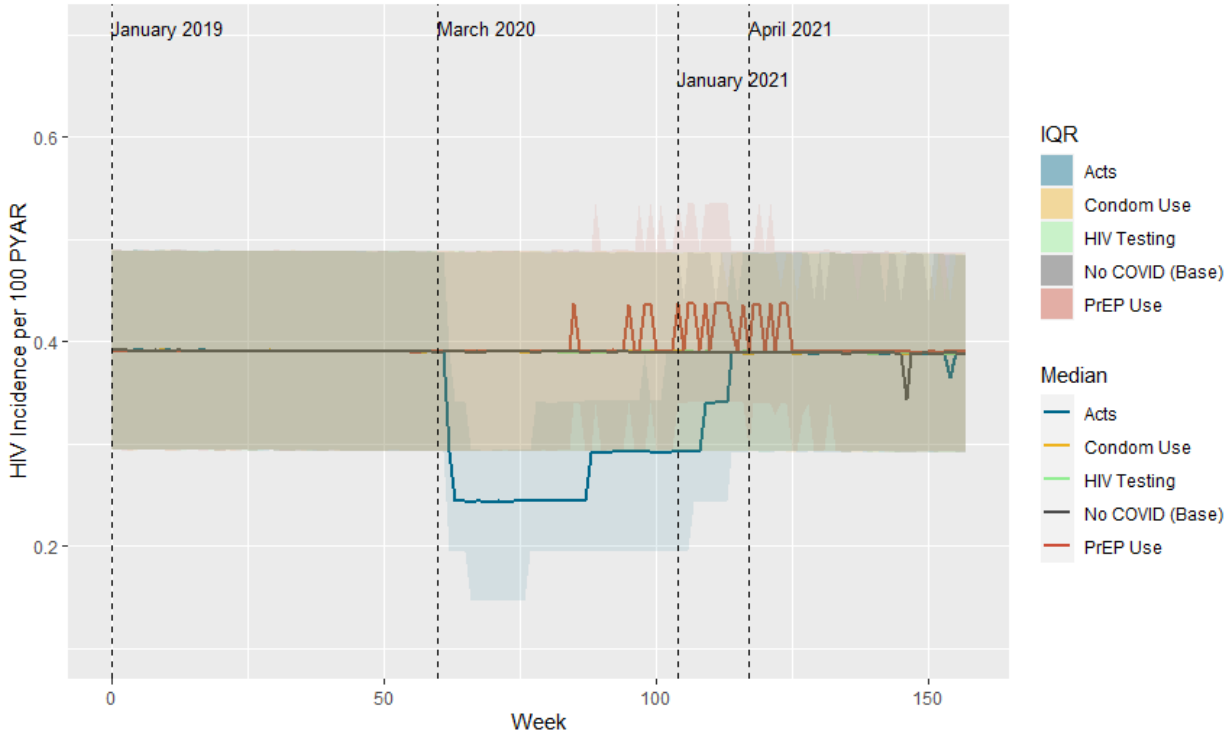
†Difference, compared to base scenario, in 5-year cumulative incidence (March 2020–March 2025) for full US MSM population (approximately 4,503,080 MSM).[181]

Figure 3.1. *Estimated HIV Incidence among US MSM over 500 Simulations, Compared to Base (No COVID Pandemic) Scenario, 2019–2021.*



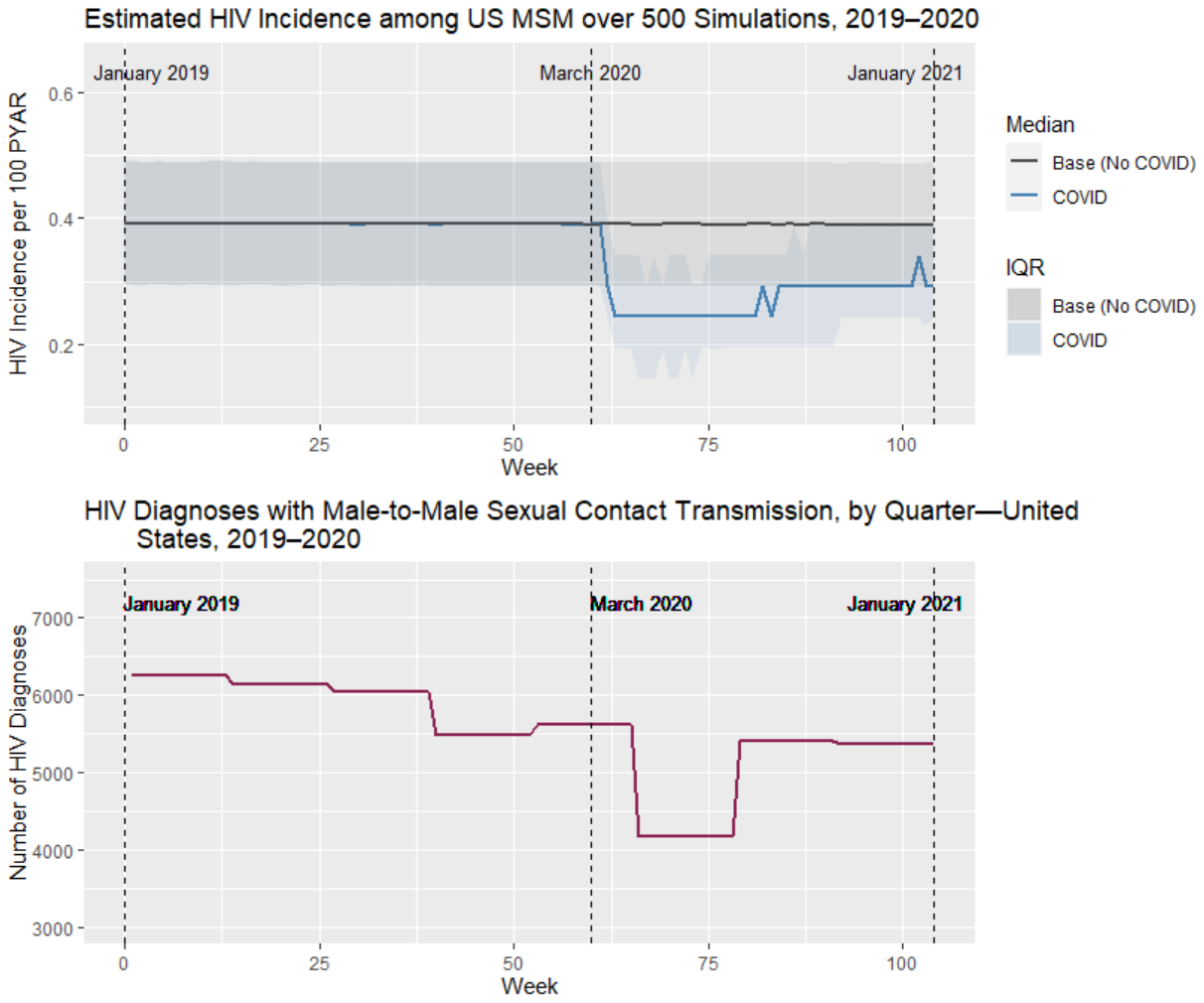
Abbreviations: MSM, gay, bisexual, and other men who have sex with men; PYAR, person-years at risk

***Figure 3.2**. Isolated and Combined Impacts of Sexual Acts, Condom Use, PrEP Use, and HIV Testing Changes on HIV Incidence among US MSM, Compared to Base (No COVID Pandemic) Scenario, Over 500 Simulations, 2019–2021*



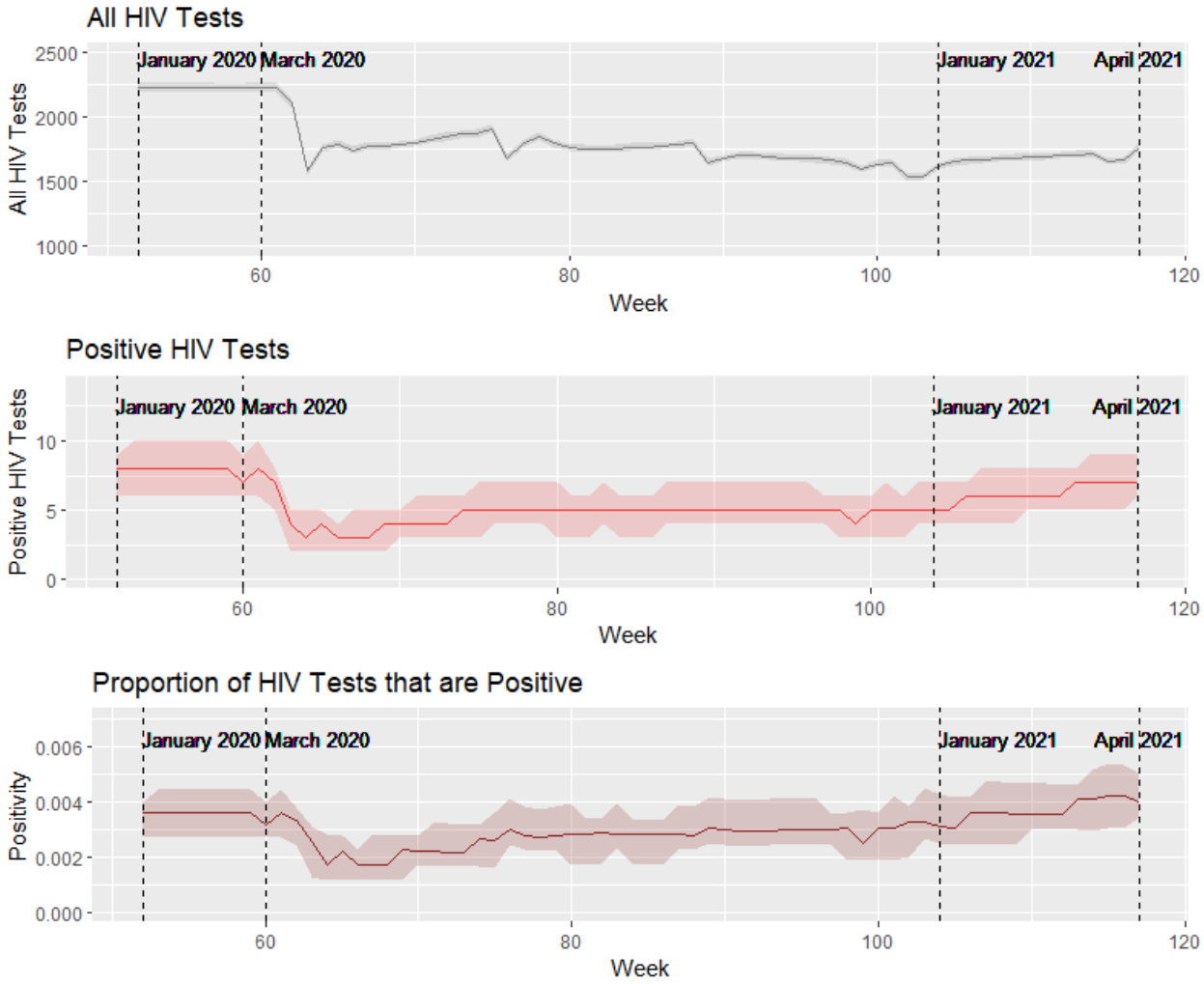
Abbreviations: PrEP, pre-exposure prophylaxis; MSM, gay, bisexual, and other men who have sex with men; PYAR, person-years at risk

Figure 3.3. *Comparison of Model-Based HIV Incidence Estimation and Quarterly HIV Diagnoses with Male-to-Male Sexual Contact Transmission,[147] 2019–2021*



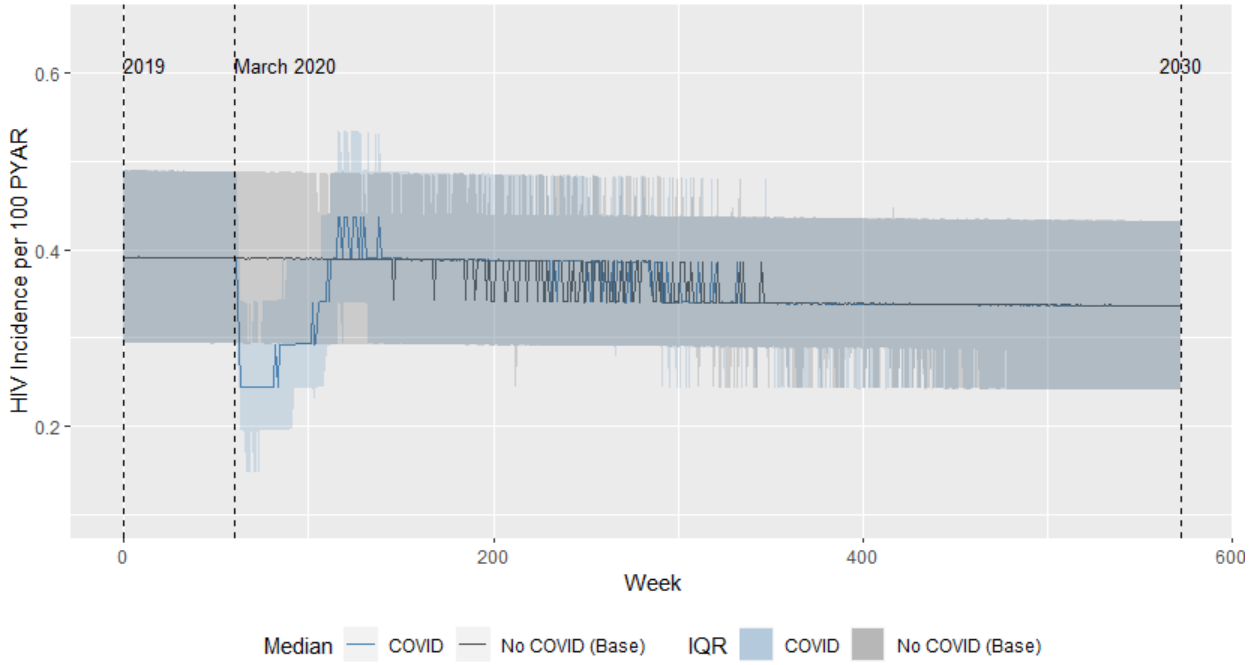
Abbreviations: MSM, gay, bisexual, and other men who have sex with men; PYAR, person-years at risk

Figure 3.4. *Comparison of HIV Tests, Positive HIV Tests, and HIV Test Positivity, Over 500 Simulations, January 2020–April 2021*



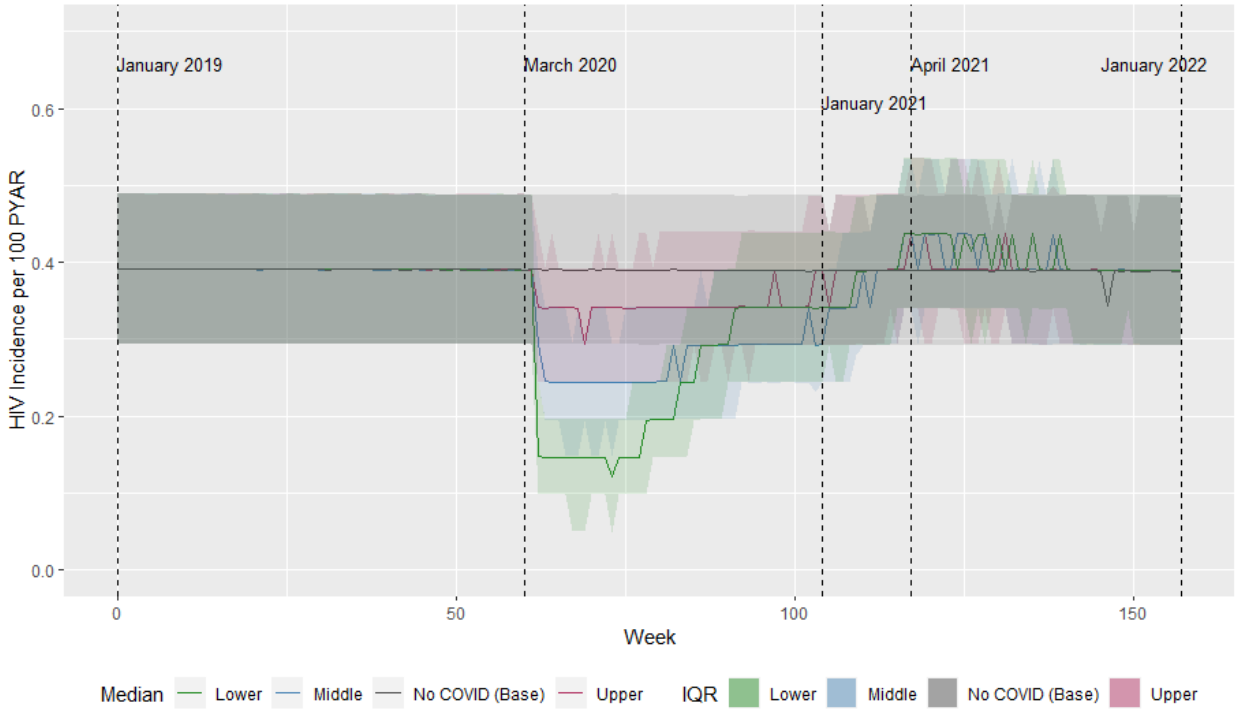
Note: The sudden sharp drops/spikes in all HIV tests are due to PrEP-based testing patterns. The model uses an interval-based approach where it is retesting with a testing interval of 12.86 weeks. This follows from PrEP guidance that individuals who are HIV-negative and take PrEP to prevent HIV acquisition should test quarterly.

***Figure 3.5**. Estimated HIV Incidence among US MSM, Incorporating COVID-Related Changes Through Mid-2021, Compared to Base (No COVID Pandemic) Scenario, over 500 Simulations, 2019–2030*



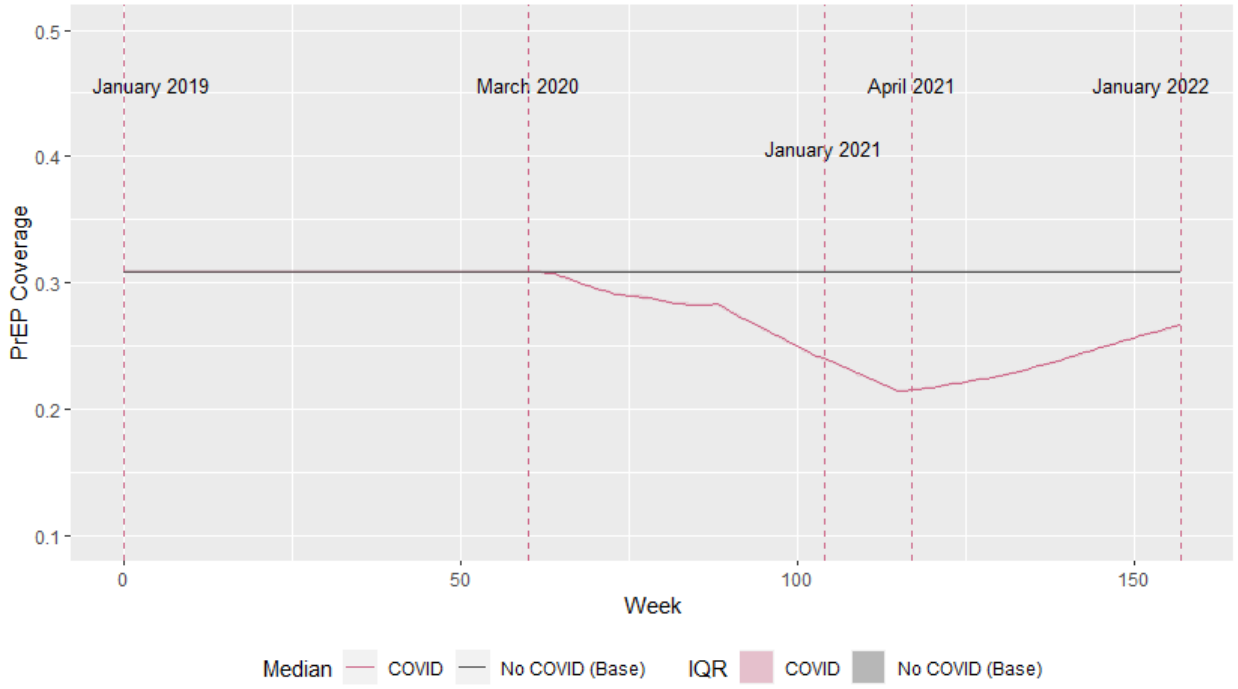
Abbreviations: MSM, gay, bisexual, and other men who have sex with men; PYAR, person-years at risk

***Figure 3.6**. Range of Estimated HIV Incidence Generated from Upper, Middle, and Lower Estimates of Sexual Behavior and Service Utilization Changes among US MSM, Over 500 Simulations, 2019–2021*



Abbreviations: MSM, gay, bisexual, and other men who have sex with men; PYAR, person-years at risk

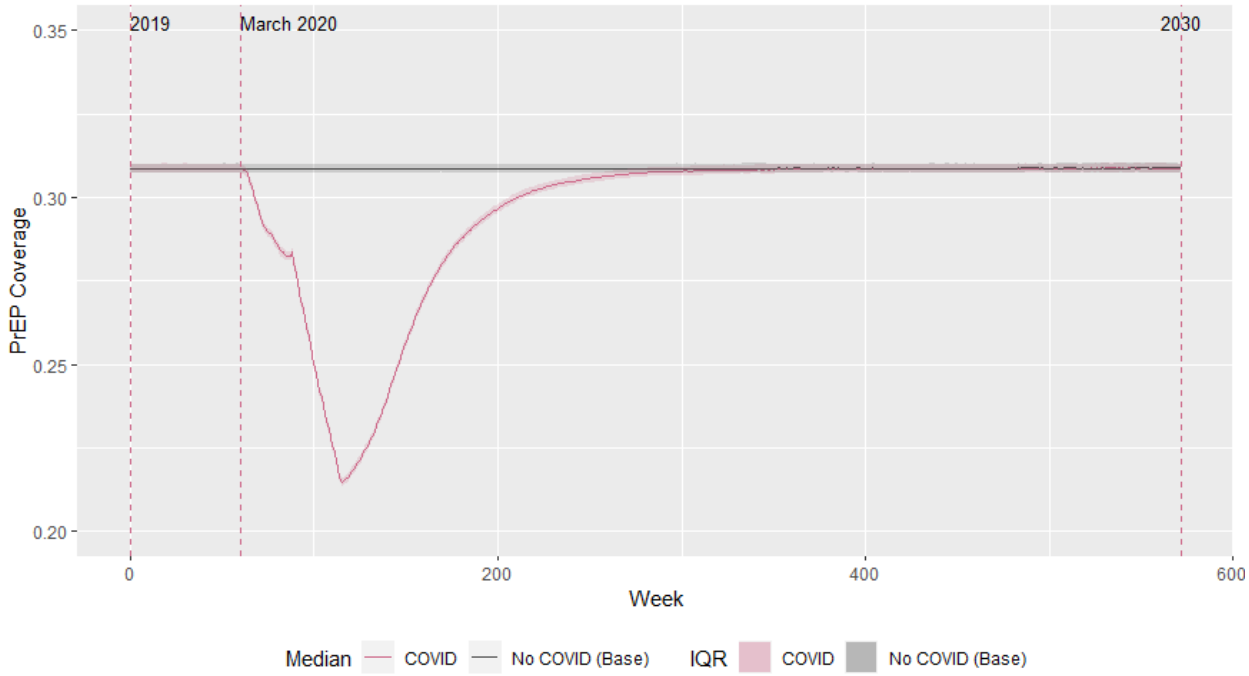
***Figure 3.7**. Estimated PrEP Coverage among Eligible US MSM Resulting from Incorporating COVID-Related Changes Through Mid-2021, Over 500 Simulations, 2019–2021*



PrEP coverage is calculated as the proportion of PrEP eligible MSM not known to be living with HIV with current PrEP use.

Abbreviations: PrEP, pre-exposure prophylaxis; MSM, gay, bisexual, and other men who have sex with men; PYAR, person-years at risk

***Figure 3.8**. Estimated PrEP Coverage among Eligible US MSM Resulting from Incorporating COVID-Related Changes Through Mid-2021, Over 500 Simulations, 2019–2021*



PrEP coverage is calculated as the proportion of PrEP eligible MSM not known to be living with HIV with current PrEP use.

Abbreviations: PrEP, pre-exposure prophylaxis; MSM, gay, bisexual, and other men who have sex with men; PYAR, person-years at risk

Chapter 4. Assessing the Epidemiologic Impact of Home-Based HIV Prevention Interventions During the COVID-19 Pandemic

ABSTRACT

BACKGROUND

Home-based HIV prevention interventions may help address reductions in HIV prevention services caused by the COVID pandemic. Several home-based interventions focused on PrEP use and HIV testing have recently been developed outside of a pandemic context. However, their potential population-level impact within a pandemic context has not yet been assessed.

METHODS

In our review of CDC's Compendium of Evidence-Based Interventions and Best Practices for HIV Prevention: Prevention Research Synthesis we identified two interventions for MSM with a PrEP retention component and two with an HIV testing component designed that were not delivered in in-person clinics. We used intervention efficacy estimates and data on changes of HIV-related behaviors during the COVID pandemic to parameterize a network-based model of HIV transmission among Atlanta MSM. Model scenarios were designed to represent COVID-era changes in sexual behavior and service utilization, and investigate the isolated epidemiologic impact of these home-based HIV testing and PrEP retention interventions with varying levels of intervention coverage, length, persistence, and efficacy.

RESULTS

Decreases in rates of HIV testing and PrEP use resulting from the COVID pandemic disruptions could be partially offset by the HIV testing and PrEP retention interventions when interventions had 20% coverage of the eligible population and lasted for one year. However, these

interventions had minimal impact on overall HIV incidence when examined in isolation. In order for a single intervention to yield meaningful reductions in HIV transmission in a pandemic context, an intervention would need to be significantly scaled up in terms of coverage, length, and post-intervention persistence, or its efficacy would need to improve.

CONCLUSIONS

Home-based interventions can play a role in offsetting pandemic-related changes to HIV prevention services. However, because in isolation interventions do not have a major impact on population-level HIV transmission in the context of reduced population-level sexual activity, interventions may need to be combined and/or scaled up to translate to meaningful impacts in pandemic-era transmission.

INTRODUCTION

The COVID-19 pandemic has created new challenges to the control and prevention of HIV. Alongside behavioral changes to sexual behavior resulting from more general patterns of social distancing during the early COVID era, widespread interruptions to HIV prevention services have been noted. The impact of the COVID pandemic on HIV clinical care and viral load suppression was a concern early in the pandemic,[50] but several reports have shown that HIV viral load was not greatly impacted by the pandemic due to limited impacts on HIV clinical care and treatment.[161,176,177,179] However, some HIV prevention services were interrupted.

For HIV testing, several reports documented MSM not being able to access HIV testing services during the COVID pandemic.[45,49,161] In one study, an estimated 67% of MSM not known to be living with diagnosed HIV reported barriers to obtaining an HIV test in April 2020.[161] In another study that used data from 60 state and local health departments, a 46% reduction in the number of HIV tests conducted in 2020 compared to 2019 was observed.[167] Overall across the

US, it is estimated that hundreds of thousands of HIV screening tests were either delayed or skipped during 2020.[195]

Regarding PrEP, there were reports of MSM experiencing trouble accessing PrEP: in one study in April 2020, 20% of PrEP-using MSM reported trouble getting PrEP prescription and 27% reported trouble getting their PrEP prescription filled at the pharmacy.[45,161] Both new PrEP users and PrEP prescriptions decreased during the COVID pandemic.[174] These interruptions are of particular concern in US areas with a high burden of HIV. In 2019, among all US states (not including the District of Columbia), Georgia had the highest rate of HIV diagnoses in the US, with the majority of these diagnoses occurring in the Atlanta metropolitan area.[3,132]

COVID-19-related interruptions to HIV prevention and clinical care may increase the rate of HIV acquisition and transmission. For example, reduced access to PrEP for indicated persons can lead to additional risk of HIV acquisition, and reduced HIV testing can lead to more undiagnosed HIV, and therefore more population-level risk of HIV transmission as newly infected individuals do not know their HIV status (and therefore may not take precautions to prevent transmitting it to others) and cannot then seek treatment to become virally suppressed (and are therefore infectious).

Home-based HIV prevention approaches may have curtailed the impact of the pandemic on HIV transmission. Such approaches could include home-based HIV testing and telehealth services for PrEP initiation or retention.[196,197] Home-based self-testing is an effective HIV screening method for MSM that can facilitate access to PrEP, antiretroviral treatment, and other prevention services.[38,198] Currently, the only FDA-approved HIV self-test currently available in the United States is an oral fluid test.[80] Home-based PrEP services may include home-based PrEP eligibility screening, telehealth visits for PrEP care, HIV prevention counseling, PrEP education, support for PrEP adherence, or home-based HIV self-testing.[196] These home-based

interventions could potentially be used to offset decreased access or availability of clinic-based HIV prevention services.

However, because resources are finite, population-level projection modeling is needed to estimate the impact of home-based HIV prevention interventions on the HIV epidemic. This information may be used in order deploy the most impactful interventions. Randomized controlled trials (RCTs) have been completed on several home-based HIV prevention interventions outside of a pandemic context to assess home-based intervention efficacy,[196] but the impact of these interventions in a real-world pandemic setting has not yet been quantified. Studies which determine the impact of certain home-based HIV prevention services on HIV transmission among MSM are needed. These studies can help fill the gap in the literature regarding the unknown effectiveness of home-based HIV prevention approaches on HIV transmission in pandemic settings.

In this study, we use efficacy data from home-based RCTs of HIV testing and PrEP retention interventions to parameterize a network-based mathematical model to estimate the population impact of these interventions among Atlanta MSM in the context of the COVID-19 pandemic. Empirical data were used in order to represent COVID-related changes to HIV prevention behaviors; home-based interventions were introduced within this setting. This allowed us to assess the epidemiologic impact of individual home-based HIV prevention interventions on HIV transmission during the COVID-19 pandemic.

METHODS

Study Design. This model of HIV transmission dynamics for US MSM was built on the *EpiModel* software platform.[171] *EpiModel* simulates HIV epidemics over dynamic contact networks of US MSM using temporal exponential random graph models (TERGMs).[172] Specific model

extensions were built to: 1) simulate HIV transmission among MSM during the COVID pandemic to estimate the impact of reported COVID-related changes in sexual behavior and HIV clinical services on HIV transmission during the COVID pandemic period (March 2020–January 2021); and 2) simulate the selected home-based HIV prevention interventions. Our goal was to represent COVID-related changes to HIV prevention behaviors, so that the effectiveness of home-based HIV prevention interventions could be assessed in this setting.

Network Model. Components of the model representing sexual network structure were fit using data from ARTnet, a cross-sectional web-based study of US MSM conducted between 2017 and 2019.[91] ARTnet participants were recruited through the annual American Men's Internet Survey (AMIS) study.[124] ARTnet eligibility criteria included male sex at birth, current male cisgender identity, lifetime history of sexual activity with another man, and age between 15 and 65 years. The use of ARTnet data in *EpiModel* network models has been described previously.[67,173]

Our model represented main, casual, and one-time sexual partnerships. Age and race/ethnicity mixing, the formation and dissolution of persistent partnerships, and the rate of one-time partnership formation were represented based on ARTnet data. Behavior within sexual partnerships, including the rate of intercourse per partnership per time step, condom use per sexual act, and sexual role were modeled based on individual and partnership characteristics, with probabilities estimated from ARTnet data.

The model also represented demography of the population, HIV interhost epidemiology (disease transmission), HIV intrahost epidemiology (disease progression), and HIV clinical epidemiology.[91] Demography included aging, entries, and exits. HIV interhost epidemiology included HIV transmission (per-act transmission probability). HIV intrahost epidemiology represented HIV disease progression, including HIV viral load progression, within HIV-positive

individuals. HIV clinical epidemiology included disease diagnosis, ART initiation, ART adherence and viral load suppression, and AIDS disease progression and mortality.

The HIV prevention care cascade and HIV care continuum were both represented in the model. The HIV prevention continuum consisted of HIV testing, PrEP initiation, PrEP adherence, and persistence in PrEP care for daily oral tenofovir/emtricitabine.[23] Weekly pre-COVID HIV testing rates were race-stratified and determined by ARTnet HIV testing rates, surveillance data on diagnosed fraction of HIV-infected MSM, and model calibration.[33,91] After testing negative for HIV, MSM who met indications for PrEP based on CDC guidelines were eligible to start PrEP.[18] They then started PrEP based on an initiation probability generating a coverage level of approximately 30%, which approximates Atlanta estimates of PrEP coverage.[33] Heterogeneity in PrEP adherence was modeled, with 78% of PrEP users reaching a high-adherence level that resulted in a 99% relative reduction in HIV acquisition risk. Pre-COVID PrEP discontinuation was based on estimates of the proportion of MSM who were retained in PrEP care at 6 months,[141] and weekly pre-COVID PrEP discontinuation rates were 0.0048, 0.0041, 0.0058, for Black, Hispanic, and White/other MSM in Atlanta, respectively.

COVID-era and post-COVID-era PrEP discontinuation was based on the number of PrEP prescriptions over time in a national pharmacy database (IQVIA Real World Data—Longitudinal Prescriptions Database).[174] PrEP care consisted of routine HIV and STI screening. For the HIV care continuum, MSM initiated ART after testing positive for HIV. ART lowered their HIV viral load and increased their longevity. Lower viral load with sustained ART use was associated with a reduced probability of HIV transmission per act. HIV transmission probability was also modified by PrEP use, condom use, sexual position, and circumcision. Additional full methodological details of HIV interhost, intrahost, and clinical epidemiology; network generation; parameter selection; calibration; and modeling are provided in the Supplemental Appendix.

Modeling COVID-19-Related Impacts. Changes in sexual behavior and condom use among MSM during March 2020–January 2021 were included in the model. These changes were parameterized based on behavioral data from the AMIS COVID Impact Survey and the Love and Sex in the Time of COVID studies. Although these were national surveys, we assumed that they approximated Atlanta MSM behavior. The AMIS COVID-19 Impact Survey collected data on sexual distancing and HIV service utilization/care engagement from 1,051 US MSM at three time points during the COVID-19 pandemic: April, July, and September–December 2020.[45] The Love and Sex in the Time of COVID-19 survey also collected data from 696 US MSM on sexual distancing and HIV service utilization/care engagement during the COVID-19 pandemic, at two time points: April–May 2020 and November 2020–January 2021.[49] Where applicable, such as for sexual behavior by partnership type, sexual behavior parameters were standardized using the proportions of partnership types obtained from the ARTnet study. This approach allowed us to stratify COVID-era sexual behavior results to best map to *EpiModelHIV* partnership-stratified parameters. Because these surveys did not collect data in all months of the COVID pandemic (e.g., in August 2020, between July 2020 and September 2020 AMIS COVID-19 Impact Survey time points), we assumed that during these periods, changes in outcomes were steady and continuous. Therefore, where applicable between survey points, we implemented weekly gradual changes in model parameters (e.g., to fill the gap in COVID-19 Impact Survey data, outcomes steadily changed in magnitude by week in August 2020). Full details on all parameter estimates, ranges, sources, and calculations (where applicable) are included in the Supplemental Appendix.

Before implementing COVID-related changes, we first ran a base scenario in which we assumed model parameters remained at their 2019 levels for the full model simulation period. Changes in HIV prevention and clinical care services, including race-stratified HIV testing and PrEP use rates, were incorporated from March 2020–April 2021 as indicated by national

estimates of HIV screening tests from three overlapping data sources (Health Resources and Services Administration's Uniform Data System, CDC's National HIV Prevention Program Monitoring and Evaluation system, National Syndromic Surveillance Program's commercial laboratory data)[175] and PrEP prescriptions and new PrEP users in national pharmacy database (IQVIA Real World Data—Longitudinal Prescriptions Database).[174] Changes in ART initiation, ART adherence and viral load suppression, and AIDS disease progression were not incorporated during the pandemic, since meaningful changes in ART use among men living with diagnosed HIV were not observed in either the AMIS COVID Impact Survey nor the Love and Sex in the Time of COVID study, nor in external reports examining ART prescriptions during the COVID pandemic.[176–178]

Because we found that in a subset of individuals (in both the AMIS COVID Impact Survey and the Love and Sex in the Time of COVID study), decreases in sexual behavior occurred alongside decreases in HIV testing and/or PrEP use, we introduced a behavior changer feature/attribute into our model. This feature allowed us to modify persistent partnership act rates and one-time partnership formation rates alongside HIV testing and PrEP use in the same group of individuals. Modification rates were determined from our primary data sources (additional details are in the Supplemental Appendix).

Sexual distancing and clinical care interruptions were integrated into the model by changing the appropriate parameters for behavior and HIV prevention and clinical services use. Because at the time of this study, data on the sexual behavior and HIV testing of US MSM was not available after April 2021, we assumed parameters reverted to their pre-pandemic value in the latter half of 2021 and did not change after 2021 (though for PrEP and HIV testing, data has shown that PrEP use and HIV testing have returned to and/or exceeded pre-pandemic levels).[180] Our modeling and analytic code is available in a Github repository at https://github.com/EpiModel/COVIDHIVAim3 *[to be renamed/made public]*.

Home-Based HIV Prevention Interventions. We searched the CDC's Compendium of Evidence-Based Interventions and Best Practices for HIV Prevention: Prevention Research Synthesis (PRS) Compendium Intervention[199] for HIV testing and PrEP interventions that were intended for MSM that were not delivered in in-person clinics. We identified three interventions that met our search parameters that were solely home-based: M-CUBED (Mobile Messaging for Men) (PrEP retention and HIV testing only),[200] DOT Mobile App (PrEP retention only),[201] and eSTAMP (Evaluation of Rapid HIV Self-testing Among MSM Project) (HIV testing only).[202] A full description of each intervention is available in Table 4.1. M-CUBED did have addition clinic-based components, such as PrEP initiation, so we only focused on its PrEP retention and HIV testing components for this model. Since there were two interventions for both the testing and PrEP retention, this allowed us to give a range of effectiveness estimates for both HIV testing and PrEP. We did not focus on PrEP adherence because previous studies have found that PrEP adherence and persistence are interlinked, such that those who persist generally have high adherence.[203]

We translated the efficacy of the intervention RCT data into model parameters for HIV testing and PrEP retention by adjusting race/ethnicity-stratified HIV testing rates and PrEP discontinuation rates, respectively, by an RCT-sourced modifier. The details of these modifiers/calculations are shown in Table 4.2. Although the RCTs did not provide race-specific efficacy data, because we applied these modifiers to baseline race/ethnicity-stratified rates, we still were able to account for differences in HIV screening and PrEP retention by race/ethnicity (i.e., we did not have to assume rates were the same for all race/ethnic groups). Rates were adjusted weekly because HIV testing rates and PrEP discontinuation rates continuously changed through the COVID pandemic. Intervention discontinuation rates were incorporated based on RCT retention rates (as described in Table 4.2).[200–202]

For the standard scenarios, all interventions were assumed to be deployed for one year for 20% of the eligible population. For HIV testing, that was 20% of all HIV-negative MSM, and for PrEP retention, that was 20% of MSM currently using PrEP. Although in the DOT, M-CUBED, and eSTAMP RCTs the interventions had a length of 6 weeks, 3 months, 12 months, respectively, but because we expect the real-world implementation of these interventions is not the same as the RCT length, we assumed a length of one year to better observe intervention effects. For PrEP retention interventions only, we assumed the intervention had a persistence of one year. This meant that after the intervention ended for any individual, PrEP discontinuation rates gradually returned to their pre-intervention levels for intervention participants after one year. We included this post-intervention persistence effect to represent retained PrEP education gained from the PrEP interventions. We did not assume any intervention persistence for HIV testing interventions because of the resource constraints that intervention participants would face post-intervention (i.e., they would have to buy home-based HIV testing kits since they were no longer mailed to them). For all scenarios, the interventions were assumed to start two weeks after the onset of the COVID pandemic in mid-March 2020. This was chosen so that we could model the lag time between pandemic-induced intervention need and intervention deployment.

Sensitivity analyses were used to determine how varying the population coverage, length of intervention, and persistence of intervention may impact the impact of the intervention on HIV testing, PrEP use/retention, and HIV incidence. In order to compare the epidemiologic impact of the interventions, we ran an additional base scenario (separate from the base scenario of no COVID pandemic) of no intervention.

We additionally ran scenarios that explored how modification of HIV testing rates and PrEP discontinuation rates by set values could impact our outcomes. For this subset of analyses, we assumed that interventions had 50% coverage, a length of one year, and persistence of one year (for PrEP retention intervention only). This allowed us to determine what

level of effectiveness an HIV testing or PrEP retention intervention would need to have on HIV testing rates and PrEP discontinuation rates to approach a meaningful impact on HIV transmission. All intervention effects were run in isolation (i.e., we did not estimate the combined intervention effects).

Calibration and Simulation. The model was calibrated with a Bayesian approach that defined prior distributions for parameters and fit the model to empirical surveillance-based estimates of diagnosed HIV for all Atlanta MSM in 2019. After calibration, we simulated the model 500 times and summarized the distribution of results with medians and 95% simulation intervals (SIs). COVID-related model scenarios were compared to the baseline (no COVID) scenario in order to assess how the COVID pandemic affected HIV transmission, relative to a no pandemic state.

The primary outcomes were HIV incidence per 100 person-years at risk (PYAR), three-year cumulative incidence per the total HIV-susceptible MSM population in Atlanta (sexually active HIV-negative MSM in Atlanta was approximately 87,723 MSM),[6] the number of infections averted among the total HIV-susceptible MSM population in Atlanta (relative to a scenario in which there was no intervention), the total person-time on PrEP over a three-year period (per the HIV-susceptible MSM population of Atlanta), the excess (additional) person-time on PrEP (relative to a scenario in which there was no intervention), the total number of HIV tests over a three-year period (per the HIV-susceptible MSM population of Atlanta), and the excess (additional) number of HIV tests (relative to a scenario in which there was no intervention). Because of the stochastic framework of our model, 95% simulation intervals were calculated for all primary outcome measures along with simulation medians.

RESULTS

Among Atlanta MSM, the COVID pandemic resulted in reductions in model-simulated HIV testing and PrEP coverage (Figures 4.1, 4.2, 4.3) during 2020–2023, consistent with empirical data used to parameterize the model. During March–December 2020, the COVID pandemic increased the number of MSM stopping PrEP, but it then decreased the number of MSM stopping PrEP during 2021–2023 (Figure 4.4). Overall, the COVID pandemic decreased HIV transmission among Atlanta MSM (Figure 4.5), with the largest relative decrease (compared to a no pandemic scenario) occurring in May 2020 (HIV incidence of 0.66 (95% SI: 0.29, 1.09) and 1.01 (95% SI: 0.57, 1.55), respectively) (Table 4.3).

Neither implementation of a PrEP retention intervention nor a HIV testing intervention resulted in reduced HIV incidence in a pandemic context. For HIV testing, both eSTAMP and M-CUBED increased the number of HIV tests: over a three-year period following its start, eSTAMP generated 5,463 (95% SI: 3,440, 7,494) additional completed HIV tests among Atlanta MSM, whereas M-CUBED generated 2,238 (95% SI: 237, 4,058) (Figure 4.1). However, neither eSTAMP nor M-CUBED (HIV testing only) had meaningful impacts on HIV incidence, and only averted 19.6 (95% SI: -75.4, 118.0) (1.0% infections averted) and 13.2 (95% SI: -75.3, 107.5) (0.7% infections averted) HIV infections, respectively, over a three-year period. For PrEP, both DOT and M-CUBED increased the number of MSM currently on PrEP and PrEP coverage compared to a no intervention scenario. DOT and M-CUBED generated an additional 24,058 (95% SI: 1,020, 46,745) and 7,552 (95% SI: -15,021, 29,005) person-years on PrEP among Atlanta MSM over a three-year period (Figure 4.2, 4.3, 4.4). However, neither DOT nor M-CUBED (PrEP retention only) had meaningful impacts on HIV incidence, and only averted 7.8 (95% SI: -89.8, 111.1) (0.4% infections averted) and 3.4 (95% SI: -94.4, 107.3) (0.2% infections averted) HIV infections, respectively, over a three-year period.

Increasing the coverage, length, and persistence of the PrEP retention interventions only minimally increased the effectiveness of the interventions. While increasing the coverage of

DOT from 10% to 50% increased the total person-time on PrEP from 1,445,029 to 1,491,773 over a three-year period, a 3.2% increase, this did not translate to a change in HIV incidence during the pandemic nor cumulative incidence over a three-year period (Figure 4.6). For M-CUBED, increasing its coverage from 10% to 50% increased the total person-time on PrEP from 1,435,609 to 1,451,002 over a three-year period, a 1.1% increase, but this did not ultimately affect HIV incidence during the pandemic nor cumulative incidence over a three-year period. The same was true for increasing the length or persistence of the interventions (Figure 4.7, Figure 4.8).

Similarly, increasing the coverage and length of the HIV testing interventions did not have a meaningful impact on HIV transmission. These changes only minimally increased the effectiveness of the interventions. While increasing the coverage of eSTAMP and M-CUBED from 10% to 50% increased the number of HIV tests from 171,880 to 182,785 and 170,254 to 174,766 over a three-year period (a 6.3% and 2.6% change), respectively, HIV incidence and cumulative incidence were not affected by these interventions (Figure 4.9). Increasing the length of the HIV testing interventions eSTAMP and M-CUBED from 6 weeks to 2 years did prevent 32.3 and 12.0 HIV cumulative infections among Atlanta MSM, however simulations intervals were wide and overlapped (Figure 4.10).

In exploring how intervention efficacy may impact HIV transmission in a meaningful way, we found that reducing PrEP discontinuation by 50% or more would avert infections, but only a few (12.9 (95% SI: -81.6, 109.5) over a three-year period). The number of infections averted increased in a stepwise fashion for further decreases in PrEP discontinuation (Figure 4.12). For HIV testing, increasing the weekly rate of HIV testing would avert HIV infections, but doubling it would only avert 1.1% of infections, and modifying it by 5, 10, and 25 would avert 3.4%, 5.4%, and 8.2% of infections only (Figure 4.11).

Although the impact of the interventions was assessed in isolation, we did observe that the HIV testing intervention affected PrEP use, and vice versa. For example, increasing the coverage, length, and persistence of the PrEP interventions all independently increased the number of HIV tests completed. On the other hand, increasing the coverage and length of the HIV testing interventions actually decreased the total person-time on PrEP. However, these effects were all small with overlapping SIs.

DISCUSSION

In this study, we assessed the epidemiologic impact of the home-based HIV testing and/or PrEP retention interventions DOT, eSTAMP, and M-CUBED during the COVID pandemic. We found that although these home-based interventions were effective at increasing PrEP use and HIV testing, they had minimal impact on HIV incidence. In order for isolated intervention effects to translate into more meaningful reductions in HIV transmission in a pandemic context, they would need to be scaled up in terms of coverage, length, and post-intervention persistence, and/or their efficacy would need to improve.

Our results align with previous studies showing that changes in HIV prevention parameters (and therefore HIV prevention interventions) have very minimal impact on HIV transmission. For example, one study found that general reductions in ART adherence may have a more severe impact on HIV incidence than reductions in other HIV prevention measures, such as PrEP use.[67] Additionally, in the context of the COVID pandemic, modeling studies have shown that changes to viral load may have the most impact on HIV incidence. One study based in China found that new HIV infections would be increased most by disruptions to viral suppression, compared to disruptions in HIV testing, ART initiation, and condom use.[101] A study focused on Baltimore MSM found that maintaining access to ART and adherence support

should be the priority to minimize excess HIV-related mortality.[69] These studies complement the findings of Jenness et al. that reductions in ART adherence during the COVID pandemic may have more relative impact on HIV incidence among Atlanta MSM than reductions in other HIV prevention measures.[67] HIV viral load interventions could include telehealth services, multi-month ART prescriptions, home-based HIV testing, and potential home-based HIV viral load tests. However, since there were not significant changes to HIV viral load during the pandemic, development of HIV care retention interventions would be unlikely to impact transmission in a pandemic context. The impact of such interventions should be studied however outside of a pandemic context.

In our sensitivity analyses, we explored how varying intervention coverage, length, or post-intervention persistence may increase the effectiveness of DOT, eSTAMP, and M-CUBED. We found that although differences in coverage, length, and persistence did slightly lower HIV incidence, it did not translate to meaningful changes in incidence. This is not necessarily surprising given that changes in HIV prevention services during a pandemic has only small impacts on HIV transmission, and that the interventions were examined in isolation. Although some of the interventions, for example M-CUBED, have multiple HIV prevention components to them, we chose to examine the effects independently in order to measure how important individual components are for home-based HIV prevention interventions. Future studies should examine how combined home-based interventions (e.g., interventions that provide a combination of home-based PrEP care, HIV testing, HIV care, etc.) may impact HIV transmission, both in and out of a pandemic context.

We also explored how varying the efficacy of theoretical home-based PrEP retention and HIV testing interventions may impact HIV transmission. Even when the efficacy of such interventions was dramatically increased, for example increasing the HIV testing rate by 25 times its baseline value, we still do not see major changes in HIV transmission. In order for

these interventions to have an effect on HIV transmission, they first must be effective in increasing PrEP/HIV testing. Then, the population-level increases in PrEP/HIV testing must translate into a decrease in HIV transmission. For PrEP, this can occur because PrEP is very effective at preventing HIV acquisition,[18] and having more people on PrEP means that less people in a population are susceptible to HIV. However, for this to translate to a decrease in HIV transmission, these additional individuals remaining on PrEP (relative to not having the intervention and discontinuing PrEP) must actively be at risk of HIV transmission; that is, they need to have unprotected sex with a non-virally-suppressed sexual partner living with diagnosed or undiagnosed HIV.

Because the COVID pandemic did not cause population-level changes to viral suppression,[177,204] but did decrease sexual behavior,[49,155,161,177] particularly with non-main partners (i.e., decreased sexual risk behavior), there was less likelihood during the COVID pandemic that an individual not on PrEP would acquire HIV. This may explain why we did not see reductions in PrEP discontinuation translate into reductions in HIV incidence.

For HIV testing, increased HIV testing would impact HIV incidence if the increased testing diagnoses individuals who would otherwise go undiagnosed until and after their incubation period (to the point that their viral load causes them to be infectious), and then spread HIV to others via unprotected intercourse with HIV-negative partners not currently on PrEP. However, if increased HIV testing is mostly occurring in individuals who already undergo routine HIV screening, or who are not at risk of HIV (either by PrEP use or by a lack of sexual risk behavior), then this would not translate into meaningful changes in HIV incidence. Further, if undiagnosed individuals are experiencing a reduction in sexual activity, such as that experienced during the COVID pandemic by the majority of MSM,[161] there is less of an opportunity to newly infect another individual. Therefore, even if HIV testing rates increase, this does not necessarily mean that it will translate to changes in transmission.

It is possible that if these interventions were targeted to those most at risk of HIV acquisition, they may have had more of a real-world impact. There are disparities in the risk of HIV across demographic groups of MSM: historically and in present day, Black and Hispanic MSM have been the populations most disproportionately impacted by HIV.[3] This is a result of social and structural factors, including but not limited to structural racism, lack of access to quality health care, provider bias, discrimination, and poverty, which exist in the environments in which sexual risk behaviors occur.[12,156] This is particularly relevant in the southern US, where there is a higher concentration of Black MSM. In a 2016 analysis of CDC-funded HIV testing data from 20 different Southern health department jurisdictions, Black MSM received only 6% of HIV tests provided at community-based facilities, despite making up 36% of new diagnoses at these non–health care facilities.[205] However, this is not just an issue with HIV testing. For PrEP, MSM who are indicated for but not currently on PrEP are more likely to be Black.[194] If home-based interventions were targeted towards these groups, it is possible that they may have more impact on HIV transmission.

One interesting finding from our analysis was that increasing the coverage, length, and persistence of the PrEP interventions all slightly increased the number of completed HIV tests. This is likely due to the increased HIV testing (reduction in HIV screening interval) required to maintain PrEP: the clinical guidelines is that HIV testing should be repeated at least every 3 months after PrEP initiation.[206] Further, we found that increasing the coverage and length of the HIV testing interventions actually decreased the total person-time on PrEP. This may be because with increased HIV testing, the time to HIV diagnosis is reduced, which means people may be on PrEP for less time. However, this would only impact individuals with low PrEP adherence, since those with high PrEP adherence have a 99% relative reduction in HIV acquisition risk in our model (and are therefore essentially immune to HIV infection), so additional mechanisms may explain this finding. Moreover, these effects were all small with

overlapping SIs, so these results should be interpreted with appropriate skepticism—we cannot deduce that HIV testing interventions would worsen PrEP outcomes.

Limitations. This study has several limitations. First, the effectiveness of the interventions were drawn from individual RCTs, all with different study periods, populations, and outcomes. Most of the intervention effects did not perfectly map onto model parameters. For example, the M-CUBED study measured current PrEP use in the intervention and control groups and presented it as an adjusted OR, but did not measure weekly PrEP discontinuation. For the DOT study, we used a measure of PrEP adherence to estimate PrEP discontinuation. Although adherence does not map directly to PrEP discontinuation, studies examining trends of adherence over time have found that initial adherence is somewhat predictive of the likelihood of discontinuation.[207,208] If the RCTs had measured the outcomes of weekly PrEP discontinuation rate and weekly rate of HIV testing, for both the intervention and control groups, and also provided these outcomes stratified by race/ethnicity, better model parameterization would be possible. In addition, our study used data on COVID-related impacts from sources of all US MSM to parameterize a model of Atlanta MSM. It is possible that geographic differences in the COVID pandemic and associated lockdown policies, as well as behavioral adaptations to the pandemic, differed between studies. However, since changes in HIV-related behaviors during the COVID pandemic did not statistically differ by geographic region (Appendix A: Chapter 2 Supplementary Results), this may not have biased our model. Lastly, like all modeling studies, our results are subject to the limitations of the studies from which model parameters were sourced (e.g., selection biases or limited generalizability).

Conclusions. This is the first study that uses home-based HIV prevention efficacy data within a dynamic model of HIV transmission to estimate the effectiveness of isolated potential interventions on Atlanta MSM during the COVID-19 pandemic. We provide evidence that although PrEP retention and HIV testing interventions are effective at increasing PrEP use and

HIV testing, their use does not equate to meaningful changes in HIV transmission in a pandemic context when their effects are isolated. Additional HIV prevention interventions, combination HIV prevention interventions, and targeted deployment of interventions may be needed to more effectively decrease HIV incidence in this context.

TABLES

***Table 4.1**. Description of Home-based Interventions*

Intervention	Intervention Type	Intervention Description	Source
M-CUBED (Mobile Messaging for Men)	PrEP Retention HIV Testing	M-CUBED is an individual-level digital health intervention that uses a status neutral approach via a mobile app to address multiple HIV prevention and care needs for GBMSM. The app delivers tailored prevention messaging through content and videos depending on whether participants have higher risk factors for HIV or lower risk factors. It offers a suite of prevention and care services, including: self-screening for HIV and STI risk factors, scheduling and reminder system for routine HIV and STI testing, PrEP eligibility screener, non-occupational post-exposure prophylaxis (nPEP) risk factor assessment tool, ordering platform for delivery of home-based HIV- and STI-screening kits, condoms, and lubricants, and service locators for testing, PrEP, nPEP, and HIV treatment and care. The duration of the study intervention was 3 months. Participants were in Atlanta, GA; Detroit, MI; and New York City, NY.	Sullivan et al.[200]
DOT Mobile App	PrEP Retention	DOT is a PrEP adherence mobile app that combines personalized PrEP pill reminders with positive psychology-based texts to encourage PrEP adherence and provide PrEP information. The DOT app uses three different text messaging types: Daily pill reminders, Alternating daily educational or motivational texts, Weekly text: “It’s PrEP every day and condoms every time.” The duration of the study intervention was 6 weeks. Participants mostly resided in Boston, MA.	Weitzman et al.[201]
eSTAMP (Evaluation of Rapid HIV Self-testing Among MSM Project)	HIV Testing	eSTAMP examines the effectiveness of distributing HIV self-test kits via the internet to MSM in the United States. Intervention participants are mailed two oral fluid and two finger-stick HIV self-tests and can order additional HIV self-tests. Online videos on how to use HIV testing materials are also provided. Additionally, intervention participants have phone access to speak with an HIV counselor to discuss their HIV test results. Finally, participants are provided a link to AIDSvu.org that includes HIV prevention information and locations of local HIV testing services.	MacGowan et al.[202]

***Table 4.2**. Epidemiological Model Parameters and Pre-COVID, COVID Onset, and Intervention Values*

Parameter	Description (Base)	Description (Intervention)	Unit	Base Value (Pre-COVID)*	Base Value (COVID Onset)*	M-CUBED Value	DOT Value	eSTAMP Value
PrEP Discontinuation Rate	PrEP discontinuation rate for Black/Hispanic/White MSM.	The rate of spontaneous discontinuation from PrEP per time step for those in the PrEP intervention.	Weekly probability	0.0207, 0.012, 0.012 for Black/Hispanic/White MSM, respectively	0.02120, 0.01267, 0.01259 for Black/Hispanic/White MSM, respectively, then changes through the pandemic weeks (based on pandemic PrEP data)	Using expit for current PrEP use, immediate posttest after intervention: 1.26; using modifier of 0.7794	The mean percentage of participants who reported perfect (100%) PrEP adherence significantly increased from pre- to post-intervention (0.39 vs. 0.72); using modifier of 0.5416667	—
PrEP Retention Intervention Drop-off	—	The rate of drop-off from the PrEP retention intervention per time step for those in the intervention.	Weekly probability	—	—	Retention was 1065 of 1226 (86.87%) at 3 months; weekly drop-off rate of 1.25%	No attrition reported in study (0 of 54 drop-offs); weekly drop-off	

						based on 3-month length	rate set to 0%	
HIV Testing Rate	Mean probability of HIV testing per time step for Black/Hispanic/White MSM, respectively.	Mean probability of HIV testing per time step for men in the HIV testing intervention.	Weekly probability	0.0048, 0.0041, 0.0058 for Black/Hispanic/White MSM, respectively	0.00367, 0.0030, 0.0043 for Black/Hispanic/White MSM, respectively then changes through the pandemic weeks (based on pandemic HIV testing data)	Report of HIV testing immediately post-intervention (aOR = 2.02); using modifier of 2.02	—	HIV testing (number of any type of testing over 12 months) was significantly higher among intervention participants than comparison participants: 5.29 vs. 1.50 tests; using modifier of 3.5267
HIV Testing Intervention Drop-off	—	The rate of drop-off from the HIV testing intervention per time step for those in the HIV testing intervention.	Weekly probability	—	—	Retention was 1065 of 1226 (86.87%) at 3 months; weekly drop-off rate of 1.25%	—	Retention rate of Participants who initiated any follow-up survey: 74.7%; weekly drop-off rate for 12 week is 2.6%

* Values are set during model calibration. See supplemental appendix for full details on model calibration including sourcing of target model parameters.

Table 4.3. *The Effect of COVID-Related Changes and PrEP Retention and HIV Testing Interventions Set to Various Coverage, Length, and Persistence Levels on Epidemiologic Outcomes, Over 500 Simulations*

Inter-vention	Scenario	Incidence Rate, May 2020 (95% SI)*	3-Year Cumulative Incidence (95% SI)**,†	Number Infections Averted (95% SI)†,‡	Percent Infections Averted†,‡	Total Person-Time on PrEP Over 3 Years (in Weeks)† (95% SI)	Relative Excess Person-Time on PrEP (in Weeks)†,§ (95% SI)	Number of HIV Tests Over 3 Years† (95% SI)	Relative Excess Number of HIV Tests†,‖ (95% SI)
	No Inter-vention	0.66 (0.29, 1.09)	1,971.0 (1,870.4, 2,066.0)	—		1,432,327 (1,408,967, 1,453,985)	—	169,132 (167,200, 170,951)	—
	Coverage								
	10%	0.65 (0.29, 1.09)	1,963.2 (1,867.6, 2,060.2)	7.79 (-89.17, 103.43)	0.40%	1,445,029 (1,422,536, 1,466,887)	12,581 (-9,912, 34,439)	170,027 (168,099, 171,828)	880 (-1,048, 2,681)
	20%	0.65 (0.29, 1.03)	1,963.2 (1,860.0, 2,060.9)	7.82 (-89.84, 111.05)	0.40%	1,456,462 (1,433,424, 1,479,149)	24,058 (1,020, 46,745)	170,839 (168,893, 172,688)	1,698 (-249, 3,547)
	30%	0.65 (0.29, 1.03)	1,961.1 (1,860.6, 2,061.4)	9.92 (-90.40, 110.46)	0.50%	1,468,108 (1,447,025, 1,490,802)	35,842 (14,760, 58,536)	171,663 (169,921, 173,513)	2,538 (796, 4,388)
	40%	0.64 (0.34, 1.03)	1,959.6 (1,861.4, 2,054.0)	11.39 (-82.96, 109.67)	0.58%	1,480,218 (1,457,078, 1,500,357)	47,885 (24,745, 68,024)	172,513 (170,544, 174,256)	3,380 (1,411, 5,123)
	50%	0.66 (0.34, 1.03)	1,958.2 (1,865.9, 2,053.2)	12.83 (-82.19, 105.12)	0.65%	1,491,773 (1,470,434, 1,513,278)	59,468 (38,129, 80,973)	173,344 (171,502, 175,169)	4,215 (2,373, 6,039)
DOT	Length								
	6 weeks	0.65 (0.29, 1.03)	1,961.6 (1,860.8, 2,053.4)	9.41 (-82.38, 110.25)	0.48%	1,448,714 (1,426,295, 1,473,466)	16,272 (-6,146, 41,024)	170,299 (168,511, 172,329)	1,153 (-634, 3,183)
	3 months	0.65 (0.29, 1.08)	1,961.6 (1,866.6, 2,060.0)	9.38 (-88.95, 104.45)	0.48%	1,451,180 (1,429,699, 1,474,799)	18,895 (-2,587, 42,513)	170,473 (168,718, 172,423)	1,345 (-410, 3,296)
	6 months	0.65 (0.29, 1.03)	1,964.6 (1,866.9, 2,061.0)	6.41 (-89.98, 104.15)	0.33%	1,452,931 (1,430,005, 1,476,457)	20,456 (-2,470, 43,982)	170,603 (168,768, 172,479)	1,454 (-381, 3,329)
	12 months	0.65 (0.29, 1.03)	1,963.2 (1,860.0, 2,060.9)	7.82 (-89.84, 111.05)	0.40%	1,456,462 (1,433,424, 1,479,149)	24,058 (1,020, 46,745)	170,839 (168,893, 172,688)	1,698 (-249, 3,547)
	24 months	0.65 (0.29, 1.04)	1,963.0 (1,866.1, 2,061.7)	8.07 (-90.66, 104.93)	0.41%	1,465,864 (1,444,468, 1,487,300)	33,413 (12,017, 54,848)	171,486 (169,634, 173,335)	2,339 (487, 4,188)
	Persistence of Intervention Effects (PrEP Interventions Only)								

	0 months	0.65 (0.29, 1.09)	1,964.0 (1,868.4, 2,059.4)	6.99 (-88.41, 102.65)	0.35%	1,453,499 (1,429,609, 1,476,002)	21,037 (-2,854, 43,540)	170,648 (168,673, 172,495)	1,500 (-475, 3,347)
	6 months	0.65 (0.29, 1.08)	1,960.9 (1,867.3, 2,056.8)	10.14 (-85.77, 103.75)	0.51%	1,454,859 (1,430,271, 1,478,548)	22,658 (-1,930, 46,346)	170,744 (168,754, 172,607)	1,626 (-363, 3,489)
	12 months	0.65 (0.29, 1.03)	1,963.2 (1,860.0, 2,060.9)	7.82 (-89.84, 111.05)	0.40%	1,456,462 (1,433,424, 1,479,149)	24,058 (1,020, 46,745)	170,839 (168,893, 172,688)	1,698 (-249, 3,547)
	24 months	0.66 (0.34, 1.09)	1,964.7 (1,870.4, 2,061.5)	6.28 (-90.44, 100.60)	0.32%	1,459,186 (1,434,432, 1,481,217)	26,890 (2,136, 48,921)	171,021 (168,998, 172,886)	1,893 (-131, 3,758)
M-CUBED (PrEP Retention Only)	Coverage								
	10%	0.65 (0.29, 1.03)	1,967.9 (1,866.6, 2,061.5)	3.11 (-90.47, 104.39)	0.16%	1,435,609 (1,412,537, 1,458,559)	3,304 (-19,768, 26,254)	169,375 (167,627, 171,231)	245 (-1,502, 2,101)
	20%	0.66 (0.34, 1.08)	1,967.6 (1,863.7, 2,065.4)	3.44 (-94.41, 107.28)	0.17%	1,439,982 (1,417,409, 1,461,435)	7,552 (-15,021, 29,005)	169,679 (167,804, 171,478)	535 (-1,341, 2,334)
	30%	0.66 (0.29, 1.09)	1,967.2 (1,868.2, 2,065.3)	3.87 (-94.30, 102.83)	0.20%	1,443,683 (1,422,234, 1,465,952)	11,326 (-10,123, 33,595)	169,924 (168,186, 171,762)	788 (-950, 2,626)
	40%	0.65 (0.29, 1.09)	1,965.2 (1,872.0, 2,065.4)	5.83 (-94.36, 98.99)	0.30%	1,447,243 (1,425,907, 1,470,640)	14,870 (-6,465, 38,268)	170,180 (168,382, 172,107)	1,043 (-756, 2,970)
	50%	0.64 (0.29, 1.03)	1,966.8 (1,868.3, 2,065.5)	4.18 (-94.47, 102.68)	0.21%	1,451,002 (1,428,235, 1,474,072)	18,544 (-4,223, 41,614)	170,427 (168,567, 172,286)	1,280 (-581, 3,138)
	Length								
	6 weeks	0.65 (0.29, 1.03)	1,969.5 (1,871.4, 2,067.7)	1.51 (-96.72, 99.67)	0.08%	1,440,786 (1,417,493, 1,463,568)	8,339 (-14,954, 31,121)	169,729 (167,808, 171,591)	582 (-1,338, 2,444)
	3 months	0.65 (0.29, 1.03)	1,965.5 (1,863.6, 2,066.8)	5.54 (-95.73, 107.39)	0.28%	1,441,590 (1,418,518, 1,463,056)	9,289 (-13,784, 30,755)	169,779 (167,994, 171,560)	650 (-1,136, 2,431)
	6 months	0.66 (0.34, 1.08)	1,968.8 (1,871.4, 2,069.3)	2.19 (-98.26, 99.63)	0.11%	1,440,515 (1,417,376, 1,462,838)	8,049 (-15,089, 30,372)	169,713 (167,852, 171,634)	564 (-1,297, 2,486)
	12 months	0.66 (0.34, 1.08)	1,967.6 (1,863.7, 2,065.4)	3.44 (-94.41, 107.28)	0.17%	1,439,982 (1,417,409, 1,461,435)	7,552 (-15,021, 29,005)	169,679 (167,804, 171,478)	535 (-1,341, 2,334)

	24 months	0.65 (0.34, 1.09)	1,964.7 (1,865.9, 2,069.1)	6.29 (-98.03, 105.13)	0.32%	1,447,223 (1,425,196, 1,469,180)	14,898 (-7,128, 36,856)	170,191 (168,343, 171,919)	1,059 (-789, 2,787)
	Persistence of Intervention Effects (PrEP Interventions Only)								
	0 months	0.66 (0.29, 1.04)	1,967.9 (1,870.3, 2,067.4)	3.13 (-96.38, 100.73)	0.16%	1,439,765 (1,417,604, 1,461,572)	7,554 (-14,608, 29,360)	169,664 (167,844, 171,473)	545 (-1,275, 2,354)
	6 months	0.66 (0.29, 1.08)	1,966.5 (1,872.1, 2,068.5)	4.53 (-97.45, 98.92)	0.23%	1,440,122 (1,418,092, 1,462,375)	7,679 (-14,351, 29,933)	169,670 (167,816, 171,472)	524 (-1,330, 2,326)
	12 months	0.66 (0.34, 1.08)	1,967.6 (1,863.7, 2,065.4)	3.44 (-94.41, 107.28)	0.17%	1,439,982 (1,417,409, 1,461,435)	7,552 (-15,021, 29,005)	169,679 (167,804, 171,478)	535 (-1,341, 2,334)
	24 months	0.65 (0.29, 1.04)	1,968.1 (1,873.6, 2,066.9)	2.92 (-95.88, 97.46)	0.15%	1,439,840 (1,416,605, 1,461,848)	7,449 (-15,785, 29,458)	169,648 (167,713, 171,534)	508 (-1,427, 2,394)
eSTAMP	Coverage								
	10%	0.65 (0.29, 1.03)	1,956.0 (1,862.9, 2,057.1)	14.98 (-86.03, 108.09)	0.76%	1,430,953 (1,409,467, 1,453,901)	-1,411 (-22,897, 21,537)	171,880 (170,001, 173,769)	2,744 (864, 4,632)
	20%	0.65 (0.29, 1.03)	1,951.4 (1,853.1, 2,046.5)	19.63 (-75.43, 117.96)	1.00%	1,429,188 (1,404,886, 1,453,795)	-3,132 (-27,435, 21,474)	174,594 (172,572, 176,626)	5,463 (3,440, 7,494)
	30%	0.66 (0.29, 1.04)	1,940.7 (1,842.6, 2,035.2)	30.30 (-64.15, 128.43)	1.54%	1,428,071 (1,405,124, 1,450,256)	-4,310 (-27,257, 17,875)	177,343 (175,389, 179,282)	8,204 (6,251, 10,143)
	40%	0.64 (0.29, 1.03)	1,931.0 (1,832.5, 2,027.3)	40.02 (-56.32, 138.50)	2.03%	1,425,802 (1,402,560, 1,449,236)	-6,383 (-29,626, 17,051)	180,018 (178,145, 181,879)	10,903 (9,030, 12,763)
	50%	0.65 (0.34, 1.03)	1,927.3 (1,835.8, 2,022.3)	43.76 (-51.29, 135.25)	2.22%	1,424,708 (1,401,784, 1,446,846)	-7,669 (-30,594, 14,469)	182,785 (180,843, 184,671)	13,647 (11,705, 15,532)
	Length								
	6 weeks	0.65 (0.29, 1.09)	1,966.6 (1,871.4, 2,061.0)	4.43 (-89.94, 99.62)	0.22%	1,433,383 (1,409,621, 1,458,569)	910 (-22,852, 26,096)	169,558 (167,622, 171,609)	409 (-1,527, 2,459)
	3 months	0.66 (0.29, 1.03)	1,962.4 (1,868.1, 2,056.9)	8.67 (-85.92, 102.87)	0.44%	1,432,715 (1,408,696, 1,454,037)	409 (-23,610, 21,731)	170,053 (168,108, 171,879)	923 (-1,022, 2,749)
	6 months	0.66 (0.34, 1.04)	1,956.3 (1,862.9, 2,052.4)	14.69 (-81.40, 108.14)	0.75%	1,431,722 (1,409,655, 1,454,128)	-585 (-22,652, 21,821)	171,564 (169,703, 173,448)	2,434 (573, 4,318)

	12 months	0.65 (0.29, 1.03)	1,951.4 (1,853.1, 2,046.5)	19.63 (-75.43, 117.96)	1.00%	1,429,188 (1,404,886, 1,453,795)	-3,132 (-27,435, 21,474)	174,594 (172,572, 176,626)	5,463 (3,440, 7,494)
	24 months	0.65 (0.29, 1.09)	1,934.3 (1,841.8, 2,030.6)	36.76 (-59.57, 129.24)	1.87%	1,424,160 (1,400,206, 1,448,060)	-8,197 (-32,150, 15,703)	182,026 (179,956, 183,906)	12,890 (10,820, 14,771)
M-CUBED (HIV Testing Only)	Coverage								
	10%	0.65 (0.29, 1.09)	1,961.2 (1,861.3, 2,063.7)	9.80 (-92.64, 109.75)	0.50%	1,431,925 (1,408,160, 1,454,636)	-323 (-24,088, 22,388)	170,254 (168,290, 172,065)	1,130 (-833, 2,942)
	20%	0.65 (0.29, 1.04)	1,957.8 (1,863.6, 2,046.3)	13.24 (-75.29, 107.46)	0.67%	1,431,240 (1,407,915, 1,453,176)	-1,012 (-24,337, 20,924)	171,362 (169,360, 173,182)	2,238 (237, 4,058)
	30%	0.66 (0.34, 1.04)	1,956.0 (1,858.4, 2,058.6)	15.03 (-87.60, 112.59)	0.76%	1,430,923 (1,407,693, 1,454,402)	-1,447 (-24,676, 22,032)	172,508 (170,573, 174,438)	3,371 (1,436, 5,300)
	40%	0.64 (0.29, 1.04)	1,951.8 (1,849.4, 2,045.0)	19.23 (-73.97, 121.67)	0.98%	1,429,873 (1,408,713, 1,452,402)	-2,524 (-23,684, 20,005)	173,576 (171,808, 175,426)	4,435 (2,668, 6,286)
	50%	0.64 (0.29, 1.03)	1,950.0 (1,857.7, 2,048.1)	21.03 (-77.11, 113.33)	1.07%	1,430,152 (1,407,007, 1,452,918)	-2,257 (-25,402, 20,508)	174,766 (172,862, 176,703)	5,624 (3,720, 7,561)
	Length								
	6 weeks	0.65 (0.29, 1.08)	1,964.4 (1,869.0, 2,057.1)	6.58 (-86.03, 102.06)	0.33%	1,432,943 (1,409,215, 1,454,793)	591 (-23,137, 22,441)	169,321 (167,422, 171,085)	186 (-1,714, 1,949)
	3 months	0.66 (0.29, 1.04)	1,966.1 (1,874.3, 2,060.1)	4.96 (-89.07, 96.76)	0.25%	1,432,338 (1,408,983, 1,454,555)	-52 (-23,407, 22,165)	169,498 (167,596, 171,316)	358 (-1,543, 2,177)
	6 months	0.65 (0.29, 1.03)	1,961.4 (1,866.6, 2,063.7)	9.64 (-92.69, 104.44)	0.49%	1,433,032 (1,410,664, 1,454,488)	771 (-21,597, 22,228)	170,201 (168,415, 171,950)	1,077 (-709, 2,825)
	12 months	0.65 (0.29, 1.04)	1,957.8 (1,863.6, 2,046.3)	13.24 (-75.29, 107.46)	0.67%	1,431,240 (1,407,915, 1,453,176)	-1,012 (-24,337, 20,924)	171,362 (169,360, 173,182)	2,238 (237, 4,058)
	24 months	0.64 (0.29, 1.04)	1,952.5 (1,850.7, 2,061.4)	18.53 (-90.38, 120.31)	0.94%	1,428,738 (1,406,049, 1,451,360)	-3,518 (-26,207, 19,104)	174,334 (172,432, 176,107)	5,210 (3,308, 6,983)
	No COVID Pandemic	1.01 (0.57, 1.55)	2,076.2 (1,975.5, 2,189.3)	-105.16 (-218.28, -4.51)	-5.34%	1,684,523 (1,658,778, 1,708,016)	252,078 (226,333, 275,570)	193,986 (191,944, 195,939)	24,840 (22,798, 26,793)

*Rate per 100 person-years at risk during May 2020.
**Cumulative incidence over 3 year period (from March 2020-March 2023) for full susceptible Atlanta MSM population.
†For susceptible Atlanta MSM population (approximately 87,723 HIV-negative MSM).
‡Difference in 3-year cumulative incidence compared to base scenario.
§Difference in total person-time on PrEP between given scenario and base scenario.
‖Difference in all HIV tests between given scenario and base scenario.

Table 4.4. *The Effect of Modifying the Efficacy of Home-Based PrEP Retention and HIV Testing Interventions on Epidemiologic Outcomes in a COVID Pandemic Context, Over 500 Simulations*

Scenario	Incidence Rate, May 2020 (95% SI)*	3-Year Cumulative Incidence (95% SI)**,†	Number Infections Averted (95% SI)†,‡	Total Person-Time on PrEP Over 3 Years† (95% SI)	Relative Excess Person-Time on PrEP†,§ (95% SI)	Number of HIV Tests Over 3 Years† (95% SI)	Relative Excess Number of HIV Tests†,‖ (95% SI)
No Intervention	0.66 (0.29, 1.09)	1,971.0 (1,870.4, 2,066.0)	—	1,432,327 (1,408,967, 1,453,985)	—	169,132 (167,200, 170,951)	—
Efficacy of PrEP Retention Intervention							
Modifier of 0.75 (25% Change)	0.64 (0.29, 1.09)	1,966.1 (1,873.3, 2,068.2)	4.9 (-97.18, 97.71)	1,459,299 (1,438,992, 1,479,970)	27,070 (6,764, 47,741)	171,023 (169,258, 172,768)	1,902 (137, 3,647)
Modifier of 0.50 (50% Change)	0.66 (0.29, 1.03)	1,958.2 (1,861.6, 2,052.6)	12.86 (-81.62, 109.47)	1,498,735 (1,475,283, 1,520,668)	66,288 (42,836, 88,220)	173,808 (171,845, 175,639)	4,661 (2,698, 6,492)
Modifier of 0.25 (75% Change)	0.64 (0.34, 1.09)	1,940.9 (1,844.8, 2,039.7)	30.17 (-68.69, 126.2)	1,549,469 (1,525,595, 1,571,837)	117,067 (93,193, 139,434)	177,428 (175,535, 179,276)	8,287 (6,393, 10,135)
Modifier of 0 (100% Change)	0.64 (0.29, 1.03)	1,920.3 (1,821.5, 2,019.3)	50.75 (-48.31, 149.55)	1,614,751 (1,589,241, 1,638,772)	182,347 (156,837, 206,368)	182,066 (180,080, 184,014)	12,925 (10,939, 14,873)
Efficacy of HIV Testing Intervention							
Modifier of 2.0 (2x)	0.65 (0.29, 1.08)	1,948.8 (1,854.3, 2,047.6)	22.25 (-76.6, 116.75)	1,429,182 (1,405,304, 1,451,961)	-2,937 (-26,816, 19,841)	174,533 (172,604, 176,376)	5,425 (3,496, 7,268)
Modifier of 5.0 (5x)	0.65 (0.29, 1.04)	1,904.6 (1,811.6, 1,997.4)	66.38 (-26.35, 159.45)	1,419,455 (1,396,729, 1,443,151)	-12,897 (-35,622, 10,800)	190,616 (188,606, 192,619)	21,480 (19,470, 23,484)

Modifier of 10.0 (10x)	0.65 (0.29, 1.03)	1,863.6 (1,767.1, 1,955.2)	107.39 (15.83, 203.89)	1,400,837 (1,378,449, 1,424,110)	-31,589 (-53,977, -8,316)	217,083 (215,113, 219,092)	47,939 (45,969, 49,948)
Modifier of 25.0 (25x)	0.64 (0.29, 1.03)	1,809.5 (1,720.3, 1,895.5)	161.52 (75.51, 250.73)	1,357,208 (1,335,901, 1,380,088)	-75,207 (-96,514, -52,327)	297,052 (294,872, 299,384)	127,909 (125,729, 130,241)
Modifier of 50.0 (50x)	0.64 (0.29, 1.09)	1,783.9 (1,691.6, 1,873.7)	187.13 (97.35, 279.41)	1,322,718 (1,300,210, 1,343,936)	-109,744 (-132,251, -88,525)	433,437 (430,419, 436,550)	264,289 (261,271, 267,402)

*Rate per 100 person-years at risk during May 2020.

**Cumulative incidence over 3 year period (from March 2020-March 2023) for full susceptible Atlanta MSM population.

†For susceptible Atlanta MSM population (approximately 87,723 HIV-negative MSM).

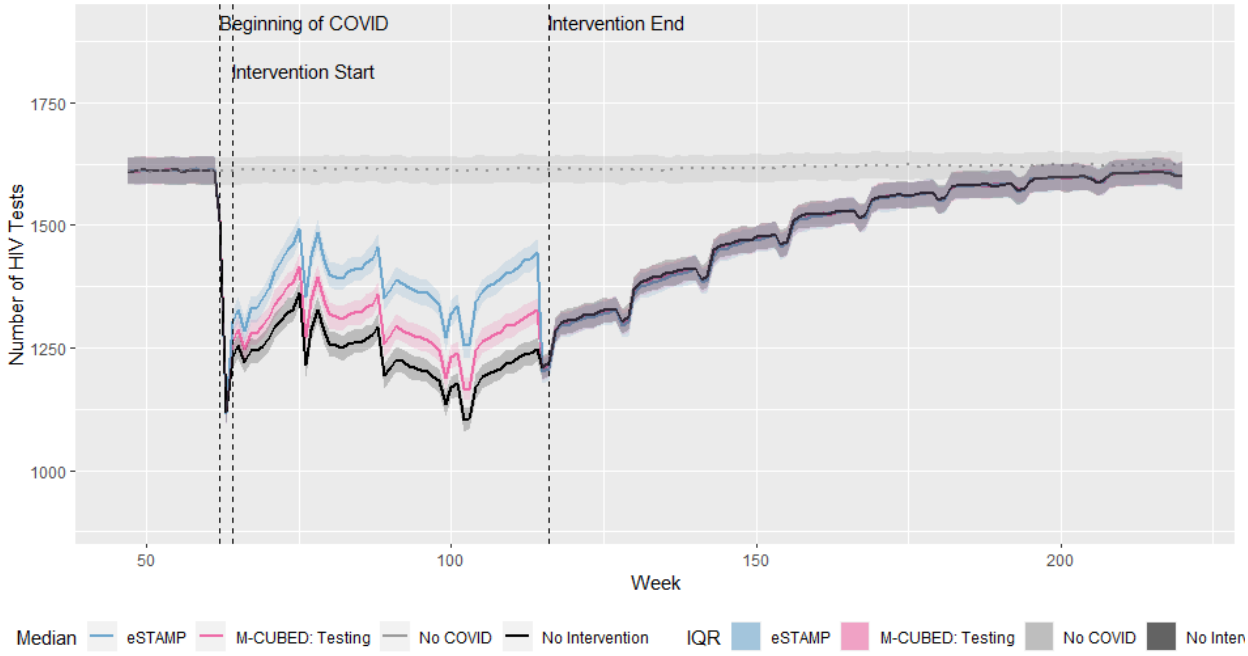
‡Difference in 3-year cumulative incidence compared to base scenario.

§Difference in total person-time on PrEP between given scenario and base scenario.

‖Difference in all HIV tests between given scenario and base scenario.

FIGURES

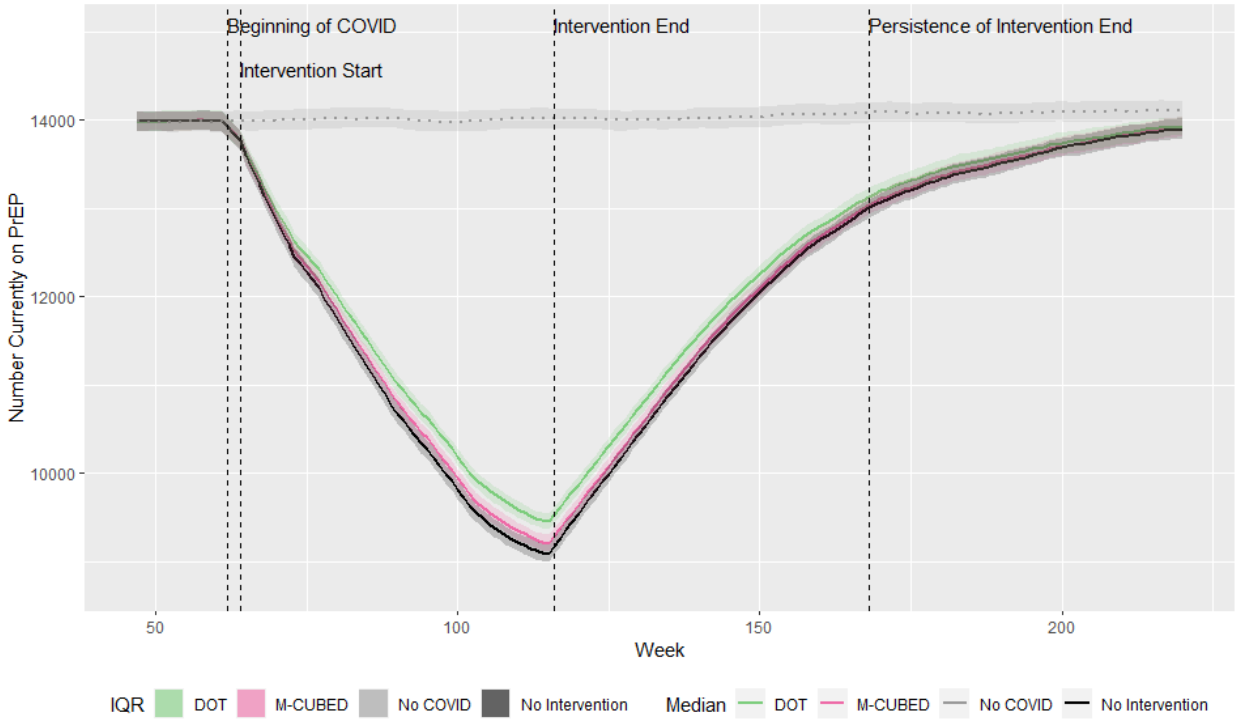
***Figure 4.1**. Number of HIV Tests by Home-Based HIV Testing Intervention,* Over 500 Simulations*



*Assumes intervention length of 1 year, intervention coverage of 20% of eligible, intervention began 2 weeks into pandemic, with no intervention persistence

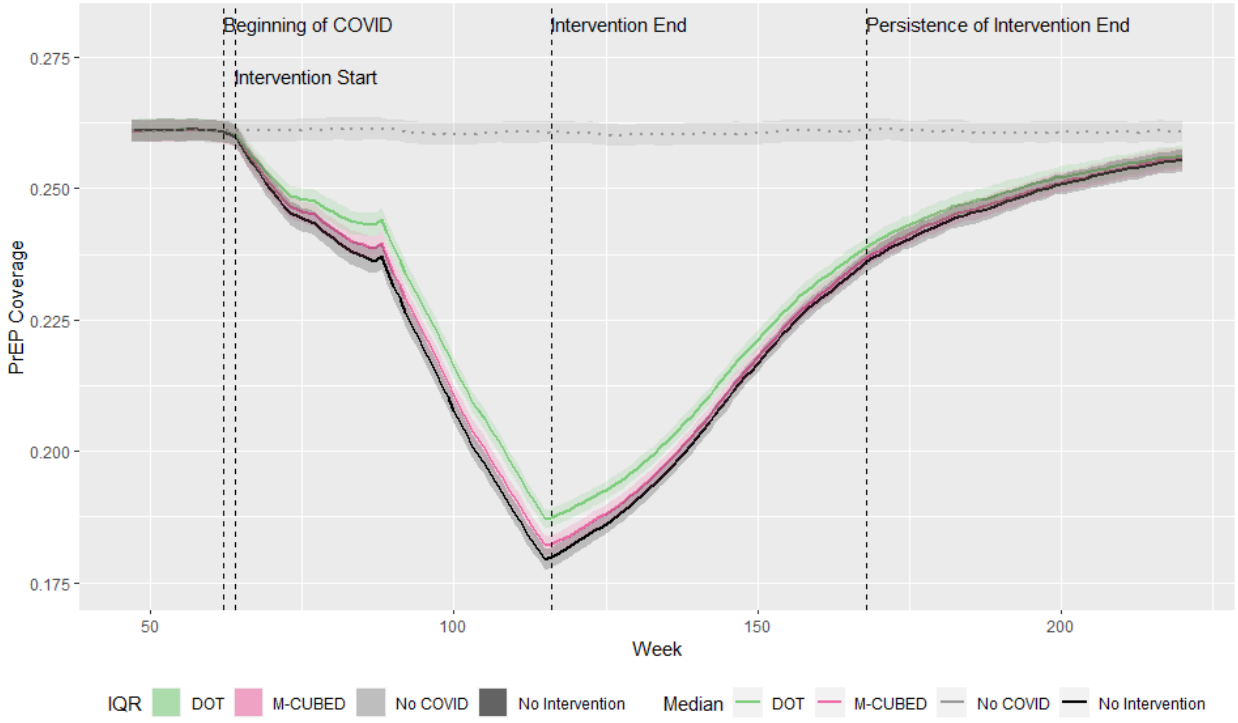
Note: The sudden sharp drops/spikes in all HIV tests are due to PrEP-based testing patterns. The model uses an interval-based approach where it is retesting with a testing interval of 12.86 weeks. This follows from PrEP guidance that individuals who are HIV-negative and take PrEP to prevent HIV acquisition should test quarterly.

***Figure 4.2**. Current PrEP Use by Home-Based PrEP Retention Intervention,* Over 500 Simulations*



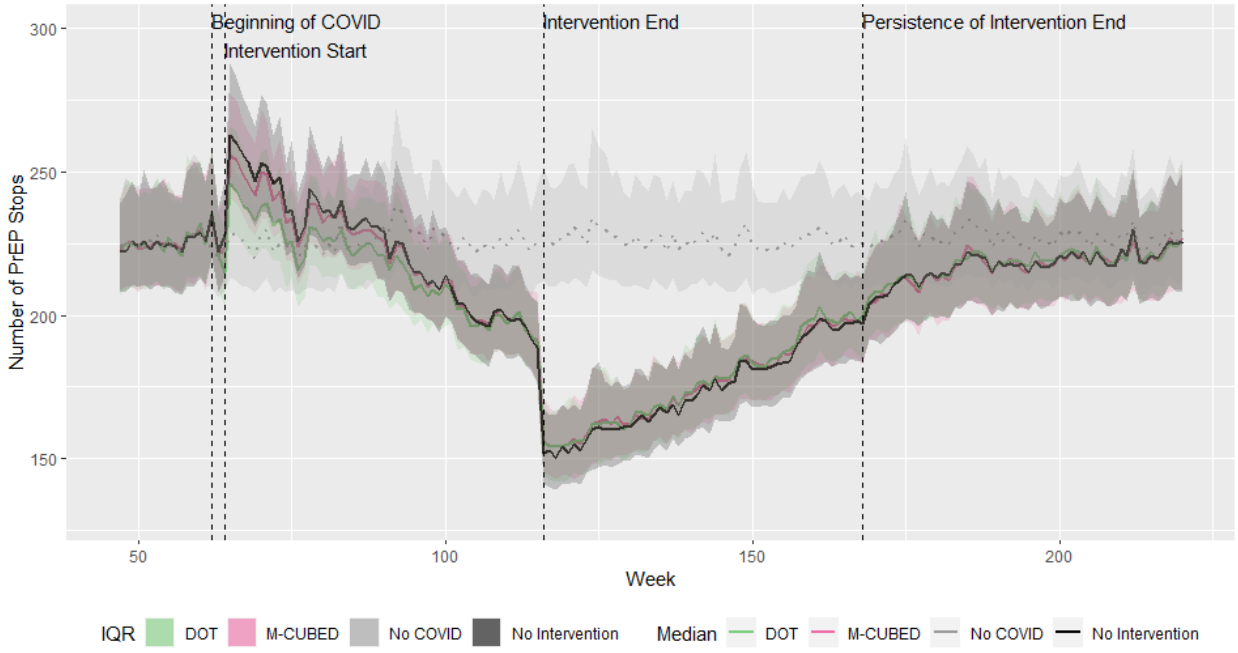
*Assumes intervention length of 1 year, intervention coverage of 20% of eligible, intervention began 2 weeks into pandemic, with 1 intervention persistence of 1 year

***Figure 4.3**. PrEP Coverage among Atlanta MSM by Home-Based PrEP Retention Intervention,* Over 500 Simulations*



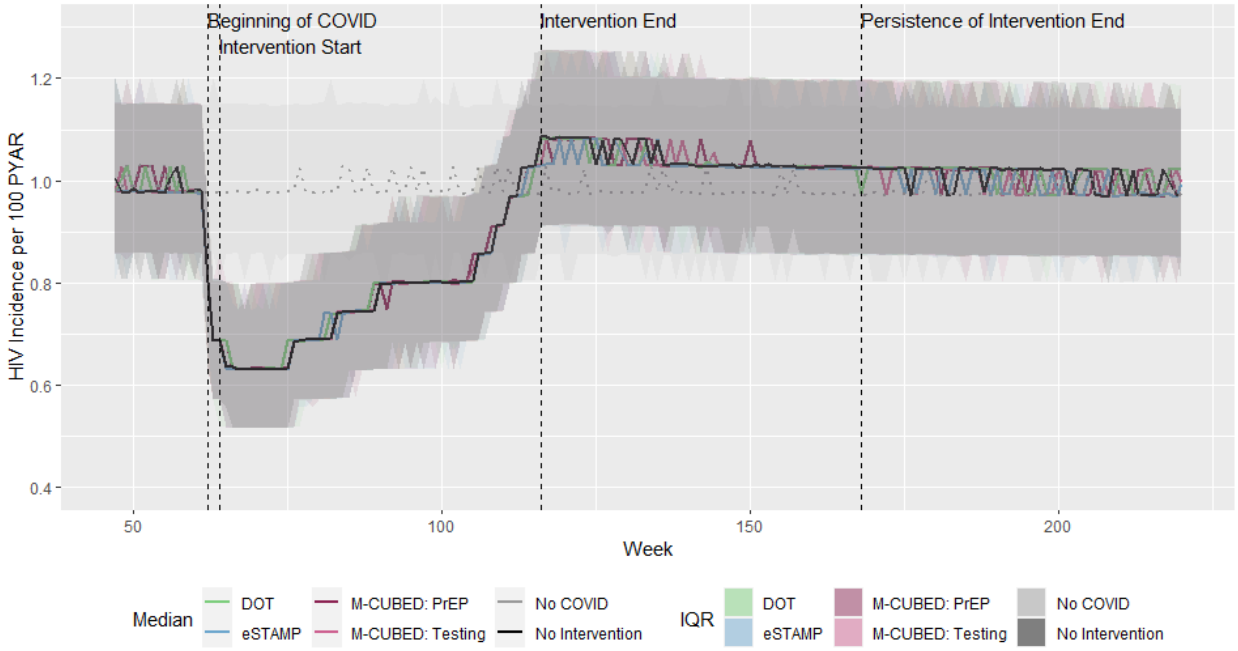
*Assumes intervention length of 1 year, intervention coverage of 20% of eligible, intervention began 2 weeks into pandemic, with 1 intervention persistence of 1 year

Figure 4.4. *Number of PrEP Stops by Home-Based PrEP Retention Intervention,* Over 500 Simulations*



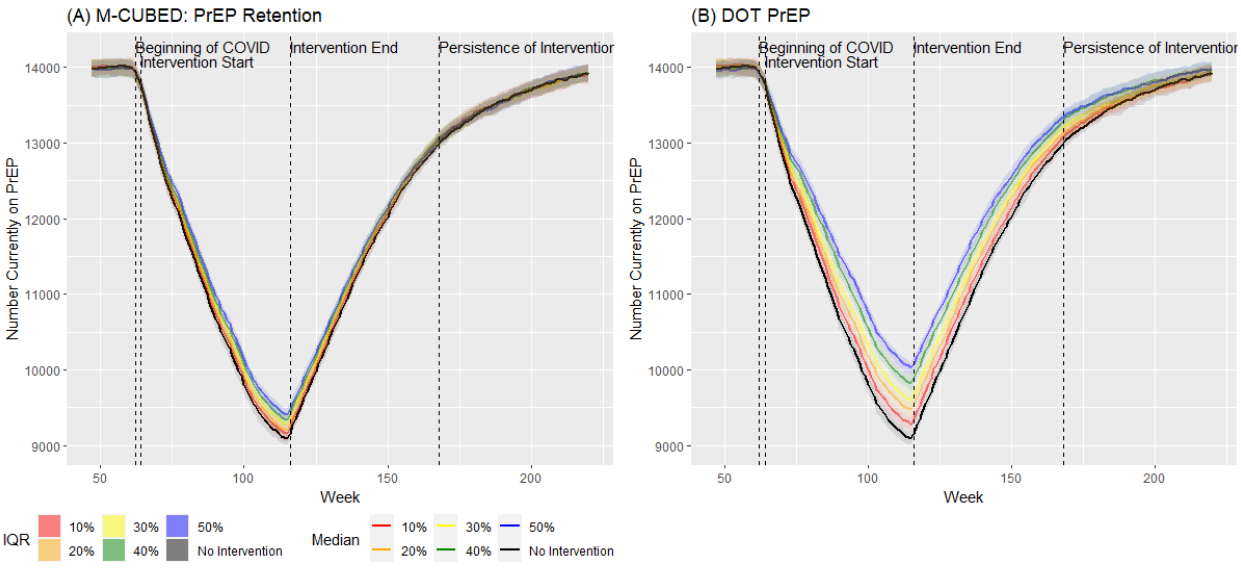
*Assumes intervention length of 1 year, intervention coverage of 20% of eligible, intervention began 2 weeks into pandemic, with 1 intervention persistence of 1 year

***Figure 4.5**. Isolated Impact of Home-Based Interventions on Incidence among Atlanta MSM,* Over 500 Simulations, 2020–2023*



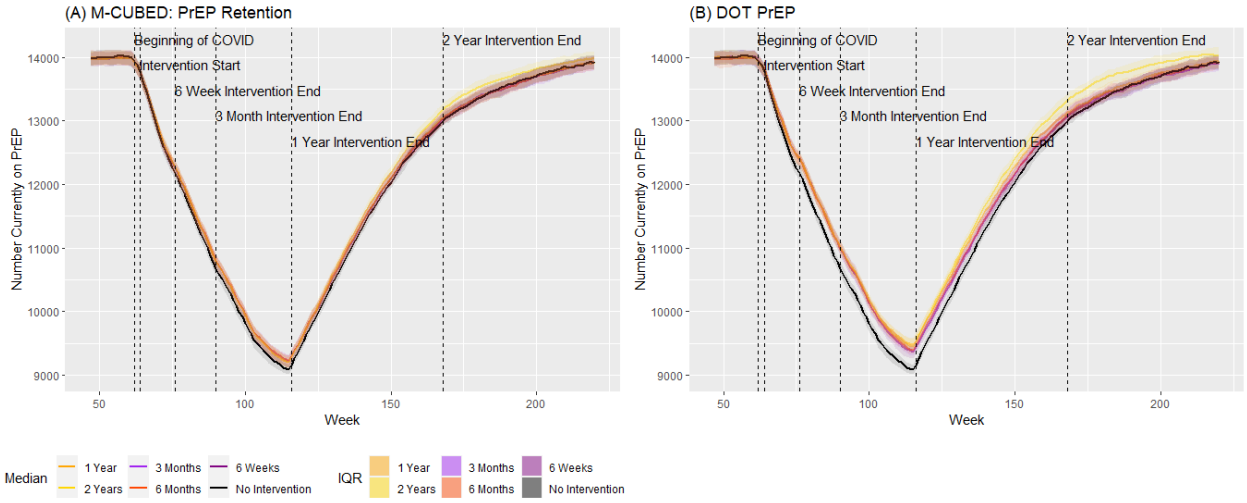
*Assumes intervention length of 1 year, intervention coverage of 20% of eligible, intervention began 2 weeks into pandemic, with 1 intervention persistence of 1 year for PrEP retention interventions and 0 years for HIV testing interventions.

***Figure 4.6**. Current PrEP Use per week by coverage level of eligible population for (A) M-CUBED and (B) DOT,* Over 500 Simulations*



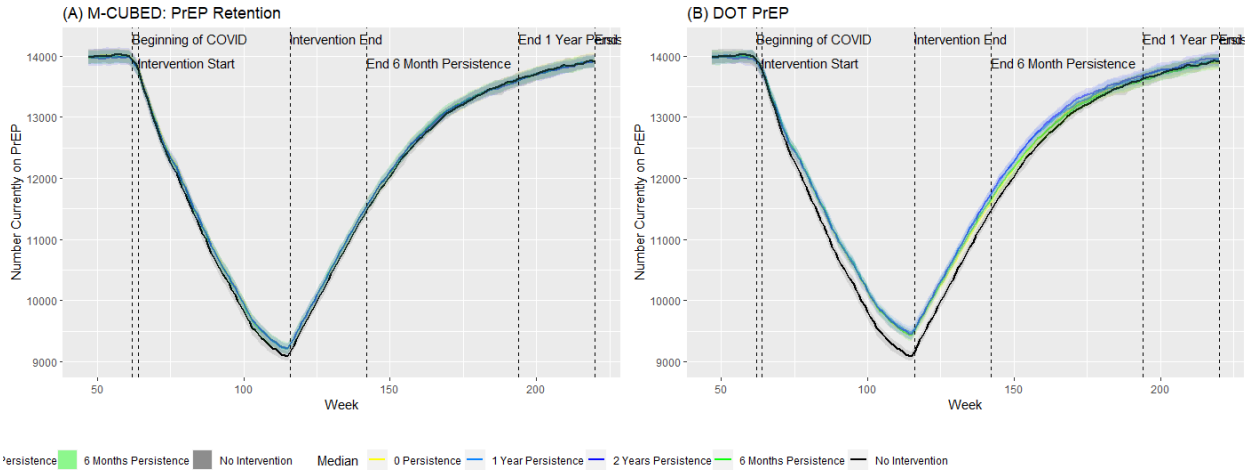
*Assumes intervention length of 1 year, intervention coverage of 20% of eligible, intervention began 2 weeks into Pandemic, with 1 intervention persistence of 1 year

***Figure 4.7**. Current PrEP Use per week by length of intervention for (A) M-CUBED and (B) DOT,* Over 500 Simulations*



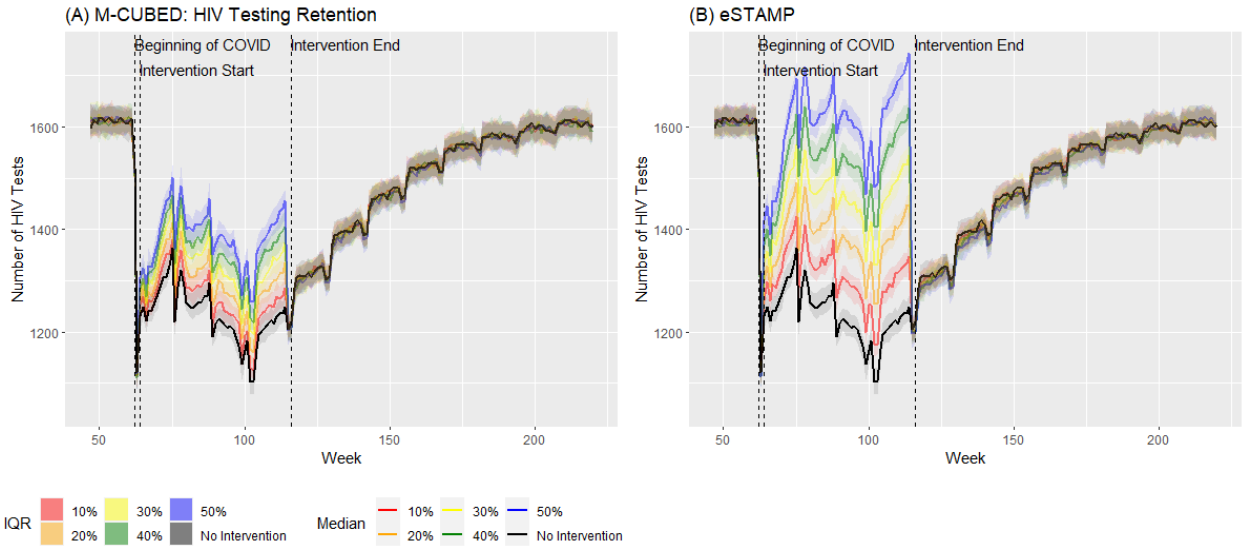
*Assumes intervention length of 1 year, intervention coverage of 20% of eligible, intervention began 2 weeks into pandemic, with 1 intervention persistence of 1 year

***Figure 4.8**. Current PrEP Use per week by length of persistence for (A) M-CUBED and (B) DOT,* Over 500 Simulations*



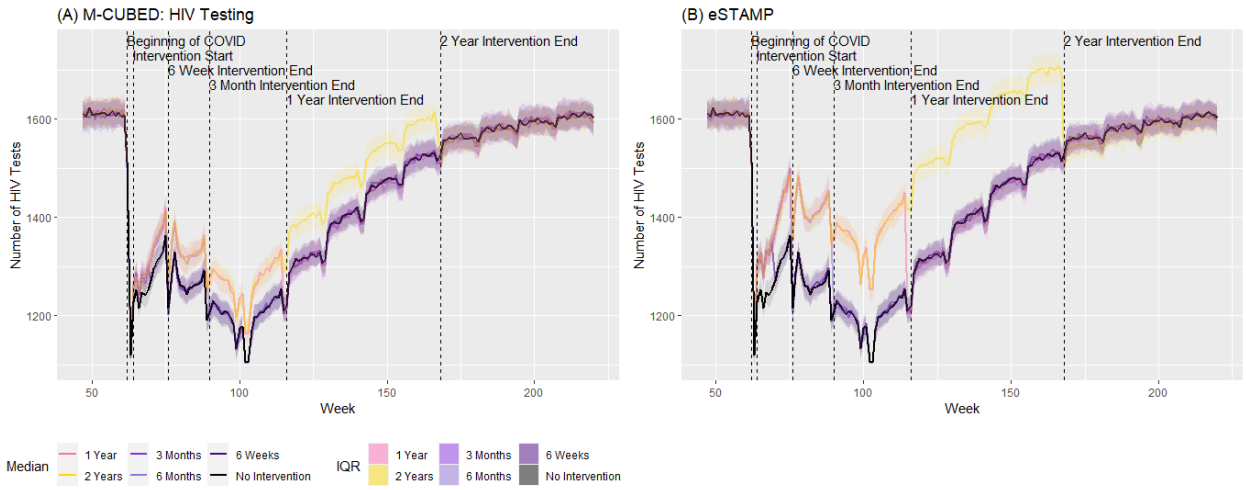
*Assumes intervention length of 1 year, intervention coverage of 20% of eligible, intervention began 2 weeks into pandemic, with 1 intervention persistence of 1 year

***Figure 4.9**. Number of HIV Tests per week by coverage level of eligible population for (A) M-CUBED and (B) eSTAMP,* Over 500 Simulations*



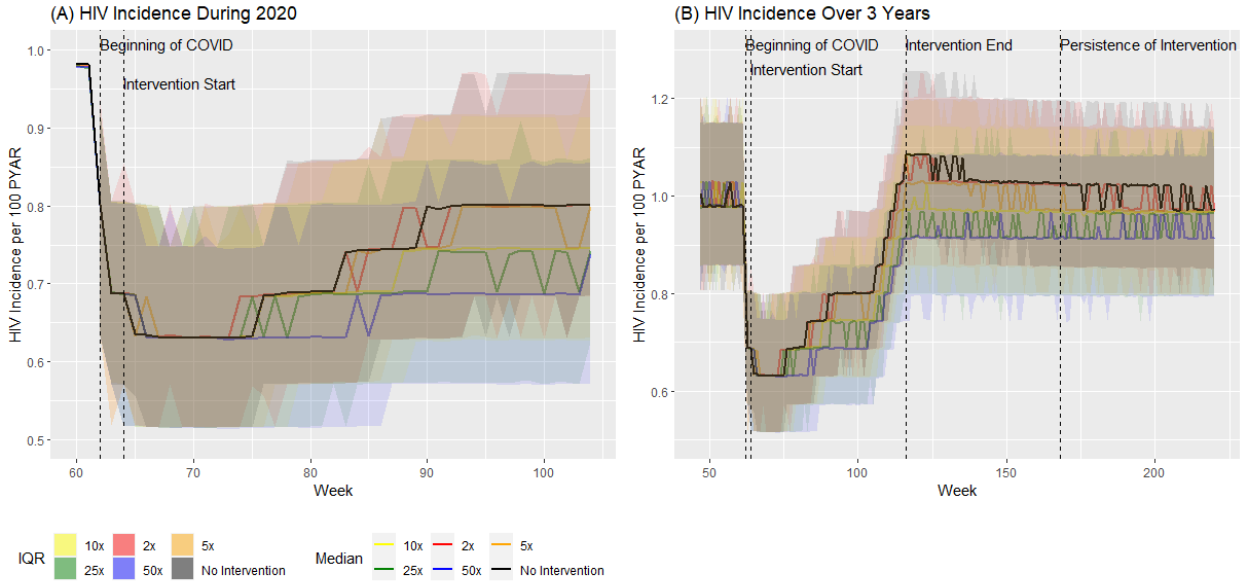
*Assumes intervention length of 1 year, intervention coverage of 20% of eligible, intervention began 2 weeks into Pandemic, with no intervention persistence

***Figure 4.10**. Number of HIV Tests per week by length of intervention for (A) M-CUBED and (B) eSTAMP,* Over 500 Simulations*



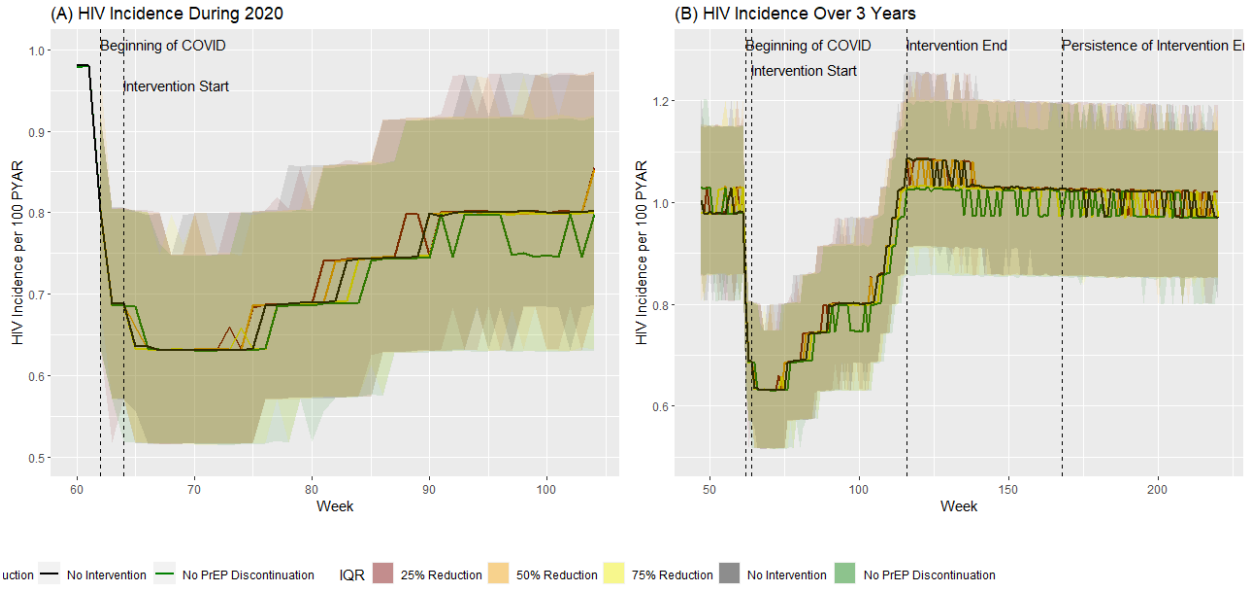
*Assumes intervention length of 1 year, intervention coverage of 20% of eligible, intervention began 2 weeks into pandemic, with no intervention persistence

***Figure 4.11**. Impact of Increasing Efficacy of HIV Testing Intervention on (A) HIV Incidence During 2020-2022 and (B) 2020,* Over 500 Simulations*



*Assumes intervention length of 1 year, intervention coverage of 50% of eligible, intervention began 2 weeks into pandemic, with no intervention persistence

***Figure 4.12**. Impact of Increasing Efficacy of PrEP Retention Intervention on (A) HIV Incidence During 2020-2022 and (B) 2020,* Over 500 Simulations*



*Assumes intervention length of 1 year, intervention coverage of 50% of eligible, intervention began 2 weeks into pandemic, with intervention persistence of 1 year

Chapter 5. Public Health Implications

With over 1.2 million Americans currently living with HIV, and nearly 40,000 new infections every year,[3,119] HIV remains a major public health challenge in the United States. To address this, the US Ending the HIV Epidemic (EHE) initiative aims to reduce new HIV infections in the US by 75% by 2025 and 90% by 2030 by addressing disparities and expanding HIV prevention and treatment efforts in high-need areas like the Southeast US.[38] However, EHE strategies were developed before the pandemic-era changes. Economic and social disruptions from the COVID-19 global pandemic have created new challenges in the control of HIV, prompting major behavioral changes, but also disrupting access to HIV prevention, screening, and clinical care services. These changes have the potential to dramatically impact the trajectory of the US HIV epidemic.

A better understanding of how the COVID-19 pandemic has affected and will continue to affect HIV dynamics in the US is required in order to shape future HIV prevention and care services and research. The goal of this dissertation was to elucidate pandemic-era HIV-related behaviors and HIV transmission dynamics and assess the potential impact of contextually relevant home-based HIV prevention interventions.

Review of Major Findings

In **Chapter 2**, we conducted an empirical analyses of a web-based survey of US MSM to assess the impact of the pandemic on HIV-related behaviors and service interruptions. We found that COVID-related disruptions to HIV prevention and treatment services and changes in sexual behavior continued from early lockdown periods through early 2021. Extended disruptions were observed in HIV testing, STI testing, HIV care clinical visits, and HIV viral load testing, with only small improvements over time. Although sexual behaviors including number of

sexual partners and opportunities to have sex remained below pre-pandemic levels in later 2020 for many MSM, reduced access to HIV prevention, testing, and treatment services that lasted through the year created additional challenges for the control of HIV, which could result in an overall increased HIV transmission rate.

These findings demonstrate that some, though not all, HIV-related pandemic effects continued into early 2021. Our results suggest that the gaps in access to HIV prevention and treatment services have worsened in the pandemic era. In addition to elucidating behavioral patterns that may occur during future pandemics, and therefore aiding in pandemic preparedness, our findings highlight that additional resources and programs may be needed to address existing disparities in HIV prevention and treatment, in addition to solving the new challenges created by the COVID-19 pandemic.

In **Chapter 3**, we used a dynamic network-based HIV transmission model to estimate the incidence of HIV among US MSM during and after the COVID-19 pandemic. We found that HIV incidence among US MSM decreased during 2020, but that incidence returned to pre-pandemic levels in subsequent years, and COVID-related impacts did not translate to long-term increases in HIV transmission in the post-pandemic period. Although we observed temporary decreases in HIV incidence (compared to if the COVID pandemic had not occurred), these reductions were not significant enough to sustain lasting decreases to HIV transmission that will affect the trajectory of the US HIV epidemic.

Our results draw attention to the ongoing need for HIV prevention programs for MSM at risk of HIV infection, HIV testing for those with newly acquired HIV, and for HIV treatment services for men living with diagnosed HIV, both within and outside of a pandemic context. Although our findings demonstrate we may expect long-term marginal/slight decreases in HIV incidence, the trajectory of the US HIV epidemic is still far from the EHE goal of reducing new HIV infections in the US by 90% by 2030; in our study, we noted a decrease in HIV incidence

from 2019 to 2030 of only 14%. Our findings support that additional HIV prevention services are needed in high burden areas to better approach EHE goals.

Lastly, in **Chapter 4**, we used a network-based mathematical model to estimate the effectiveness of at-home HIV testing and PrEP retention interventions among Atlanta MSM in the context of the COVID-19 pandemic. We found that although home-based PrEP retention and HIV testing interventions were effective at increasing PrEP use and/or HIV testing, in isolation they had minimal impact on HIV incidence during a period of decreased transmission. We found that for these individual interventions to translate into meaningful reductions in HIV transmission in a pandemic context, they would need to be scaled up in terms of coverage, length, and post-intervention persistence, or their efficacy and real-world effectiveness would need to improve.

These results demonstrate firstly that home-based interventions can play a role in offsetting the impact of pandemic disruptions on HIV services. However, they also demonstrate that in a pandemic context where widespread decreases in sexual behavior are occurring, increases in HIV testing and PrEP use (non-discontinuation) may not translate into meaningful population-level public health impact.

Strengths and Limitations

A major strength of this dissertation is that is used several independent data sources to determine the impact that the COVID pandemic had on the US HIV epidemic among MSM. First, we used empirical data from the AMIS COVID Impact Survey on COVID-era HIV-related behavior change of US MSM. Then, we used this data alongside other data sources, including the Love and Sex in the Time of COVID study as well as surveillance-based national sources, in order to determine the combined impact of COVID-related change on HIV transmission. From

this, we were then able to combine these data sources to investigate the effect of COVID-related changes on the HIV epidemic and HIV dynamics. If not for combining multiple data sources within a mathematical model, we would not have been able to determine the overall effect these changes had on the US HIV epidemic, nor investigate approaches to counteract their detrimental effects.

On the flipside, the main limitation of this dissertation is that it bears the limitations of all of the data sources it utilized. Our results for each Aim are therefore subject to limitations and biases of the studies from which their data were sourced. In addition, our results were limited by the availability of granular data that appropriately mapped to our study outcomes or model parameters. For example, in Aims 2 and 3, the data that were used to set model parameters did not always map perfectly. For all Aims, we were limited by a lack of granularity of primary data by temporal, demographic, and geographic stratification (because COVID impacts may have changed over short time periods, and impacts may have differed with certain demographic and geographic strata). Our results would be strengthened if data for model parameters, for example, were available at the very specific time points for each key demographic subgroup.

Public Health Implications

Despite recent advancements in biomedical prevention and treatment, HIV risk still remains high for US MSM. Disruptions from the COVID-19 global pandemic created new challenges in the control of HIV, including reducing access to HIV prevention, screening, and clinical care services. However, the actual impact of COVID-related changes on HIV transmission had remained largely unclear. This dissertation investigated the impact and implications of the COVID pandemic on the US HIV epidemic. We demonstrated that the pandemic presented challenges in HIV prevention, but at a population-level, the epidemiologic

impact of behavioral changes resulting from the pandemic outweighed the impact of changes in HIV services to the extent that HIV transmission temporarily decreased because of the COVID pandemic.

This work aids in our understanding of the epidemiologic impact of disruptions to sexual behaviors and HIV prevention and clinical care on HIV incidence during and after the COVID-19 pandemic. Our results advance knowledge of how US MSM change health behaviors during pandemic restrictions, how network-based mathematical models can be used to estimate HIV transmission in a period of service disruptions, and how home-based HIV prevention interventions may affect transmission in a pandemic context.

Though this research is timely at present given its temporal proximity to the COVID pandemic, the questions it addressed will continue to be relevant for years to come. For example, information about how MSM alter their behaviors during periods of service interruptions have implications for HIV prevention outside of a pandemic context, such as in settings of decreasing funding to HIV clinics, which is an ongoing challenge. In addition, COVID-19 is just one extreme example of a respiratory pandemic; inferences drawn from this project will be useful for future pandemic preparedness.

Future Directions

This dissertation has prompted several new research questions that merit investigation.

1. This dissertation only explored the impact of the COVID pandemic on sexual behaviors and clinical services among US MSM through early 2021. Although there are some local US studies that have examined the impact beyond early 2021, large scale nationally representative studies are needed given that the COVID pandemic was still occurring in 2021 and onward, even if most COVID lockdowns had elapsed by early 2021.

2. Although Aim 2 explored how simulated HIV incidence may track with the general trend of real-time HIV diagnoses, a study that disentangles HIV diagnoses from HIV infection/incidence would be useful. That is, a model-based study could incorporate HIV diagnosis data within it (beyond calibration) to assess if HIV diagnoses are a representation of fewer HIV infections or an artifact of reduced screening.
3. Because home-based HIV prevention and HIV care are somewhat novel, there are many important research questions that should be investigated regarding their effectiveness and implementation. Studies are needed that (1.) examine the combined impact of interventions within a pandemic context, (2.) explore how targeted deployment of interventions based on demographic features (e.g., racial/ethnic, age, geography, etc.) or by HIV risk group (i.e., higher risk MSM based on behavior) could affect the epidemiologic impact of interventions, (3.) investigate the general impact that home-based HIV prevention interventions can have outside of pandemic context (given that home-based care could transform HIV prevention and care in the coming years), and (4.) explore the possible impact that home-based event-driven PrEP[209] and long-acting injectable PrEP[210] (assuming it can be dispensed at home) interventions could have, both in and out of a pandemic context.
4. Because our results demonstrated that the US is far from reaching 2030 EHE targets, implementation science studies that examine how we can get to EHE goals given what occurred during the COVID pandemic are needed. This is of particular importance given that approved federal funding for EHE during FY 2019–FY 2023 has fell short of proposed funding.[186]

Appendix A. Technical Appendix for Chapters 3 and 4

Assessing the Impact of COVID-19-Related Behavioral Changes and Clinical Service Disruptions on the HIV Epidemic in the United States: *Supplemental Appendix*

This supplemental technical appendix is based on a previous technical appendix written by Dr. Samuel Jenness (Dissertation Advisor). It has been modified and included in numerous studies that use the *EpiModel* software platform. It has been adapted and expanded here by Laura Mann to support Aims 2 and 3 of her dissertation.

1 Introduction

This supplementary technical appendix describes the mathematical model structure, parameterization, and statistical analysis of dissertation Aims 2 and 3 in further detail.

1.1 Model Framework

The mathematical models for HIV transmission dynamics presented in this study are network-based transmission models in which uniquely identifiable sexual partnership dyads were simulated and tracked over time. This partnership structure is represented using temporal exponential-family random graph models (TERGMs), described in Section 3. On top of this dynamic network simulation, the epidemic model represents demography (entries, exits, and aging), interhost epidemiology (disease transmission), intrahost epidemiology (disease progression), and clinical epidemiology (disease diagnosis and treatment and prevention interventions). Individual attributes related to these processes are stored and updated in discrete time over the course of each epidemic simulation.

The modeling methods presented here utilize and extend the *EpiModel* software platform to incorporate HIV-specific epidemiology and transmission dynamics. The HIV extensions for gay, bisexual and other men who have sex with men (MSM) were originally developed by Goodreau et al. for use in prior modeling studies of MSM in the United States and South America,[211–213] and subsequently used for a model for HIV preexposure prophylaxis (PrEP) among US MSM.[214–217] The most recent innovation in our modeling platform has been to incorporate primary data from the ARTnet study of MSM in the United States directly into the workflow for parameterizing the network and behavioral components.[218]

1.2 Model Software

The models in this study were programmed in the R and C++ software languages using the *EpiModel* [http://epimodel.org/] software platform for epidemic modeling. *EpiModel* was

developed by the authors for simulating complex network-based mathematical models of infectious diseases, with a primary focus on HIV and sexually transmitted infections (STIs).[219] *EpiModel* depends on *Statnet* [http://statnet.org/], a suite of software in R for the representation, visualization, and statistical analysis of complex network data.[220]

EpiModel allows for a modular expansion of its built-in modeling tools to address novel research questions. We have developed a set of extension modules into a software package called *EpiModelHIV*. This software is available for download, along with the scripts used in the execution of these models. The tools and scripts to run these models are contained in two GitHub repositories:

- [http://github.com/statnet/EpiModelHIV] contains the general extension software package. Installing this using the instructions listed at the repository homepage will also load in *EpiModel* and the other dependencies. We use a branching repository architecture on Github; the branch of the repository associated with this research project is CombPrevNet.
- [http://github.com/EpiModel/CombPrevNet] contains the scripts to execute the models and to run the statistical analyses provided in the manuscript.

1.3 Core Model Specifications

For Aim 2, we started with a network size of 100,000 MSM aged 15 to 65 to represent the larger population of sexually active US MSM. For Aim 3, we started with a network size of 100,000 MSM aged 15 to 65 to represent the larger population of sexually active MSM in the Atlanta metropolitan area. The population size was allowed to increase and decrease with arrivals into the sexually active population at age 15 and departures related to mortality or aging out of the sexually active population at age 65. MSM were stratified as Black, Hispanic/Latino (hereafter in the text called Hispanic), and White/Other (hereafter in the text, called White) race/ethnicity in proportions equivalent to Census-derived proportions. Further details on the demography (race and age) are provided in Section 5. We used a three-stage simulation framework, first

calibrating the model to HIV diagnosis rates and HIV care continuum parameters for 60 years of burn-in time (Stage 1), then calibrating the model to current estimated levels of PrEP coverage for 5 years of burn-in time (Stage 2), and then simulating the reference and counterfactual intervention scenarios for 10 years (Stage 3). The time unit used throughout the simulations was one week. Unless otherwise noted, all rate-based parameters listed below are to be interpreted as the rate per week and all duration-based estimates are to be interpreted as the duration in weeks.

2 The ARTnet Study

This model featured an innovative parameterization design in which primary individual-level and partnership-level data were used to fit statistical models for summary statistics that were then entered into the epidemic model. The primary data source for network structure and behavioral data was the ARTnet study, described below. Wherever possible, we used primary data from this study for model parameterization, and only relied on the secondary published literature for model parameters that could be generalized across target populations (e.g., HIV natural history or clinical response parameters).

2.1 Study Design

This analysis used data collected in the ARTnet study of MSM in the United States in 2017–2019.[218] MSM were recruited directly after participating in the American Men's Internet Study (AMIS),[221] a parent web-based study about MSM sexual health that recruited through banner ads placed on websites or social network applications. At the completion of AMIS, MSM were asked to participate in ARTnet, which focused on sexual network features. ARTnet data collection occurred in two waves (following AMIS): July 2017 to February 2018 and September 2018 to January 2019.

Eligibility criteria for ARTnet were male sex at birth, current male cisgender identity, lifetime history of sexual activity with another man, and age between 15 and 65. Respondents were deduplicated within and across survey waves (based on IP and email addresses), resulting in a final sample of 4904 participants who reported on 16198 sexual partnerships. The Emory University Institutional Review Board approved the study.

2.2 Primary Measures

ARTnet participants were first asked about demographic and health-related information. Covariates used in this analysis included race/ethnicity, age, ZIP Code of residence, and current HIV status. ZIP Codes were transformed into Census regions/divisions and urbanicity levels by matching against county databases (using standardized methods for selecting county in the small number of cases when ZIP Codes crossed county lines). Participants reporting as never testing for HIV, having indeterminate test results, or never receiving test results were classified as having an unknown HIV status.

Participants were then asked detailed partner-specific questions for up to most recent 5 partners. The detailed partner-specific questions included attributes of the partner and details about the partnership itself. Partner attributes considered here included age, race/ethnicity, and HIV status. Participants were allowed to report any partner attribute as unknown. When partner age was unknown, age was imputed based on a response to a categorical question (e.g., 5–10 years younger/older, 2–5 years younger/older). Partnerships were classified into three types: “main” (respondent reported they considered this partner a “boyfriend, significant other, or life partner”) casual (someone they have had sex with more than once, but not a main partner), and one-time.[222] For one-time partners, we asked for the date that sexual activity occurred. For persistent (main and casual) partnerships, we asked for the date of most recent sex, the date first sex (which could have been prior to the past year), and whether the partnership was ongoing (if the participant expected sexual activity would occur in the future). For each

partnership, we asked whether (for one-time) or how frequently (for persistent) anal sex occurred.

Outcome measures include descriptive statistics for characteristics of participants and their reported partnerships, and the aggregate network statistics used to estimate the TERGMs underlying epidemic simulations on dynamic networks. The network statistics include ego degree, attribute mixing in partnerships, and the current length of ongoing partnerships, stratified by the attributes of persons and partnerships. Degree is a property of individuals, whereas mixing and length are properties of partnerships. Degree was defined as the ongoing number of persistent partners measured on the day of the survey (includes main and casual partnerships). Degree is not defined for one-time partnerships, so for these we instead calculated a weekly rate of new contacts by subtracting the total main and casual partners from the total past-year partners, and dividing by 52. Partnership length for ongoing main and casual partnerships was calculated by taking the difference between the survey date and the partnership start date. The mean length of ongoing partnerships is the network statistic needed for TERGM estimation; the logic and derivation are explained here.[219] Mixing was measured by the relative frequency of partnerships that occurred within and between groups defined by race/ethnicity, and age.

2.3 Statistical Analysis

We fit a series of generalized linear models (GLMs) to estimate summary statistics for features of the sexual network structure and the behavior within partnerships. Specific GLM parameterizations are detailed below in the discussion of each set of model parameters. Common across all models was the general approach of including geography of residence as a main effect with two levels (Atlanta versus all other areas). This allowed for the model coefficients and predicted summary statistics to vary by geography while ensuring stability of outcomes under the assumption of conditional exchangeability.

3 Networks of Sexual Partnerships

We modeled networks of three interacting types of sexual relations: main partnerships, casual (but persistent) partnerships, and one-time anal intercourse contacts. We first describe the methods conceptually, including the parameters used to guide the model and their derivation, and then present the formal statistical modeling methods. Consistent with our parameter derivations, all relationships are defined as those in which anal intercourse is expected to occur at least once.

3.1 Conceptual Representation of Sexual Networks

Our modeling methods aim to preserve certain features of the cross-sectional and dynamic network structure as observed in our primary data, while also allowing for mean relational durations to be targeted to those reported for different groups and relational types. Our methods do so within the context of changing population size (due to births, deaths, arrivals, and departures from the population) and changing composition by attributes such as age. The broader motivation, methodological details, and link between models and primary data are described here.[219]

The network features that we aim to preserve are as follows:

- Persistent (Main and Casual) Partnerships
    - The mean degree (number of ongoing partners), stratified by main and casual partnership types, and the proportion of men with concurrency (2 or more ongoing partners) for each partnership type, at any time point.
    - Variations in the mean degree specific to each persistent partnership type by:
        - Race/ethnicity group (3 categories for Black, Hispanic, and White MSM).
        - Age group (5 categories for 15–24, 25–34, 35–44, 45–54, and 55–64).

        - Cross-type degree: Degree in the other persistent partnership type (e.g., mean degree of MSM for main partnerships given current casual degree of 0, 1, 2, 3).
    - Selection of partners within the same race/ethnicity group (mixing by race/ethnicity).
    - Selection of partners within the same age group (mixing by age).
    - Mean partnership durations, stratified by main and casual partnership types, and by mixing within age groups.
- One-Time Partnerships
    - The overall rate of having one-time anal intercourse partnerships per week.
    - Variations in this contact rate by:
        - Race/ethnicity group.
        - Age group.
        - Total persistent degree (sum of main and casual partnerships ongoing).
        - Risk level heterogeneity above variations by these three factors (mean partnership rates for five quintiles of MSM stratified by mean one-time rates).
    - Selection of partners within the same race/ethnicity group (mixing by race/ethnicity).
    - Selection of partners within the same age group (mixing by age).
- Common to Persistent and One-Time Partnership Types
    - Prohibitions against MSM with incompatible sexual positioning roles (e.g., no partnerships between exclusively receptive MSM).

3.1.1 Overall Mean Degree for Persistent Partnerships

Ongoing persistent partnerships (whether main or casual) were defined from the partnership-level ARTnet dataset as those in which sex had already occurred more than once, and in which the respondent anticipated having sex again. The momentary main or casual mean degree is then defined as the mean of the degree of all MSM for main or casual partnerships on the day of

study. We estimated this with a Poisson model with main or casual degree as the outcome and a dummy variable for Atlanta residence as the predictor and then exponentiating the coefficients, resulting in an estimated mean main degree of 0.396 and a mean casual degree of 0.541.

In addition, we modeled the proportion of MSM with concurrency (degree of 2 or more) by partnership type. This was estimated with logistic regression models for binary outcomes with a dummy variable for Atlanta residence as the predictor. Taking the inverse of the logit of the coefficient yielded the predicted probabilities of 0.9% for main concurrency and 14.5% for casual concurrency.

3.1.2 Heterogeneity in Mean Degrees for Persistent Partnerships

We estimated the heterogeneity in main and casual mean degree by fitting three Poisson regression models. For race/ethnicity, we estimated the mean degree for each group within the target population by including dummy variables for city and race/ethnicity. For age, we modeled the non-linear relationship between age and mean degrees by including city, age group, and square root of age group to allow for a non-linear relationship between age and the outcome. For cross type degree, we modeled the mean degree for main partnerships as a function of degree of casual partnerships, and vice versa, again with city also as a predictor. For each of the 6 models (2 partnership types times three predictors of interest), we fit the statistical models and then exponentiated the coefficients to obtain the rates for each stratum. Those are shown in the Table below.

Supplemental Table A.1. Heterogeneity in Mean Main and Casual Degree by Race/Ethnicity, Age Group, and Cross		
Predictor	**Main Mean**	**Casual Mean**
Race/Ethnicity		
Black	0.279	0.605

Hispanic	0.423	0.513
White	0.412	0.534
Age Group		
15–24	0.374	0.297
25–34	0.469	0.479
35–44	0.448	0.615
45–54	0.372	0.701
55–64	0.282	0.741
Cross Type		
0	0.440	0.632
1	0.352	0.401
2	0.282	0.255
3	0.225	—

3.1.3 Mixing by Race/Ethnicity and Age for Persistent Partnerships

Respondents reported on their perception of the race and ethnicity (Hispanic/non-Hispanic) for each partner. We categorized the respondents' and partners' races into three mutually exclusive groups: Black, Hispanic, and White. Using logistic regression models, we estimated the proportion of partnerships between MSM of the same race (within-group mixing) by evaluating relationship between the respondent group and partner group as a binary outcome (using geography of residence predictor as a main effect with two levels, Atlanta versus all other areas). The inverse logit of the coefficients is then interpreted as the predicted probability of a same-race/ethnicity partnership. The values were 76.5% for main partnerships and 63.3% for casual partnerships.

For mixing by age, we used a model parameterization for the 5-category age group that allowed for differences in the level of age mixing that could vary by age group (differential homophily). We fit a logistic regression model for partnerships, with being in a partnership of the same age group as the outcome and the age group of the respondent as the main predictor. With the

inverse logit transformation, the probabilities of partnerships within the same age group, stratified by partnership type are shown in the table below.

Supplemental Table A.2. Proportion of Main and Casual Partnerships within the Same Age Group, by Age of Ego

Age Group	Main Within Group	Casual Within
15–24	78.1%	53.2%
25–34	69.6%	42.4%
35–44	59.4%	32.4%
45–54	48.5%	23.7%
55–64	37.6%	16.8%

3.1.4 Duration of Persistent Partnerships

We model partnership dissolution as a heterogenous, geometrically distributed process with unique parameters for each relational type. The geometric distribution for relational durations implies a “memoryless process,” which is a common assumption within ordinary differential equation modeling. Although this assumption implies that the rate of dissolution does not depend on the current age of the partnership, the overall exponential shape of the dissolution distribution matches reasonably well to empirical data on relational durations. The fit is improved considerably when the partnership types are stratified, as we do here, implying a mixture of geometric distributions. Once one-time contacts are removed, and longer-duration main partnerships are separated from shorter-term causal partnerships, the set of distributions fits the empirical data on partnership durations well.

The fit is improved further by stratifying based on the interaction between partnership type and age of both members within the dyad. For this analysis, we explored how relationship duration varied by multiple demographic characteristics, and unsurprisingly age was most strongly associated with duration. For this model parameterization, we specifically elected to estimate

and input based on matched age groups (that is, partnerships between two persons of the same age).

As detailed in previous work,[211,219] for memoryless processes, the expected age of an extant (ongoing) relationship at any moment in time is an unbiased estimator of the expected uncensored duration of relationships, given the balancing effects of right-censoring and length bias for this distribution. Raw relational ages were calculated as the difference between first sex date and the study date for each dyad the ego reported sex with more than once in the interval. To derive our estimator of relational age, we take the median of the observed distribution and then calculate the mean for the geometric distributions associated with that median. To account for estimation within the Atlanta target population, we weighted this estimator by the inverse of the relative differences in Atlanta partnerships to non-Atlanta partnerships.

The resulting expected relational ages are summarized in the table below.

Supplemental Table A.3. Duration of Main and Casual Partnerships by Group of Ego (Respondent) and Alter (Partner)

Dyadic Age Group	Main Relational Age (Weeks)	Casual Relational Age (Weeks)
Both 15–24	71.2	50.5
Both 25–34	253.5	72.5
Both 35–44	523.3	112.1
Both 45–54	637.1	161.3
Both 55–64	903.1	147.4
Different Groups	217.9	106.4

3.1.6 Overall Mean One-Time Contact Rate

In addition to persistent main and casual partnerships, we modeled one-time sexual contacts involving anal intercourse based on ARTnet reports on the number and variation in these types

of relations. As noted above, degree is not defined for one-time contacts, so for these we instead calculated a weekly rate of new contacts by subtracting the total main and casual partners from the total past-year partners. We estimated the weekly rate by fitting a Poisson regression model with the count of one-time contacts as a function of city, exponentiating the coefficient to get the predicted count, and dividing by 52 to get the week rate. The overall mean one-time contact rate was 0.076 AI contacts per week.

3.1.7 Heterogeneity in One-Time Contact Rates

Heterogeneity in one-time contact rates was modeled with four Poisson regression models to estimate the rates as a function of race/ethnicity, age group, risk level strata, and total persistent (main plus casual) degree. Similar to the one-time rate, we fit these models with geography of residence as a main effect (which had two levels, Atlanta versus all other areas, with the former level used for predictions) and exponentiated the coefficients and then divided by 52 to get the group-specific rates. For age group, similar to the estimation of degree, we modeled this non-linearly by including age group and the square root of age group as the joint predictors (along with city). The results are shown in the table below.

Supplemental Table A.4. Weekly One-Time Contact Rates by Race/Ethnicity, Age Group, Risk Level, and Total Persistent Degree of Ego (Respondent)

Predictor	**Weekly Contact**
Race/Ethnicity	
Black	0.062
Hispanic	0.071
White	0.079
Age Group	
15–24	0.048
25–34	0.075
35–44	0.089

45–54	0.093
55–64	0.087
Risk Level Quintile	
1	0.000
2	0.000
3	0.012
4	0.043
5	0.326
Total Persistent	
0	0.049
1	0.057
2	0.121
3+	0.284

3.1.8 Mixing by Race/Ethnicity and Age for One-Time Contacts

We used a similar approach to within-group mixing by race/ethnicity and age group for one-time contacts to the one used for persistent contacts, with one difference that we did not model differential homophily by age group to improve model stability. Therefore, the overall proportion of one-time contacts that were within the same race/ethnic group was 67.6% and the proportion of one-time contacts that were within the same age group was 32.8%.

3.1.9 Mixing by Sexual Role Across All Partnership Types

We assign men a fixed sexual role preference (exclusively insertive, exclusively receptive, versatile). The model then includes an absolute prohibition, such that two exclusively insertive men cannot partner, nor can two exclusively receptive men. We estimated the proportion men were in each category (insertive, receptive, and versatile) by analyzing whether men had only insertive anal intercourse, only receptive anal intercourse, or both insertive and receptive anal intercourse (respectively) in their past five anal partnerships over the past year. These

proportions were stratified (restricted) by geography of residence to the city of Atlanta. The proportions were: 18.5% exclusively insertive, 27.1% exclusively receptive, and 54.4% versatile.

3.2 Statistical Representation of Sexual Networks

Exponential-family random graph models (ERGMs) and their dynamic extension temporal ERGMs (TERGMs) provide a foundation for statistically principled simulation of local and global network structure given a set of target statistics from empirical data. Main and casual relationships were modeled using TERGMs,[223] since they persist for multiple time steps. One-time contacts, on the other hand, were modeled using cross-sectional ERGMs.[224] Formally, our statistical models for relational dynamics can be represented as five equations for the conditional log odds (logits) of relational formation and persistence at time *t* (for main and casual relationships) or for relational existence at time *t* (for one-time contacts):

$$logit\left(P\left(Y_{ij,t}=1\middle|\, Y_{ij,t-1}=0,\, Y^{C}_{ij,t}\right)\right) = \theta_m^{+\prime}\partial\left(g_m^{+}(y)\right) \qquad \text{Main partnership formation}$$

$$logit\left(P\left(Y_{ij,t}=1\middle|\, Y_{ij,t-1}=0,\, Y^{C}_{ij,t}\right)\right) = \theta_c^{+\prime}\partial\left(g_c^{+}(y)\right) \qquad \text{Casual partnership formation}$$

$$logit\left(P\left(Y_{ij,t}=1\middle|\, Y_{ij,t-1}=1,\, Y^{C}_{ij,t}\right)\right) = \theta_m^{-\prime}\partial\left(g_m^{-}(y)\right) \qquad \text{Main partnership persistence}$$

$$logit\left(P\left(Y_{ij,t}=1\middle|\, Y_{ij,t-1}=1,\, Y^{C}_{ij,t}\right)\right) = \theta_c^{-\prime}\partial\left(g_c^{-}(y)\right) \qquad \text{Casual partnership persistence}$$

$$logit\left(P\left(Y_{ij,t}=1\middle|\, Y^{C}_{ij,t}\right)\right) = \theta_o{}'\partial\left(g_o(y)\right) \qquad \text{One-time contact existence}$$

where:

- $Y_{ij,t}$ = the relational status of persons *i* and *j* at time *t* (1 = in relationship/contact, 0 = not).
- $Y^{C}_{ij,t}$ = the network complement of *i,j* at time *t*, i.e. all relations in the network other than *i,j.*

- $g(y)$ = vector of network statistics in each model (the empirical statistics defined in the tables above).
- $\partial\big(g(y)\big)$ = the change in $g(y)$ when Y_{ij} is toggled from 0 to 1 (for formation models) or 1 to 0 (for persistence models).
- θ = vector of parameters in the model.

For $g(y)$ and θ, the superscript distinguishes the formation model (+), persistence model (-) and existence models (neither). The subscript indicates the main (m), casual (c) and one-time (o) models.

The recursive dependence among the relationships renders the model impossible to evaluate using standard techniques; we use MCMC in order to obtain the maximum likelihood estimates for the $\boldsymbol{\theta}$ vectors given the $\boldsymbol{g}(\boldsymbol{y})$ vectors.

Our method of converting the statistics laid out in Section 3.1 into our fully specified network models consists of the following steps:

1. Construct a cross-sectional network of 10,000 men with no relationships.
2. Assign men demographics (race/ethnicity and age) based on Census data for Atlanta and assign men sexual roles based on frequencies listed above, as well as one-time risk quintiles (20% of the men in each race per quintile).
3. Calculate the target statistics (i.e., the expected count of each statistic at any given moment in time) associated with the terms in the formation model (for the main and casual partnerships) and in the existence model (for one-time contacts).
4. Assign each node a place-holder main and casual degree (number of on-going partnerships) that is consistent with the estimated distributions, and store these numbers as a nodal attribute. (Note: this does not actually require individuals to be paired up into the partnerships represented by those degrees).

5. For the main and casual networks, use the mean relational durations by age group combination to calculate the parameters of the persistence model, using closed-form solutions, given that the models are dyadic-independent (each relationship's persistence probability is independent of all others).
6. For the main and casual networks, estimate the coefficients for the formation model that represent the maximum likelihood estimates for the expected cross-sectional network structure.
7. For the one-time network, estimate the coefficients for the existence model that represent the maximum likelihood estimates for the expected cross-sectional network structure.

Steps 5–7 occur within the *EpiModel* software, and use the ERGM and STERGM methods therein. They are completed efficiently by the use of an approximation in Step 6.[225] During the subsequent model simulation, we use the method of Krivitsky[226] to adjust the coefficient for the edges term in each model at each time step, in order to preserve the same expected mean degree (relationships per person) over time in the face of changing network size and nodal composition. At all stages of the project, simulated partnership networks were checked to ensure that they indeed retained the expected cross-sectional structure and relational durations throughout the simulations.

4 Behavior Within Sexual Partnerships

In this study, we model three phenomena consecutively within relationships at each time step: the number of anal intercourse sex acts, condom use per sex act, and sexual role per sex act. We simulate these within all relationships regardless of HIV status (whether diagnosed or not).

4.1 Anal Intercourse Acts Per Partnership

The rate of anal intercourse is applicable to persistent (main and casual) partnerships in which there are repeated AI acts between the start and end of the partnership. We use ARTnet data on the overall rate and predictors of variation in rates unique to each partnership type. For one-time contacts, we assumed that the number of AI exposures was one, although there could have been multiple AI acts within an exposure due to role versatility (see Section 4.4). The modeling of act rates here is based on the expectation that changes in coital frequency depend on race/ethnicity, age, diagnosed HIV status, and partnership type.

4.1.1 Measurement of Acts in ARTnet

We measured the number of acts within each reported partnership within the ARTnet study by asking participants about the frequency of AI acts. Study participants could report on the average number of acts within the partnership over the past year by week, month, year, or total partnership duration. We then scaled this into a total weekly act rate. The final ARTnet partnership-level dataset on 16198 partnerships includes this weekly rate as the outcome and predictors at the individual and dyadic level that we used for statistical modeling as described below.

4.1.2 Statistical Models of Act Rates

With this partnership-level dataset, we then modeled the count of acts per year per partnership based on the Poisson regression formula:

$$Y_i \sim b_0 + b_1X_1 + b_2X_1^2 + b_3X_2 + b_4X_3 + b_5X_1X_3 + b_6X_4 + b_7X_4^2 + b_8X_5 + b_9X_6$$

where:

Y_i = Log of the count of acts per year.

X_1 = Duration of partnership in weeks at the survey date.

X_2 = Racial/ethnic combination of the ego (respondent) and alter (partner), coded in 6 categories to capture within and across group mixing: Black-Black, Black-Hispanic/White, Hispanic-Black/White, Hispanic-Hispanic, White-Black/Hispanic, White-White.

X_3 = Partnership type (0 = main; 1 = casual).

X_4 = The combined age of ego and alter in years.

X_5 = The concordant diagnosed HIV-positive status of both ego and alter, compared to all other combinations of dyadic HIV status (1 = concordant positive; 0 = all other combinations of dyadic HIV status).

X_6 = Residence (1 = Atlanta metropolitan area; 0 = all other areas).

Note that we modeled the partnership duration and combined age of partners quadratically, and we modeled the interaction of partnership duration and partnership type. Terms within the prediction model were selection based on a combination of *a priori* theory and exploratory data analysis. The coefficients for the model, and their lower and upper 95% confidence intervals, are presented in the table below. Exponentiating any linear combination of coefficients will yield the yearly rates, which may be converted to weekly through division.

Supplemental Table A.5. Statistical Model of Act Rates in Main and Casual Partnerships

Model Parameter	**Estimate**	**Lower 95% CI**	**Upper 95% CI**
b_0 (Intercept)	4.9615	4.9208	5.002
b_1 (Duration)	-0.0013	-0.0013	-0.0012
b_2 (Duration^2)	6.3197E-07	6.0598E-07	6.5781E-07
b_3 (B-H/W Combo)	0.5196	0.4888	0.5505
b_3 (H-B/W Combo)	0.2178	0.1908	0.2449

b_3 (H-H Combo)	0.1967	0.1687	0.2250
b_3 (W-B/H Combo)	0.4758	0.4505	0.5013
b_3 (W-W Combo)	0.1765	0.1516	0.2016
b_4 (Casual Type)	-1.0373	-1.0458	-1.0287
b_5 (Duration x Casual Type)	-0.0009	-0.0010	-0.0009
b_6 (Combined Age)	-0.0113	-0.0122	-0.0104
b_7 (Combined Age^2)	5.6269E-05	5.0154E-05	6.2374E-05
b_8 (HIV+ Concordant)	0.3614	0.3452	0.3776
b_9 (Atlanta residence)	-0.0229	-0.0396	-0.0063

Abbreviations: CI, confidence interval; B-H/W, Black ego with either a Hispanic or White alter; H-B/W, Hispanic ego with either a Black or White alter; H-H, Hispanic ego with a Hispanic alter; W-B/H, White ego with either a Black or Hispanic alter; W-W, White ego with a White alter.

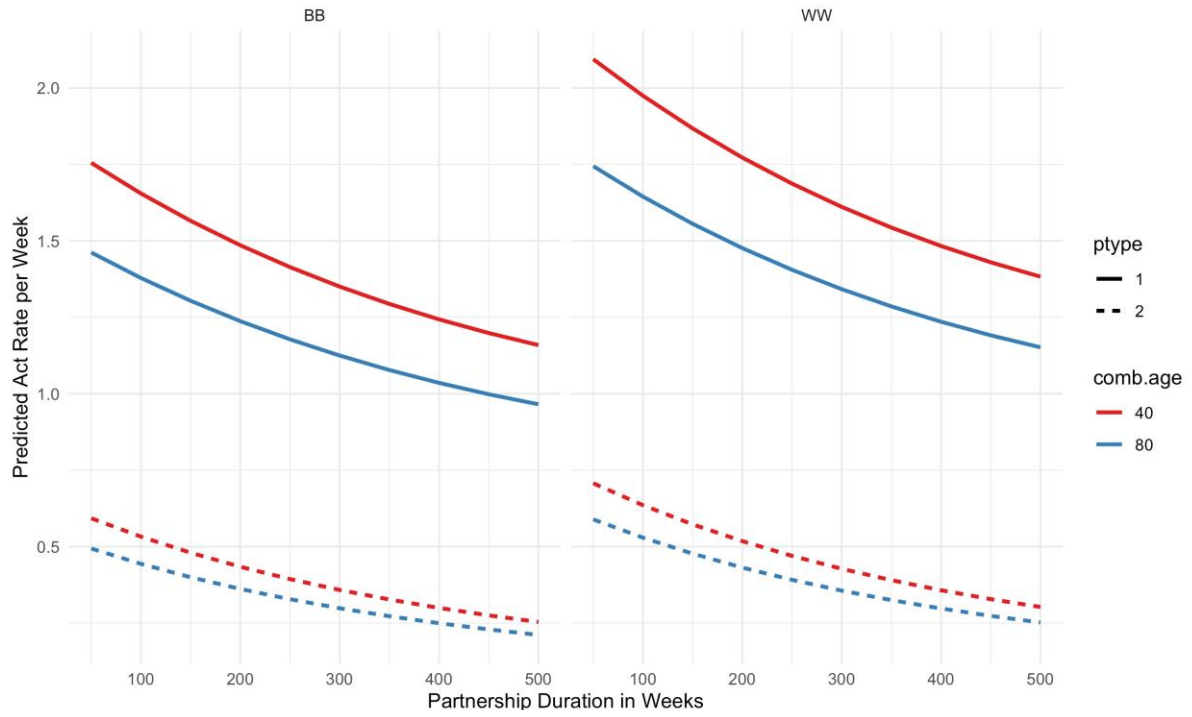
4.1.3 Predicted Rates in Epidemic Model

Predicted weekly rates of AI based on the combination of partnership and individual attributes is then obtained dynamically by predicting from the statistical model with inputs based on the current simulated population. *EpiModel* tracks the current age of partners, the duration of their partnership, their racial combination, and the partnership type. This set of predictors was input into a predict function in R to obtain the weekly mean rates in each strata. The size of the potential set of strata and corresponding predicted means is therefore nearly infinite based on all the potential combinations of input values.

In Supplemental Figure A.1 below, we display some example weekly rates based on a subset of model inputs. This figure shows that rates decline in partnerships with a longer duration, that they are higher in partnerships in which both partners are younger, they are lower for casual partnerships (ptype = 2) compared to main partnerships, and that they are higher in White-White partnerships compared to Black-Black partnerships. The act rates generally ranged from

0.5 acts per week to 2 acts per week. Other predicted rates may be obtained by exponentiating the coefficients in the table above and dividing by 52 (to convert from yearly rates to weekly rates).

Supplemental Figure A.1. Predicted Weekly Act Rates from the Poisson Statistical Model, by Partnership Duration, Partnership Type (ptype: 1 = Main; 2 = Casual), Combined Partner Age (comb.age: 40 and 80 Years).



Based on these model predictions, which represent means for each linear combination, we then drew individual counts of acts per partnership per time step in *EpiModel* using the rpois function to draw randomly from the Poisson distribution with a vector of parameters, one value for each partnership.

4.1.4 Cessation of Sexual Activity During Late-Stage AIDS

In addition to these data-driven statistical calculations, we assumed that MSM in late stages of AIDS (HIV viral load above 5.75), had no acts due to active disease that would limit their sexual activity. This reflected the mid-point between set-point viral load of chronic stage infection (4.5 $\log_{10}$) and peak viral load (7.0 $\log_{10}$, corresponding to the nadir of immunological function). We

had no primary data in ARTnet on sexual partnerships in this late disease stage, but prior analysis and modeling studies support a large decline in sexual activity due to AIDS.[227]

4.2 Condom Use Per Act

We modeled condom use within all three partnership types (main, casual, and one-time contacts) based on ARTnet data on the frequency of condom use within reported partnerships. We followed the same general approach to measuring, fitting statistical models, and dynamically predicting condom use within *EpiModel* as we used for rates of AI. The modeling of condom here is based on the expectation that changes in condom use depend on race/ethnicity, age, diagnosed HIV status, current PrEP use, and partnership type.

4.2.1 Measurement of Condom Use in ARTnet

We measured condom use within partnerships in the ARTnet study by asking about the frequency of condom use (for persistent partnerships) or whether condom use occurred (for one-time partnerships) during anal intercourse. Study participants first reported on the number of AI acts that occurred in the time intervals described above, and then we followed-up with a question on the number of those total acts that involved condom use. We then transformed these subsetted counts into proportions of acts that were condom-protected. This resulted in a U-shaped distribution of proportions, with most persistent partnerships involving either always or never condom use. For this current study, we simplified the outcome variable to any condom use (yes, no) over the past year.

4.2.2 Statistical Models of Condom Use Probabilities

With the outcome described above, we used the partnership-level dataset to fit two logistic regression models for any condom use in the partnership, with one model for persistent (main and casual) and another model for one-time partnerships. The linear model formula for persistent partnerships was as follows:

$$Y_i \sim b_0 + b_1X_1 + b_2X_1^2 + b_3X_2 + b_4X_3 + b_5X_1X_3 + b_6X_4 + b_7X_4^2 + b_8X_5 + b_9X_6 + b_{10}X_7$$

where:

Y_i = Log odds of the probability of condom use per act.

X_1 = Duration of partnership in weeks at the survey date.

X_2 = Racial/ethnic combination of the ego (respondent) and alter (partner), coded in 6 categories to capture within and across group mixing: Black-Black, Black-Hispanic/White, Hispanic-Black/White, Hispanic-Hispanic, White-Black/Hispanic, White-White.

X_3 = Partnership type (0 = main; 1 = casual).

X_4 = The combined age of ego and alter in years.

X_5 = The concordant diagnosed HIV-positive status of both ego and alter, compared to all other combinations of dyadic HIV status (1 = concordant positive; 0 = all other combinations of dyadic HIV status).

X_6 = Current use of pre-exposure prophylaxis (PrEP) by the ego (respondent).

X_7 = Residence (1 = Atlanta metropolitan area; 0 = all other areas).

Note that we modeled the partnership duration and combined age of partners quadratically, and we modeled the interaction of partnership duration and partnership type. Terms within the prediction model were selected based on a combination of *a priori* theory and exploratory data analysis. The coefficients for the model, and their lower and upper 95% confidence intervals, are presented in the table below. Taking the inverse logit of the linear combination of coefficients will yield to the strata-specific predicted probabilities of condom use within the partnership.

Supplemental Table A.6. Statistical Model of Per Act Condom Use Probability for Main and Casual Partnerships

Model Parameter	Estimate	Lower 95% CI	Upper 95% CI
b_0 (Intercept)	2.008	1.3020	2.7144
b_1 (Duration)	-0.0031	-0.0040	-0.0023
b_2 (*D*uration^2)	1.2561E-06	5.8878E-07	1.8614E-06
b_3 (B-H/W Combo)	-0.3355	-0.8549	0.1802
b_3 (H-B/W Combo)	-0.3692	-0.7798	0.04214
b_3 (H-H Combo)	-0.3989	-0.8314	0.0336
b_3 (W-B/H Combo)	-0.4402	-0.8235	-0.0557
b_3 (W-W Combo)	-0.5031	-0.8738	-0.1310
b_4 (Casual Type)	0.5710	0.4084	0.7347
b_5 (Duration x Casual Type)	-0.0467	-0.0638	-0.0294
b_6 (Combined Age)	0.0002	9.5502E-05	0.0003
b_7 (Combined Age^2)	-1.6150	-2.1624	-1.1322
b_8 (HIV+ Concordant)	-0.5248	-0.6790	-0.3724
b_9 (PrEP Use)	0.1701	-0.1385	0.4743
b_{10} (Atlanta residence)	0.0012	0.0005	0.0019

Abbreviations: CI, confidence interval; B-H/W, Black ego with either a Hispanic or White alter; H-B/W, Hispanic ego with either a Black or White alter; H-H, Hispanic ego with a Hispanic alter; W-B/H, White ego with either a Black or Hispanic alter; W-W, White ego with a White alter; PrEP, preexposure prophylaxis.

For the logistic regression model of one-time partnerships, we used a similar logistic regression approach as for persistent partnerships but dropped the partnership duration and partnership type (since there was only one type for this model) predictor variables. The corresponding linear model formula for persistent partnerships was as follows:

$$Y_i \sim b_0 + b_1X_1 + b_2X_2 + b_3X_2^2 + b_4X_3 + b_5X_4 + b_6X_5$$

where:

Y_i = Log odds of the probability of condom use per one-time contact.

X_1 = Racial/ethnic combination of the ego (respondent) and alter (partner), coded in 6 categories to capture within and across group mixing: Black-Black, Black-Hispanic/White, Hispanic-Black/White, Hispanic-Hispanic, White-Black/Hispanic, White-White.

X_2 = The combined age of ego and alter in years.

X_3 = The concordant diagnosed HIV-positive status of both ego and alter, compared to all other combinations of dyadic HIV status (1 = concordant positive; 0 = all other combinations of dyadic HIV status).

X_4 = Current use of pre-exposure prophylaxis (PrEP) by the ego (respondent) (1 = yes; 0 = no)

X_5 = Residence (1 = Atlanta metropolitan area; 0 = all other areas).

The coefficients for the model, and their lower and upper 95% confidence intervals, are presented in the table below. Taking the inverse logit of the linear combination of coefficients will yield to the strata-specific predicted probabilities of condom use within the partnership.

Supplemental Table A.7. Statistical Model of Per-Act Condom Use Probability for One-Time Sexual Contacts

Model Parameter	Estimate	Lower 95% CI	Upper 95% CI
b_0 (Intercept)	2.4287	1.6597	3.2007
b_1 (B-H/W Combo)	0.1526	-0.3728	0.6785
b_1 (H-B/W Combo)	-0.1042	-0.5311	0.3221
b_1 (H-H Combo)	-0.10538	-0.5617	0.3506
b_1 (W-B/H Combo)	-0.1189	-0.5205	0.2825
b_1 (W-W Combo)	-0.2507	-0.6414	0.1396
b_2 (Combined Age)	-0.0542	-0.0733	-0.0351
b_2 (Combined Age^2)	0.0003	0.0001	0.0004
b_3 (HIV+ Concordant)	-1.8369	-2.6547	-1.1610
b_4 (PrEP Use)	-0.7133	-0.8732	-0.5553
b_5 (Atlanta residence)	0.3102	0.0107	0.6095

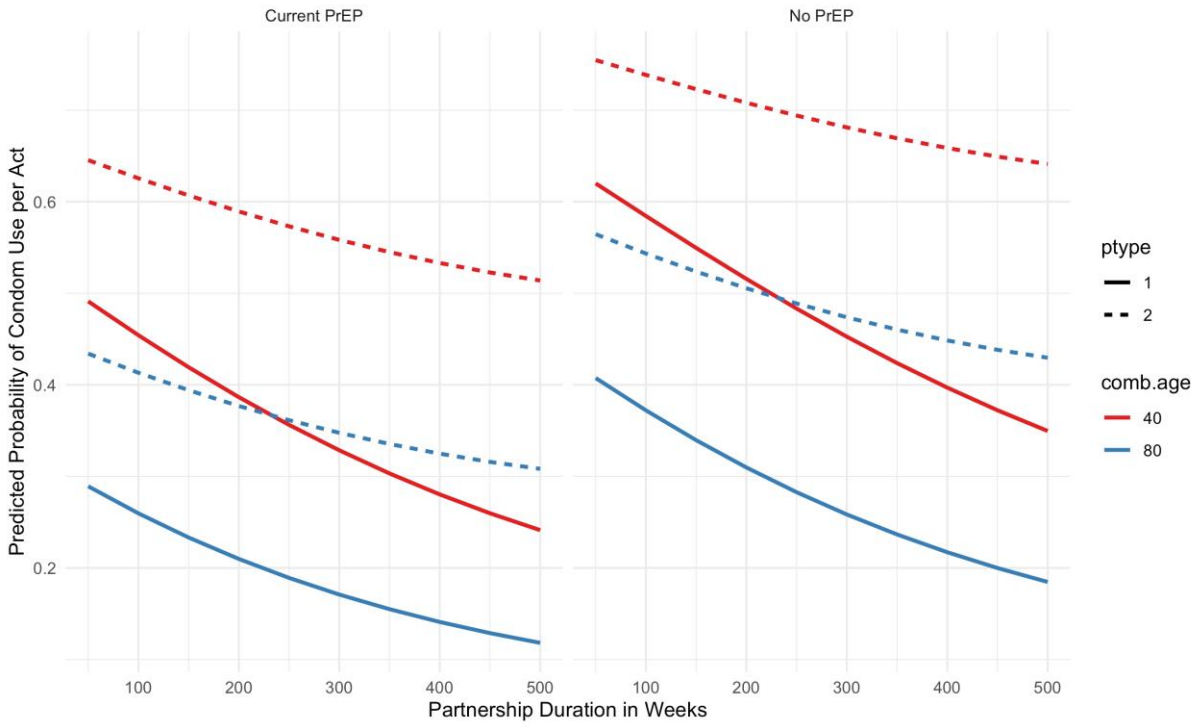
Abbreviations: CI, confidence interval; B-H/W, Black ego with either a Hispanic or White alter; H-B/W, Hispanic ego with either a Black or White alter; H-H, Hispanic ego with a Hispanic alter; W-B/H, White ego with either a Black or Hispanic alter; W-W, White ego with a White alter; PrEP, preexposure prophylaxis.

4.2.3 Predicted Probabilities in Epidemic Model

Predicted probabilities of condom use conditional on an AI act were calculated based on the linear combination of partnership and individual attributes obtained dynamically by predicting from the statistical model with inputs based on the current simulated population. This set of predictors was input into a predict function in R to obtain the expected mean probabilities.

In Supplemental Figure A.2 below, we display some example probabilities based on a subset of model inputs. This figure shows that condom use is lower in partnerships of a longer duration, higher in casual compared to main partnerships, higher when both partners are younger, and lower in partnerships in which the ego (respondent) reported currently using PrEP. Other predicted probabilities may be obtained from Supplemental Table A.6 by taking the inverse logit of the linear combination of coefficients of interest.

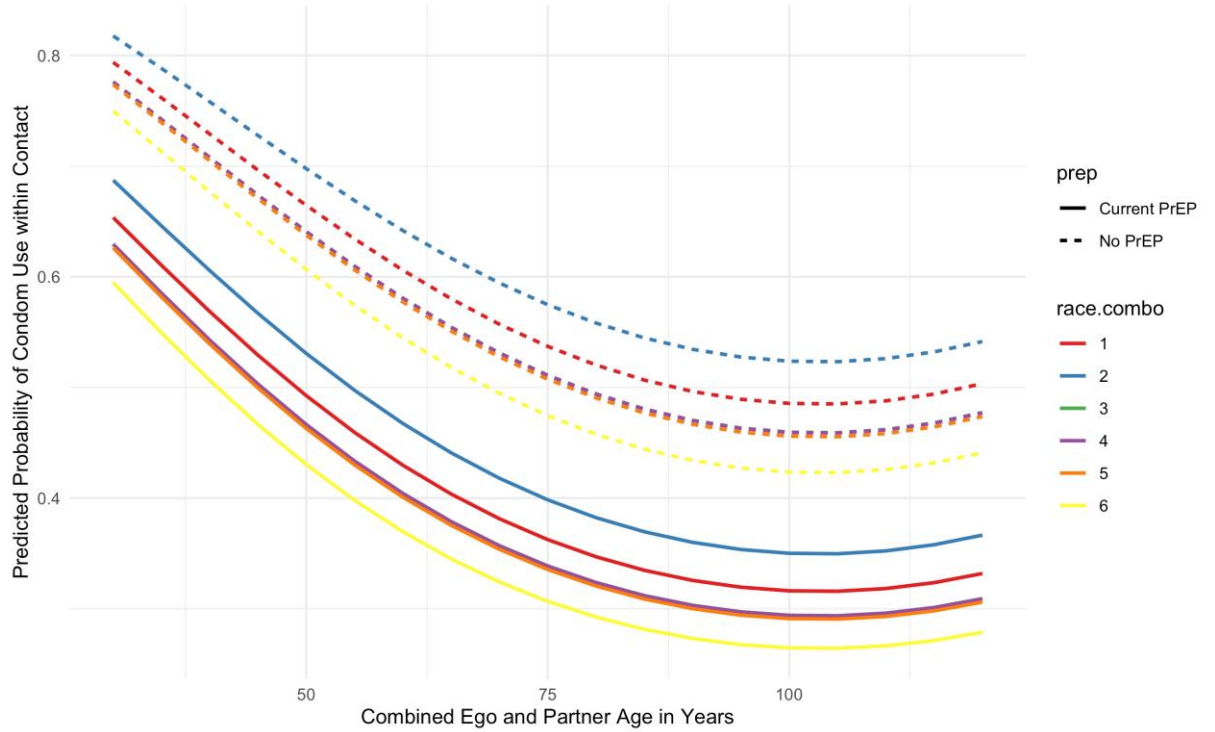
Supplemental Figure A.2. Predicted Probabilities of Condom Use Per AI Act in Persistent Partnerships from the Logistic Regression Model, by Partnership Duration, Partnership Type (ptype: 1 = Main; 2 = Casual), Combined Partner Age (comb.age: 40 or 80 years), and PrEP Use.



Supplemental Figure 3 shows the predicted probabilities for the second logistic model, for condom use within one-time AI contacts. Here we display variation in condom use by combined age of the partners, current PrEP use, and racial combination of the partners. As the figure shows, condom use is higher within partners of a lower combined age, higher in partnerships involving Black MSM (race.combo = 1 or 2), and lower among current PrEP users.

Based on these model predictions, which represent expected probabilities for each linear combination, we then drew individual probabilities of condom use per act in *EpiModel* using the rbinom function to draw randomly from the Bernoulli distribution with a vector of parameters, one value for each act. This generated a set of 0's and 1's for whether condom use occurred within the act as a function of the predictors in the statistical model.

Supplemental Figure A.3. Predicted Probabilities of Condom Use in One-Time AI Contacts from the Logistic Regression Model, by Combined Partner Age, Current PrEP Use, and Racial Combination of Partners (race.combo: 1 = black ego-black alter; 2 = black ego-Hispanic or White alter; 3 = Hispanic ego-black or White alter; 4 = Hispanic ego-Hispanic alter; 5 = White ego-black or Hispanic alter; 6 = White ego-White alter.



4.4 Sexual Role

Men were assigned an individual sexual role preference (exclusively insertive, exclusively receptive, or versatile) as described in Section 3.1.9. Relationships between two exclusively insertive or two exclusively receptive men are prohibited via the TERGM models. Versatile men were further assigned a preference for being the insertive partner drawn from a uniform

distribution between 0 and 1 upon entry into the population; we refer to this proportion as the ‘insertivity quotient’. When two versatile men are simulated to have an anal intercourse act, their sexual positions during that act must be determined (all other allowed combinations have only one direction). One option is for men to engage in intra-event versatility (IEV; i.e. both men engage in insertive and receptive anal intercourse during the act). The probability of this was derived from the partner-specific role data described in Section 3.1.9. If IEV does not occur, then each man’s probability of being the insertive partner equals his insertivity quotient divided by the sum of the two men’s insertivity quotients.

5 Demography and Initial Conditions

In this model, there are three demographic processes: entries, exits, and aging. Entries and exits are conceptualized as flows into and out of the sexually active population of interest: MSM aged 15 to 65 years old. Entry into this population represents the time at which persons become at risk of infection via male-to-male sexual intercourse, and we model these flows as starting at an age associated with sexual debut and ending at an age potentially before death (age 65). This age range also mapped directly on to the eligibility criteria of the ARTnet study.[228]

5.1 Arrivals at Sexual Onset

All persons enter the network at age 15, which was the lower age boundary of ARTnet. The number of new entries at each time step was based on a fixed rate (0.052 per 100 person-weeks) that kept the overall network size in a relatively stable state. The model parameter governing this rate was tuned iteratively to generate simulations with a population size at equilibrium, given the inherent variability in population flows related to background mortality, sexual cessation (i.e., reaching the upper age limit of 65), and disease-induced mortality. At each time step, the exact number of men entering the population was simulated by drawing from a Poisson distribution with the rate parameter.

5.2 Initialization of Attributes

Persons entering the population were assigned attributes in different categories. Some attributes remained fixed (e.g., race/ethnicity), others were fixed by assumption (e.g., insertive versus receptive sexual role), and others were allowed to vary over time (e.g., age and disease status). Here we describe attributes initialized at the outset in the model and for arrivals into the population at each time step:

- **Race/ethnicity.** This model was based on a race/ethnic population composition categorized into three mutually exclusive groups: Black, Hispanic, and White. At the outset of the model simulations, individuals were randomly assigned into one of these three groups with a probability equal to the proportions each represented in the Atlanta metropolitan target population based on 2018 Census data estimates for men aged 15 to 65. Those probabilities were: 51.5% Black, 4.6% Hispanic, and 43.9% white. Incoming nodes during the dynamic simulation were also randomly assigned a race/ethnicity in these proportions.
- **Age.** In the dynamic simulation, as noted above, all incoming nodes were assigned an age of 15, which incrementally grew in weekly time steps. At the outset of the model simulations, we assigned nodes an age based on a uniform distribution, with ages from 15 to 65. This population-level age distribution was expected to converge to a more realistic distribution during model burn-in and calibration (explained in Section 9.2).
- **HIV Status.** In the dynamic simulation, all incoming nodes were assigned an HIV status of uninfected upon arrival into the population. This reflects the assumption that arrival corresponded with sexual debut, before which exposure to HIV would be very rare. At the outset of the model simulations, we randomly seeded the nodes with HIV infection by fitting and predicting from a logistic regression of diagnosed HIV status from the ARTnet data. This model incorporated city (residence in Atlanta), age, and race/ethnicity as the

primary predictors based on the self-reported diagnosed HIV status reported by ARTnet respondents. These initial infections were all assumed to be diagnosed based on this outcome. We did not expect that this initial condition of diagnosed HIV prevalence at the outset of the burn-in model to match the calibrated disease prevalence prior to experimental intervention models; instead, this statistical modeling approach allowed for a data-driven seeding of HIV infection in the population that was distributed according to known demographic and geographic heterogeneity. Further description of the transition from initial HIV conditions to calibrated levels are provided in Section 8.2.

- **Circumcision Status.** Circumcision status was randomly assigned to incoming nodes at arrival and for all nodes as initial conditions in the simulations. Based on empirical data from Atlanta MSM,[229] 89.6% of men were circumcised before sexual onset. As described in Section 8, circumcision was associated with a 60% reduction in the per-act probability of infection for HIV- males for insertive anal intercourse only (i.e., circumcision did not lower the *transmission* probability if the HIV+ partner was insertive).[212,230]

5.3 Departures from the Network

All persons exited the network by age 65, either from mortality or by reaching the upper age bound of the MSM target population of interest. This upper limit of 65 was modeled deterministically (probability = 1), but other exits due to mortality were modeled stochastically. Departures included both natural (non-HIV) and disease-induced mortality causes before age 65. Background mortality rates were based on US all-cause mortality rates specific to age and race/ethnicity from the National Vital Statistics life tables.[231] Note that these rates include deaths due to HIV/AIDS; however, the relative fraction of those deaths to total deaths is small enough not to impact this background mortality process. Supplemental Table 8 shows the probability of mortality per year by age and race/ethnicity.

Supplemental Table A.8. Age- and Race/Ethnicity-Specific Probabilities of Mortality among Men in the United States

Age	Black	Hispanic	White
15–19	0.00166	0.00080	0.00065
20–24	0.00299	0.00153	0.00127
25–29	0.00329	0.00175	0.00174
30–34	0.00396	0.00197	0.00226
35–39	0.00473	0.00242	0.00274
40–44	0.00590	0.00309	0.00332
45–49	0.00799	0.00437	0.00444
50–54	0.01130	0.00653	0.00653
55–59	0.01699	0.01013	0.00990
60–64	0.02553	0.01488	0.01443

These yearly probabilities were transformed into weekly risks. Natural mortality was then applied to persons within the population at each time step stochastically by drawing from a Bernoulli distribution for each eligible person with a probability parameter corresponding to their age- and race-specific risk of death. Disease-related mortality, in contrast, was modeled based on clinical disease progression, as described in Section 6.

5.4 Aging

The aging process in the population was linear by time step for all persons. The unit of time step in these simulations was one week, and therefore, persons were aged in weekly steps between the minimum and maximum ages allow (15 and 65 years old). Evolving age impacted background mortality, age-based mixing in forming new partnerships, and other features of the epidemic model described below. Persons who exited the network were no longer active and their attributes such as age were no longer updated.

6 Intrahost Epidemiology

Intrahost epidemiology includes features related to the natural disease progression within HIV+ persons in the absence of clinical intervention. The main component of progression that was explicitly modeled for this study was HIV viral load. In contrast to other modeling studies that model both CD4 and viral load, our study used viral load progression to control both interhost epidemiology (HIV transmission rates) and disease progression eventually leading to mortality.

Following prior approaches,[211,212,214,216,232] we modeled changes in HIV viral load to account for the heightened viremia during acute-stage infection, viral set point during the long chronic stage of infection, and subsequent rise of VL at clinical AIDS towards disease-related mortality. The HIV viral load has a direct impact on the rates of HIV transmission within serodiscordant pairs in the model, and this interaction is detailed in Section 8. A starting viral load of 0 is assigned to all persons upon infection. From there, the natural viral load curve is fit with the following parameters.

Supplemental Table A.9. HIV Natural History Parameters

Parameter	Value	Reference
Time to peak viremia in acute stage	21 days	Robb[233]
Level of peak viremia	6.886 $\log_{10}$	Little[234]
Time from peak viremia to viral set point	21 days	Robb[233]
Level of viral set point	4.5 $\log_{10}$	Little[234]
Duration of chronic stage infection (no ART)	3550 days	Buchbinder,[235] Katz[236]
Duration of AIDS stage	728 days	Buchbinder[235]
Peak viral load during AIDS	7 $\log_{10}$	Estimated from average duration of AIDS

After infection, it takes 21 days to reach peak viremia, at a level of 6.886 $\log_{10}$. This was estimated as 13 days in Robb et al.,[233] but we added an additional 8 days to account for less than perfect sensitivity of RNA testing in that study. From peak viremia, it takes another 21 days

to reach viral set point, which is set at a level of 4.5 $\log_{10}$. Changes occur linearly on the log scale. The total time of acute stage infection is therefore 3 months. The duration of chronic stage infection in the absence of clinical intervention is 3550 days, or 9.7 years. The total duration of pre-AIDS disease from infection is therefore approximately 10 years. At onset of AIDS, HIV viral load rises linearly on the log scale from 4.5 $\log_{10}$ to 7 $\log_{10}$. The time spent in the AIDS stage is 728 days, or 2 years; this duration is used to calculate the rate of viral load increase during the AIDS stage but does not determine AIDS-related mortality. This viral load trajectory is for ART-naïve persons only, and the influence of ART on disease progression is detailed in Section 7. These transitions are deterministic for all ART-naïve persons. For persons in the AIDS stage who are not currently on ART, disease-related mortality is imposed stochastically with a homogenous weekly risk of 0.0006. This is accomplished by drawing from a binomial (Bernoulli) distribution for all eligible individuals in the AIDS stage. Mortality risk values were sourced from Krebs et al.[237] and calibrated to the HIV-related death rates in Atlanta reported by the Georgia Department of Public Health[238]. The risk of disease-related mortality is reduced for those on ART as detailed in Section 7.

7 Clinical Epidemiology

Clinical epidemiological processes in the model refer to all steps along the HIV care continuum after initial HIV infection: diagnosis, linkage to ART care, adherence to ART, and HIV viral load suppression. In this model, these clinical features have interactions with behavioral features detailed above, as well as impacts on the rates of HIV transmission, detailed in the next section. The features of our model's clinical processes generally follow the steps of the HIV care continuum, in which persons transition across states from infection to diagnosis to ART initiation to HIV viral suppression.[239]

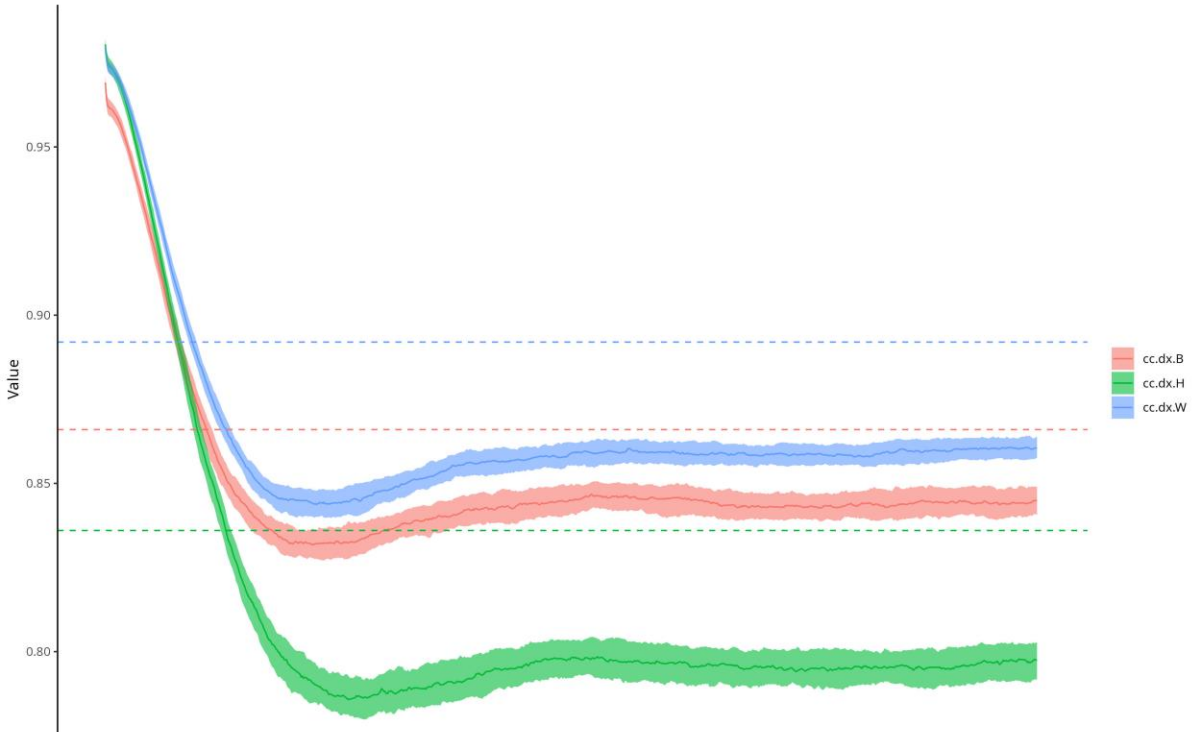
7.1 HIV Diagnostic Screening

Both HIV-uninfected and HIV-infected persons in our model were exposed to regular interval-based HIV screening that served as a common entry point for HIV prevention and HIV treatment services, respectively. Individuals screened at routine intervals first based on whether they were currently using PrEP or not. For HIV screening outside of PrEP care, based on exploratory analyses of behavioral and clinical data, and the research questions of this study, we elected to stratify these screening rates by race/ethnicity.

Our approach to parameterization for HIV screening among PrEP non-users was first to start with priors based on ARTnet data for time since last HIV test for HIV-uninfected, and then use model calibration (the technical details of which are explained in Section 9) to fit these parameters to reproduce the race-stratified levels of the first step of the HIV care continuum (the fraction of HIV-infected persons who were diagnosed). For this and the following surveillance target statistics, we have used values specific to MSM. We used that approach because self-reported HIV screening data alone may be biased, and this calibration approach allows for triangulation of diagnostic history based on more objective laboratory data.

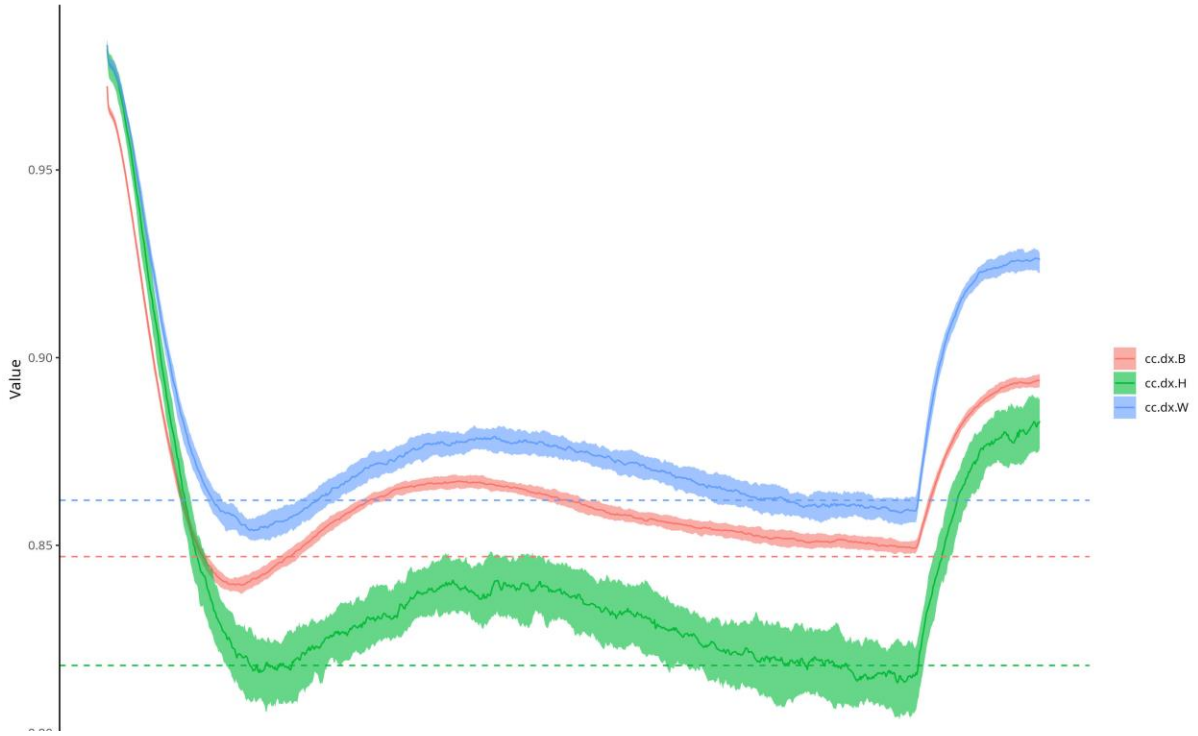
Supplemental Figure 4.1-4.2 shows the general results to this calibration. The model starts with all persons with HIV infection as undiagnosed, then the model is simulated for 60 years (x axis for plot time scale is in weeks) to establish stable equilibrium conditions for this and the other calibrated parameters. The target statistics are shown with dashed horizontal lines and the simulated statistics are shown with solid lines.

Supplemental Figure A.4.1. Fraction of MSM with HIV Who Are Diagnosed, Simulations versus Target Statistics, Stratified by Race/Ethnicity (blue = White MSM, red = Black MSM, green = Hispanic MSM), for Aim 2



Each model calibration was simulated 1000 times, so the solid lines represent the median values across those simulations and the polygon bands are the interquartile ranges. The three model parameters for the weekly screening rates were calibrated to meet the target statistics, which were the fraction of HIV-infected MSM who were diagnosed. The numerical results from this parameterization are shown in Supplemental Table 10.

Supplemental Figure A.4.2. Fraction of MSM with HIV Who Are Diagnosed, Simulations versus Target Statistics, Stratified by Race/Ethnicity (blue = White MSM, red = Black MSM, green = Hispanic MSM), for Aim 3



Supplemental Table A.10. Model Parameterization for HIV Screening			
	Black MSM	**Hispanic MSM**	**White MSM**
Target Statistic: Diagnosed Fraction[240,241] (Aim 3)	84.7%	81.8%	86.2%
Target Statistic: Diagnosed Fraction[33] (Aim 2)	86.6%	83.6%	89.2%
Simulations: Diagnosed Fractions	80.1%	81.7%	88.3%
Calibrated Rates (per Week)	0.00385	0.00380	0.00690
Mean Inter-Test Interval (Years)	5.00	5.06	2.79
Median Diagnostic Delay (Years)	2.50	2.52	1.70

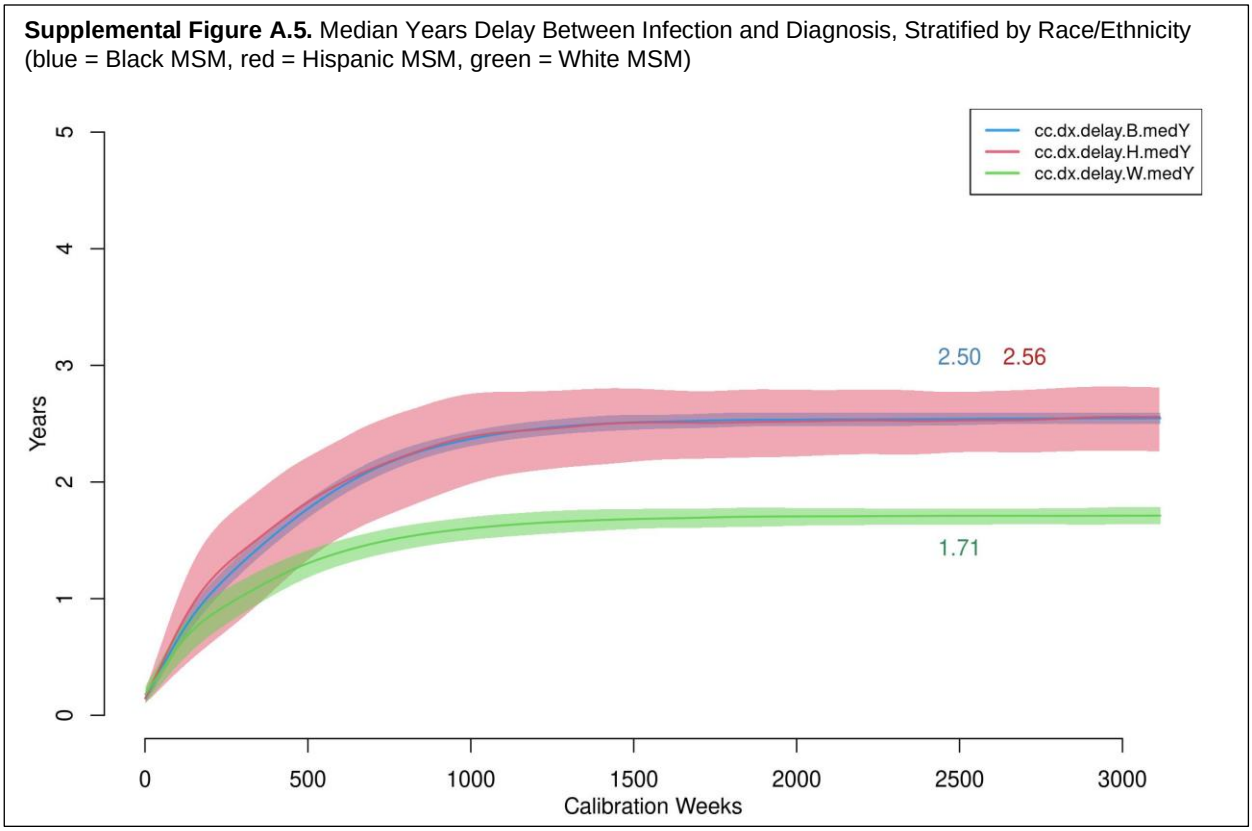
Abbreviation: MSM, men who have sex with men.

The target statistics for the diagnosed fraction were calculated from a 2019 CDC HIV surveillance report that specified the diagnosed fraction among HIV-infected MSM nationally

and from AIDSVu demographic data on the HIV-positive population in Atlanta, by assuming that the national unstratified diagnosed fraction among MSM is equivalent to the corresponding fraction among MSM in Atlanta and that the ratios between race-specific diagnosed fractions in US adults are transportable to Atlanta MSM. The diagnosed fraction was higher for White MSM compared to Black and Hispanic MSM. After calibration, the simulated diagnosed fractions were nearly identical to those targets. The calibrated screening rates per week were higher among White MSM, and lower among Black and Hispanic MSM, consistent with producing the differentials in the diagnosed fractions across the groups. These weekly rates were consistent with average inter-test intervals, or the average time between HIV negative screening events, of 2.8 to 5.1 years. Note that these intervals represent marginal averages across the target population; some MSM may screen more frequently while others screen very rarely.

We also calculated the diagnostic delay as a validation of this calibration process. Whereas the inter-test interval is calculated for HIV-negative MSM in the model, the diagnostic delay is

Supplemental Figure A.5. Median Years Delay Between Infection and Diagnosis, Stratified by Race/Ethnicity (blue = Black MSM, red = Hispanic MSM, green = White MSM)



calculated for HIV-infected MSM who are eventually diagnosed positive. This delay is the median number of years between HIV infection and HIV diagnosis. As shown in Supplemental Figure 5A, this time starts out low in the early part of the burn-in model, but converges to a stable equilibrium value by the end of the burn-in. The simulated median values were 2.5 years for Black and Hispanic MSM, and 1.7 years for White MSM. This is what would be expected given the differences in the calibrated screening rates. This is also consistent with forward projections of two external studies of national surveillance data. Hall et al. estimate race-stratified median times between infection and diagnosis for 2003 and 2011,[242] and Dailey et al. update these estimates for 2015.[183] The median delays declined substantially over this period, from 5.4 years in 2003 to 3.0 years in 2015. To compare against our other target statistics, we fit a log-linear model to estimate the relative yearly declines in median delay times, with a prediction for 2017. The 2017 projections from this model were 2.44 years overall, 2.47 years for Blacks, 2.51 years for Hispanics, and 2.09 years for Whites. The corresponding estimates from our simulation model calibrated to the Georgia Department of Public Health HIV care continuum statistics resulted in median times of 2.32 years overall, 2.50 years for Blacks, 2.56 years for Hispanics, and 1.71 years for Whites. So overall our simulations slightly (by 5%) underestimate the projected 2017 median time to diagnosis, but this gap was small (but larger for White MSM), and it captured the racial/ethnic differences.

Diagnostic testing was simulated stochastically using draws from a binomial distribution with probability parameters equal to these stratified probabilities. This generated a population-level geometric distribution of times since last test. For PrEP users, we modeled HIV screening practice based on CDC clinical practice guidelines.[243] The guidelines recommend ongoing screening at 3-month intervals for MSM actively using PrEP. This schedule was imposed for all PrEP users active in their PrEP use, regardless of PrEP adherence categories. We also assumed no racial/ethnic variation in HIV screening rates for PrEP users.

Finally, we also modeled a 21-day window period after infection during which the tests of the truly HIV+ persons would show as negative to account for the lack of antibody response immediately after infection.[244] HIV+ persons who tested after this window period would be correctly diagnosed with 100% test sensitivity. MSM with recent but undetected infection were still eligible for PrEP initiation since PrEP eligibility was based diagnosed HIV status. This would have resulted in a period in which HIV-infected but undiagnosed persons were classified as on PrEP. This did not impact their HIV transmission potential (and could not impact their acquisition potential). This undetected infection would then be identified at the next quarterly PrEP clinical visit, at which point they would be transitioned off PrEP.

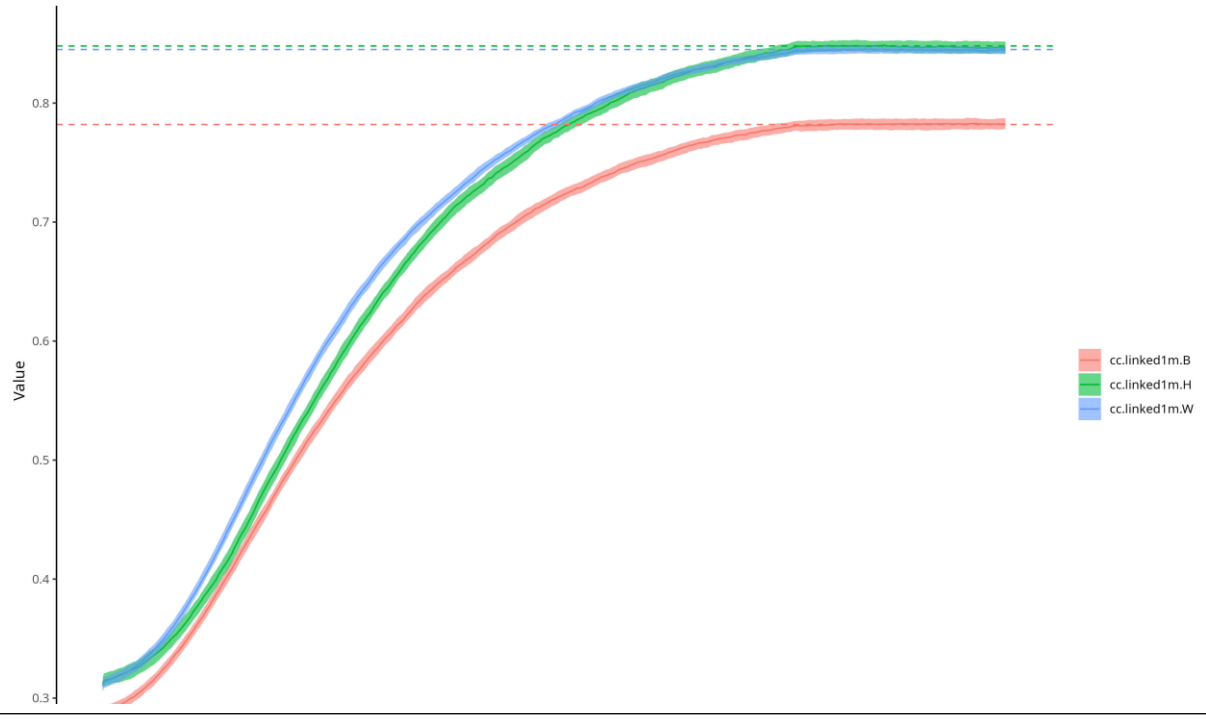
7.2 Antiretroviral Therapy (ART) Initiation

Following HIV diagnosis, individuals were linked to HIV care that provided ART. In the absence of quantitative data and based on current clinical practice guidelines for MSM in the U.S., we assumed no gap between treatment entry and ART initiation. Although the intermediate steps of the HIV care continuum are often characterized by any linkage to HIV care and/or ART, we selected a second HIV care continuum target of linkage to HIV care specifically within one month of diagnosis for two reasons. First, in the dynamic modeling context, the temporally defined threshold easily mapped on to the tracking implemented for simulated individuals in the model. Second, there were readily available surveillance estimates for this outcome. With respect to the latter, we used data from the Georgia Department of Public Health care continuum estimates for 2019, stratified by transmission risk level and race/ethnicity. We assume therefore that there is a statistical relationship between the proportion linked to care within one month and the average time to care entry following diagnosis: time-to-care entry is assumed to be exponentially distributed, where we use the data on proportion linked to care within one month to solve for the exponential rate parameter. This time-to-event estimate below

is generally consistent with recent cohort data that suggest relatively rapid ART initiation following diagnosis.[245]

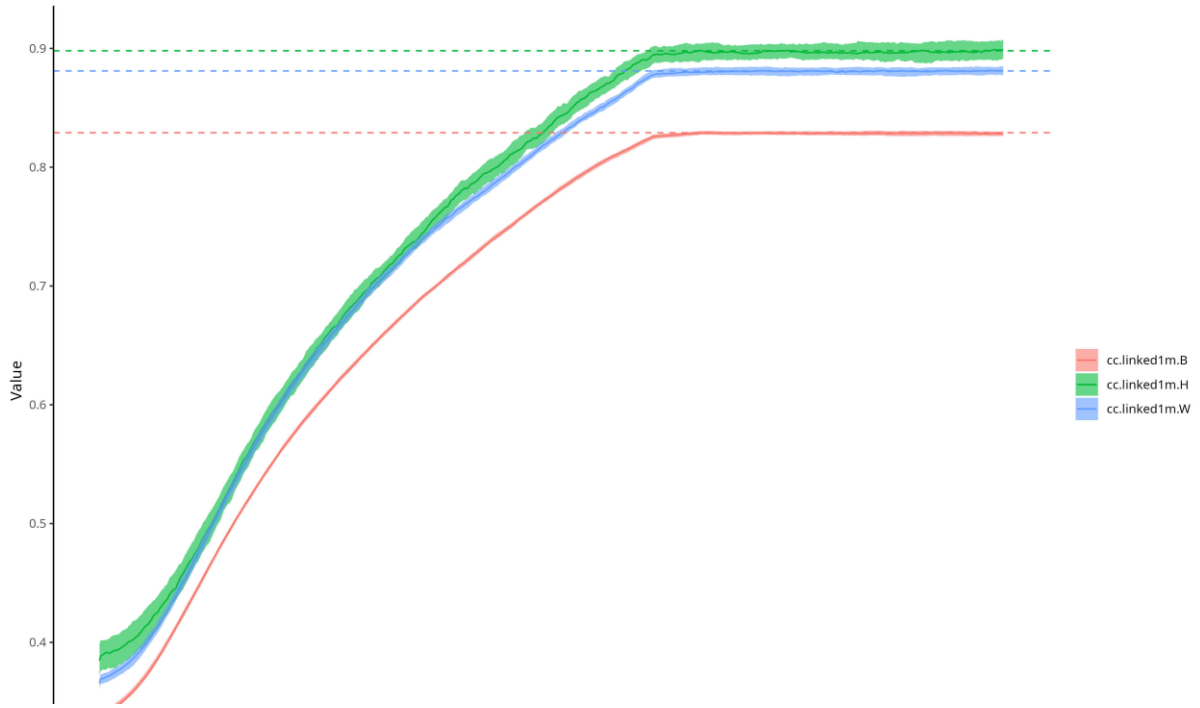
Supplemental Figure 6.1-6.2 shows the general results to this calibration. The approach was similar to calibration for HIV screening rates. Over the 60-year burn-in simulation period, persons were linked to HIV care with ART with initiation rates that were specific to race/ethnicity. The specific metric used within the simulations to compare against the target statistics was the period between diagnosis and first ART use, which were uniquely tracked for all individuals with HIV infection in the model. A group-specific proportion of persons whose difference between diagnosis and ART initiation was less than or equal to four weeks was

Supplemental Figure A.6.1. Proportion of Diagnosed HIV-Infected MSM Linked to ART Care within One Month of Diagnosis, Stratified by Race/Ethnicity (blue = White MSM, red = Black MSM, green = Hispanic MSM), for Aim 2



calculated in the model. The target statistics are shown with dashed horizontal lines and the simulated statistics are shown with solid lines. Each model calibration was simulated 1000 times, so the solid lines represent the median values across those simulations and the polygon bands are the interquartile ranges.

Supplemental Figure A.6.2. Proportion of Diagnosed HIV-Infected MSM Linked to ART Care within One Month of Diagnosis, Stratified by Race/Ethnicity (blue = White MSM, red = Black MSM, green = Hispanic MSM), for Aim 3



Supplemental Table 11 shows the numerical results of the calibration. The rate of care establishment was higher for White and Hispanic MSM than for Black MSM. With the calibrated rates, the model simulations matched these target statistics. The inverse of these rates implied that the average time to ART initiation after HIV diagnosis was between 4 to 6 weeks on average.

Supplemental Table A.11. Model Parameterization for ART Linkage After Diagnosis

	Black MSM	**Hispanic MSM**	**White MSM**
Target Statistic: Fraction Linked within 1m[246] (Aim 3)	82.9%	89.8%	88.1%
Target Statistic: Fraction Linked within 1m[33] (Aim 2)	78.2%	84.8%	84.5%
Simulations: Fraction Linked	62.3%	65.1%	76.5%

Calibrated Rates (per Week)	0.1775	0.1900	0.2521
Mean Time to ART (in Weeks)	5.6	5.3	4.0

Abbreviations: ART, antiretroviral therapy; m, month; MSM, men who have sex with men.

7.3 ART Adherence and HIV Viral Load Suppression

MSM who initiated ART could cycle on and off treatment, where cycling off treatment resulted in an increase in the VL back up to the assumed set point of 4.5 $\log_{10}$. The slope of changes to VL were calculated such that it took a total of 3 months to transition between the set point and the on-treatment viral loads.[247] Individuals on ART could reach full suppression with sustained ART use. The nadir HIV viral load level was assumed to be 1.5 $\log_{10}$ among those at full suppression levels.[247] The latter corresponds to a rounded value (on the $\log_{10}$) scale of an absolute viral load below the standard levels of detection (viral load = 50).[248] Viral load was tracked and updated continuously over time based on the natural history of HIV disease by stage, and current use of ART.

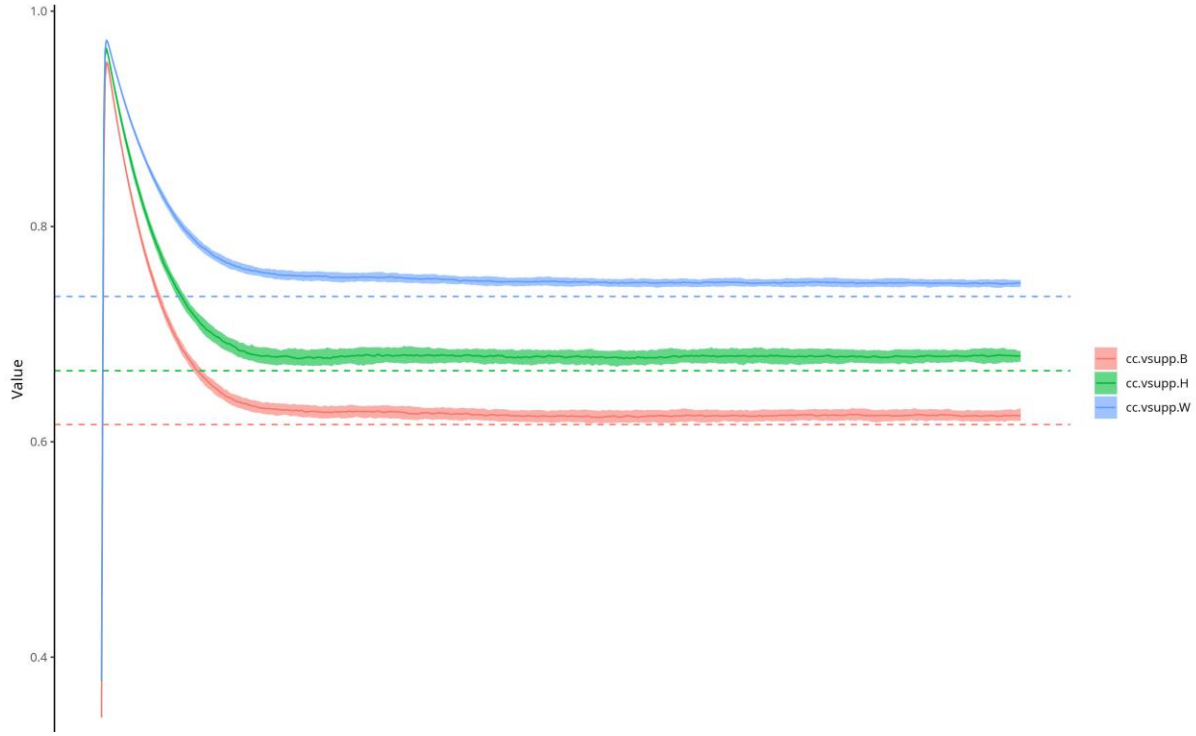
The patterns of ART adherence (cycling on and off ART) leading to full HIV viral suppression were estimated based on an analysis of HIV care patterns among MSM in the United States[249] and model calibration similar to the first two HIV care continuum steps. The rates of cycling off ART after initially starting (the “halting rate”) and the rates of cycling back on after a period of stopping (the “reinitiation rate”) controlled overall levels of HIV viral suppression. Within the intervention component of the model, improvement to HIV care retention corresponded to reductions in the halting rate by relative amounts compared to the base calibrated rates.

Because of the negative collinearity of the halting and reinitiation rates that would result in non-identifiability issues with both were simultaneously estimated, we elected to keep the reinitiation rates fixed and fit the halting rates. We started with halting and reinitiation rates and their

uncertainty intervals based on an earlier model of the HIV care continuum in the U.S.[250] These reinitiation rates were 0.1326 per year, corresponding to an average time spent off ART before reengagement of 7.5 years. With the reinitiation rates fixed there, we then allowed the halting rates to vary by race/ethnicity and fit them to generate simulations matching the race/ethnicity-specific proportions of diagnosed MSM with a suppressed VL in the cross-section. We did not model a distinct clinical typology of ART users with a lower propensity for ART discontinuation, above and beyond the differences by race/ethnicity, for two reasons. First, the empirical data to support a distinct typology at the population-level are insufficient. Second, the retention interventions currently in the scenarios are designed to shift the overall population averages rather than focus on a subgroup who would be at higher risk of ART dropout.

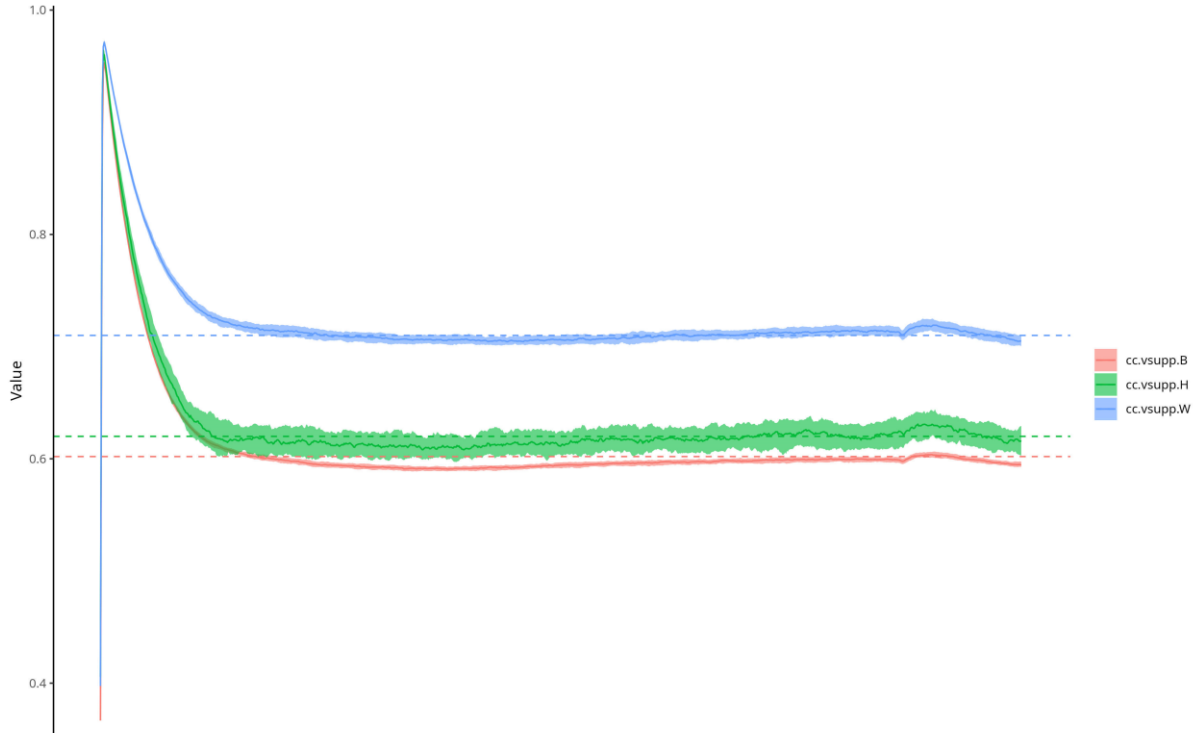
Supplemental Figure A.7.1-A.7.2 shows the general results of this calibration. The general approach was the same as for calibration of HIV screening rates and ART linkage rates. The specific metric used within the simulations to compare against the target statistics was the

Supplemental Figure A.7.1. Proportion of Diagnosed HIV-Infected MSM with HIV Viral Load Suppression, Stratified by Race/Ethnicity (blue = White MSM, red = Black MSM, green = Hispanic MSM), for Aim 2



proportion of individuals who had a HIV VL below the detectable limit of 200 copies/mL. A group-specific proportion of persons was calculated at each time step in the model. The target statistics are shown with dashed horizontal lines and the simulated statistics are shown with solid lines. Each model calibration was simulated 1000 times, so the solid lines represent the median values across those simulations and the polygon bands are the interquartile ranges.

Supplemental Figure A.7.2. Proportion of Diagnosed HIV-Infected MSM with HIV Viral Load Suppression, Stratified by Race/Ethnicity (blue = White MSM, red = Black MSM, green = Hispanic MSM), for Aim 3



Supplemental Table A.12 shows the numerical results of the calibration. Georgia Department of Public Health data for MSM in 2019 were our target statistics for the proportion of diagnosed MSM with a suppressed viral load in the cross-section. This mapped directly onto to our model simulations.

Supplemental Table A.12. Model Parameterization for ART Retention Rates After Linkage

	Black MSM	Hispanic MSM	White MSM
Target Statistic: Fraction VL Suppressed[246] (Aim 2)	60.2%	62.0%	71.0%
Target Statistic: Fraction VL Suppressed[33] (Aim 3)	61.6%	66.6%	73.5%
Simulations: Fraction VL Suppressed	55.1%	60.9%	72.5%
Calibrated Halting Rates (per Week)	0.0058	0.00475	0.0028
Mean Time to First ART Stoppage (in Weeks)	171.4	209.5	356.1
Mean Time to First ART Stoppage (in Years)	3.3	4.0	6.8

Abbreviations: ART, antiretroviral therapy; MSM, men who have sex with men; VL, viral load.

The corresponding halting rates were therefore lowest in White MSM and highest in Black MSM. The inverse of these rates implied a time to first stopping ART after initiation of 161 to 323 weeks.

7.4 AIDS Disease Progression and AIDS-Related Mortality

Progression to AIDS after ART initiation was modeled based on the cumulative time on and off ART for individuals who had been linked to treatment (persons never linked to ART progressed according to the rates in Section 6). The maximum untreated time between infection and the start of AIDS for those who never initiate treatment was 9.7 years.[235] For those with some treatment history, we assumed a slower progression time, with individuals who had ever initiated ART spending a maximum of 15 years off of ART over the life course before progression to AIDS, similar to previous models.[211] Persons who had ever initiated ART progressed to AIDS at a similar rate as those who were ART-naïve, but ART use during the

AIDS stage was associated with the same declines in HIV viral load as in pre-AIDS stages. For persons within the AIDS stage who are currently on active ART, the probability of mortality per week is reduced to 0. This mortality risk value was calibrated to the HIV-related death rates in Atlanta reported by the Georgia Department of Public Health[238].

7.5 PrEP Initiation and Adherence

In our models, we consider that PrEP initiation can only occur after a negative HIV test. This makes the PrEP initiation rate linked to the test rate. PrEP start and stop rate are thus calibrated after the other parameters (the technical details of which are explained in Section 13.2).

8 Interhost Epidemiology

Interhost epidemiological processes represent the HIV-1 disease transmission within the model. Disease transmission occurs between sexual partners who are active on a given time step. This section will describe how the overall rate is calculated as a function of the intrahost epidemiological profile of each member of a partnership, and behavioral features within the dyad.

8.1 HIV-Discordant Dyads

At each time step in the simulation, a list of active dyads was selected based on the current composition of the network. This was called an “edgelist.” Given the three types of partnerships detailed above, the full edgelist was a concatenation of the type-specific sublists. The complete edgelist reflects the work of the STERGM- and ERGM-based network simulations, wherein partnerships formed on the basis of nodal attributes and degree distributions (see Section 3). From the full edgelist, a disease-discordant subset was created by removing those dyads in which both members were HIV- or both were HIV+. This left dyads that were discordant with

respect to HIV status, which was the set of potential partnerships over which infection may be transmitted at that time step.

8.2 HIV Transmission Rates

Within HIV-discordant dyads, transmission was simulated stochastically across separate sexual acts at each timestep. The per-act probabilities were a combined function of attributes of the HIV-negative and HIV-positive partner; these probabilities were calibrated to reach the empirical HIV diagnosis rates. The final per-partnership transmission rates per time step were then a function of one minus these per-act transmission probabilities raised to the number of acts within the partnership during that time step.

8.2.1 Per-Act Transmission Probabilities

Within disease-discordant dyads, HIV transmission was modeled based on a sexual act-by-act basis, in which multiple acts of varying infectiousness could occur within one partnership within a weekly time step. Determination of the number of acts within each discordant dyad for the time step, as well as condom use and role for each of those acts, was described in Section 4. Transmission by act was then modeled as a stochastic process for each discordant sex act following a Bernoulli distribution with a probability parameter that is a multiplicative function of the following predictors of the HIV- and HIV+ partners within the dyad, as shown in Supplemental Table 13 below.

For each act, the overall transmission probability was determined first based on sexual position and HIV viral suppression status of the infected partner. If the infected partner was virally suppressed and on ART, then the base probability was 2.2/100,000, which was derived from a model-based estimate of Supervie.[251] This study estimated upper bound of the transmission probability of 4.4/100,000 for MSM; we used the mean between the observed number (zero)

and this upper bound as our base per-act transmission probability (so 2.2 transmissions per 100,000 exposures) in our model.

If the infected partner was not virally suppressed (at conditions of 200 copies/mL or higher) or not currently on ART, the base probability was a function of whether the HIV- partner was in the receptive or insertive role, with the former at a 2.6-fold infection risk compared to the latter. Then, following the parametric function of Wilson,[252] the HIV+ partner's viral load modifies this base probability in a non-linear formulation, upwards if the VL was above the VL set point during chronic stage infection in the absence of ART, and downwards if it was below the set point.

Following others, we modeled an excess transmission risk in the acute stage of infection above that predicted by the heightened VL during that period.[253] Three covariates could reduce the risk of infection: condom use within the act by either the HIV- or HIV+ partner, circumcision status of the HIV- partner (only if the HIV- partner was insertive in that act), and PrEP use at the time of the act by the HIV- partner.

Supplemental Table A.13. Per-Act Transmission Probabilities and Modifiers			
Predictor	**Partner**	**Parameters**	**References**
Sexual role (insertive or receptive)	HIV-	*Receptive:* 0.008938 base probability when HIV+ partner has 4.5 $\log_{10}$ viral load	Vittinghoff[254]
		Insertive: 0.003379 base probability when HIV+ partner has 4.5 $\log_{10}$ viral load	Vittinghoff[254]
HIV viral load (VL)	HIV+ (Not virally suppressed or not on ART)	Multiplier of $2.45^{(VL - 4.5)}$ on sexual-role specific base probabilities above	Wilson[252]
	HIV+ (Virally suppressed and on ART)	0.000022 base probability, regardless of sexual role	Supervie[251]
Acute stage	HIV+	Multiplier of 6	Leynaert,[255] Bellan[253]
Condom use	Both	Multiplier of 0.05 times (1 – 0.25)	Varghese,[256] Weller,[257] Smith[258]
Circumcision status	HIV-, insertive	Multiplier of 0.40	Gray[230]
Preexposure Prophylaxis (PrEP)	HIV-	High adherence: Multiplier of 0.01 Medium adherence: Multiplier of 0.19 Low adherence: Multiplier of 0.69	Grant[259]
Current STI	Urethral	Multiplier of 1.73	Fitted values (see Section 9.2 below)
	Rectal	Multiplier of 2.78	

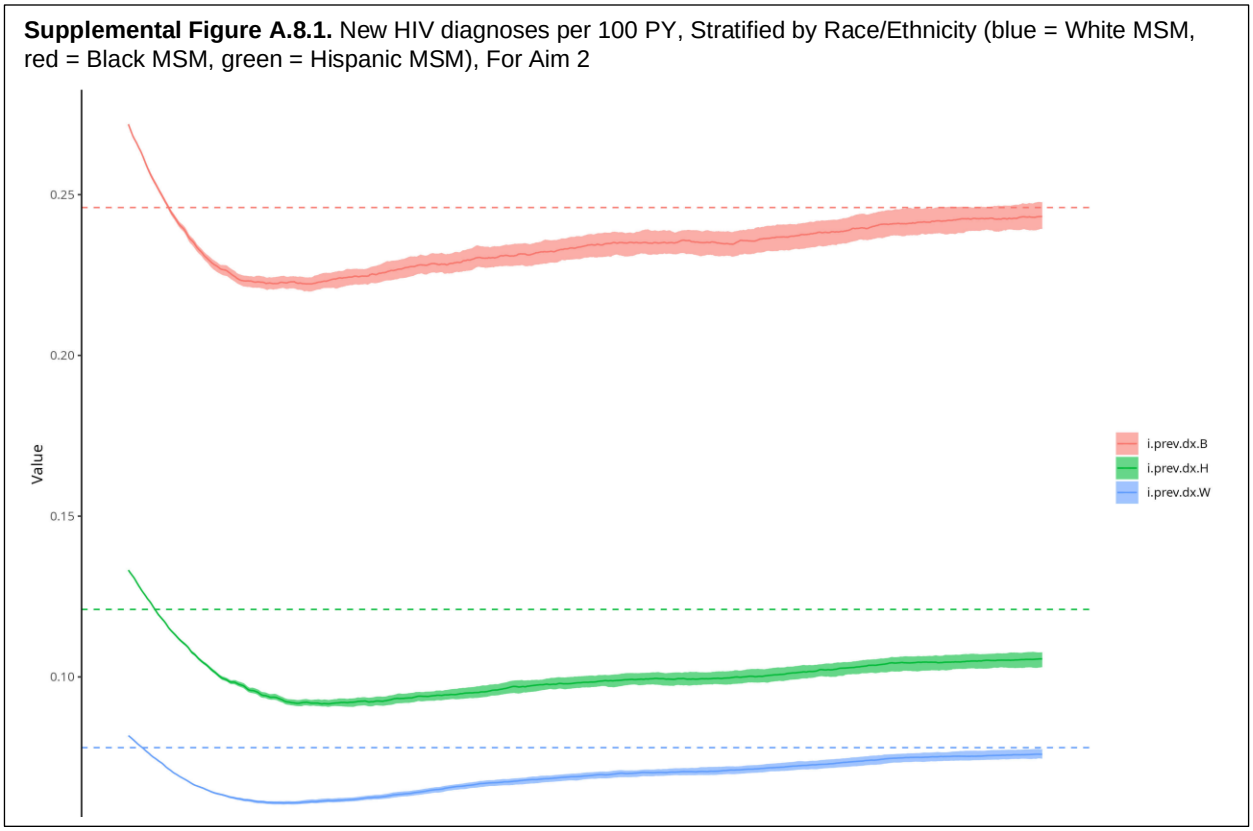
For condom use, we updated our previous approach to explicitly represent condom failure that would result in a transmission event. Our previous models used estimates of HIV incidence

comparing consistent condom users to occasional or non-condom users, resulting in a condom "efficacy" of 75–80%. However, this efficacy gap of 20–25% is the function of both the biological/physiological gaps in protection given perfect and consistent condom use during anal intercourse as well as the human error resulting in impact use. Such error could represent condom breakage, misapplication, incomplete use during sexual activity, and other related causes.[258] For this model, we assumed a 95% efficacy for the former, and a 25% absolute reduction in that efficacy as a function of condom failure to arrive at the previous range of 71% total effectiveness.

8.2.2 Calibration of Transmission Probabilities

In addition to the calibration of the HIV care continuum parameters described in Section 7, we also calibrated the per-act transmission probabilities so that the rate of new HIV diagnoses was consistent with empirical data on HIV burden in this target population. Our target statistic for this calibration step was the number of new HIV diagnoses in 2019 by race/ethnicity as reported by

Supplemental Figure A.8.1. New HIV diagnoses per 100 PY, Stratified by Race/Ethnicity (blue = White MSM, red = Black MSM, green = Hispanic MSM), For Aim 2



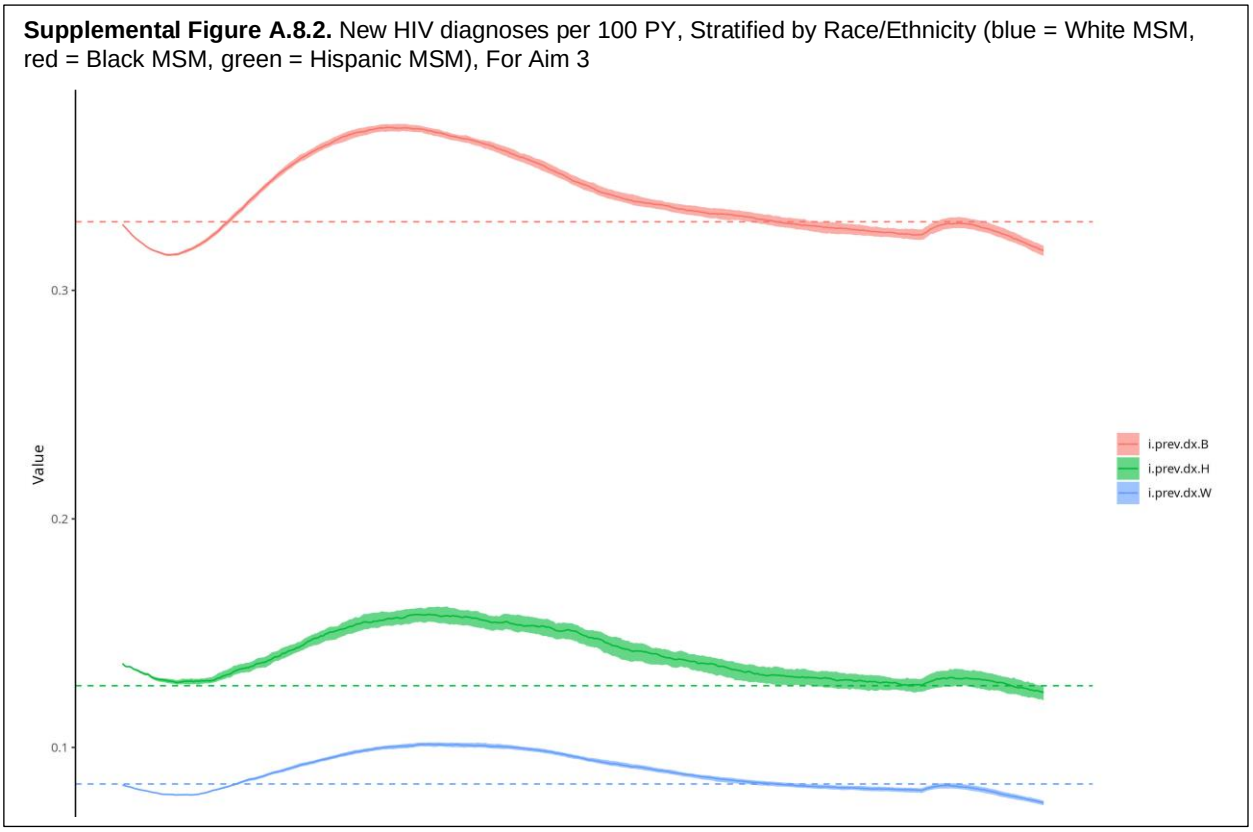
CDC,[179] scaled to the MSM population size by race/ethnicity, which was estimated in Rosenberg.[260] The target statistics of new HIV diagnoses per 100 person-years in the Atlanta area were 2.596 for Black MSM, 1.588 for Hispanic MSM, and 0.380 for White/Other MSM. We took this approach to calibration because there are no external data on the baseline estimated HIV incidence by race/ethnicity for our target population of MSM aged 15 to 65 of all race/ethnicities. There is some historical cohort data for younger (18 to 39 years old) Black and White MSM in Atlanta;[222] these were used to calibrate our earlier modeling studies.[214] But we are concerned that the cohort members may be higher risk than all demographically similar MSM in Atlanta due to selection biases. This was a main motivation to moving towards calibrating the model primarily based on population-level surveillance targets for the care continuum and diagnosis rate.

The per-act transmission probabilities defined above were then multiplied by a factor unique to each race/ethnic group. For Aim 2, the final factor levels were 4.06 for Black MSM, 0.94 for Hispanic MSM, and 0.72 for White MSM. For Aim 3, the final factor levels were 3.08 for Black MSM, 0.52 for Hispanic MSM, and 0.39 for White MSM. These calibration factors represent the additional sources of potential error in the transmission parameters that would generate the current HIV epidemic. These include co-factors not included in this model, such as untreated sexually transmitted infections.[261] The upweighting of the transmission probabilities for Black MSM and down-weighting for White and Hispanic MSM is due to the long-standing finding that race-stratified behavioral and network data do not, by themselves, explain the excess burden of HIV among Black MSM.[262,263]

The results of the calibration are visualized in Supplemental Figure A.8.1-A.8.2. The HIV prevalence was initialized based on the statistical model of diagnosed HIV prevalence with ARTnet data but allowed to change over the 60-year burn-in period to reach the specified target statistics. In the calibrated model for Aim 2, the median diagnosis rate during the final year of

the calibration period was 24 new diagnoses per 100 person-years for Black MSM, 10 new diagnoses per 100 person-years for Hispanic MSM, and 8 new diagnoses per 100 person-years for White MSM. In the calibrated model for Aim 3, the median diagnosis rate during the final year of the calibration period was 31 new diagnoses per 100 person-years for Black MSM, 13 new diagnoses per 100 person-years for Hispanic MSM, and 8 new diagnoses per 100 person-years for White MSM.

Supplemental Figure A.8.2. New HIV diagnoses per 100 PY, Stratified by Race/Ethnicity (blue = White MSM, red = Black MSM, green = Hispanic MSM), For Aim 3



8.2.3 Final Per-Partnership-Week Transmission Rates

The final transmission rate per partnership per weekly time step was a function of the per-act probability of transmission in each act and the number of acts per time step. The per-act transmission probability could be heterogeneous within a partnership due to various types of acts in each interval: for example, a HIV- man who is versatile in role may have both insertive

and receptive intercourse within a single partnership; some acts within a partnership may be protected by condom use while others are condomless. Transmission was simulated for each act within each serodiscordant dyad, based on draws from a Bernouli distribution with the probability parameter equal to the per-act transmission probabilities detailed above.

9 COVID-Related Changes

9.1 Addition of COVID-Era Parameters

Several new parameters were created in order to allow for COVID-era changes in sexual behavior and clinical service utilization. Some parameters adapted existing *EpiModelHIV* parameters to allow for additional demographic stratification, such as stratifying HIV testing rate (by race/ethnicity) also by age category. In these models, the cutoff for binary age category (young/old) for age-stratified model parameters was 30 years. Below is a list of the new model parameters with their descriptions.

- hiv.test.rate.young: Mean probability of HIV testing per time step for younger Black/Hispanic/White MSM (vector of length 3).
- hiv.test.rate.old: Mean probability of HIV testing per time step for older Black/Hispanic/White MSM (vector of length 3).
- prep.start.prob.young: Probability of a younger Black/Hispanic/White MSM starting PrEP given current indications.
- prep.start.prob.old: Probability of an older Black/Hispanic/White MSM starting PrEP given current indications.
- prep.discont.rate.young: PrEP discontinuation rate for younger Black/Hispanic/White MSM.
- prep.discont.rate.old: PrEP discontinuation rate for older Black/Hispanic/White MSM.

- part.prep.start.prob.young: Probability of a younger Black/Hispanic/White MSM individual identified through partner identification starting PrEP given current indications at the current time step.
- part.prep.start.prob.old: Probability of an older Black/Hispanic/White MSM individual identified through partner identification starting PrEP given current indications at the current time step.
- tx.init.rate.young: Probability per time step that a younger Black/Hispanic/White MSM who has tested positive will initiate treatment (vector of length 3).
- tx.init.rate.old: Probability per time step that an older Black/Hispanic/White MSM who has tested positive will initiate treatment (vector of length 3).
- tx.halt.partial.rate.young: Probability per time step that a younger Black/Hispanic/White MSM who has started treatment and assigned to the partial VL suppression category will stop treatment (vector of length 3).
- tx.halt.partial.rate.old: Probability per time step that an older Black/Hispanic/White MSM who has started treatment and assigned to the partial VL suppression category will stop treatment (vector of length 3).
- tx.halt.full.or.young: Odds ratio comparing the odds of stopping treatment for a younger Black/Hispanic/White MSM in the full VL suppression category vs. in the partial VL suppression category (vector of length 3).
- tx.halt.full.or.old: Odds ratio comparing the odds of stopping treatment for an older Black/Hispanic/White MSM in the full VL suppression category vs. in the partial VL suppression category (vector of length 3).
- tx.halt.durable.or.young: Odds ratio comparing the odds of stopping treatment for a younger Black/Hispanic/White MSM in the durable VL suppression category vs. in the partial VL suppression category (vector of length 3).

- tx.halt.durable.or.old: Odds ratio comparing the odds of stopping treatment for an older Black/Hispanic/White MSM in the durable VL suppression category vs. in the partial VL suppression category (vector of length 3).
- tx.reinit.partial.rate.young: Probability per time step that a younger Black/Hispanic/White MSM who has stopped treatment and assigned to the partial VL suppression category will restart treatment (vector of length 3).
- tx.reinit.partial.rate.old: Probability per time step that an older Black/Hispanic/White MSM who has stopped treatment and assigned to the partial VL suppression category will restart treatment (vector of length 3).
- tx.reinit.full.or.young: Odds ratio comparing the odds of re-starting treatment for a younger Black/Hispanic/White MSM in the full VL suppression category vs. in the partial VL suppression category (vector of length 3).
- tx.reinit.full.or.old: Odds ratio comparing the odds of re-starting treatment for an older Black/Hispanic/White MSM in the full VL suppression category vs. in the partial VL suppression category (vector of length 3).
- tx.reinit.durable.or.young: Odds ratio comparing the odds of re-starting treatment for a younger Black/Hispanic/White MSM in the durable VL suppression category vs. in the partial VL suppression category (vector of length 3).
- tx.reinit.durable.or.old: Odds ratio comparing the odds of re-starting treatment for an older Black/Hispanic/White MSM in the durable VL suppression category vs. in the partial VL suppression category (vector of length 3).
- part.tx.init.rate.young: Probability that a younger Black/Hispanic/White MSM who has been identified as the partner of an incident HIV+ MSM will initiate treatment during the current time step.

- part.tx.init.rate.old: Probability that an older Black/Hispanic/White MSM who has been identified as the partner of an incident HIV+ MSM will initiate treatment during the current time step.
- part.tx.reinit.rate.young: Probability per time step that a younger Black/Hispanic/White MSM who has been identified through partner identification, stopped treatment will restart treatment (vector of length 3).
- part.tx.reinit.rate.old: Probability per time step that an older Black/Hispanic/White MSM who has been identified through partner identification, stopped treatment will restart treatment (vector of length 3).
- cond.modifier.mc: Modifier for condom usage for persistent partnerships (main and casual).
- cond.modifier.oo: Modifier for condom usage for one-time partnerships.
- pr.behav.changer: Probability that an individual is a "behavior changer," i.e., changes their sexual behavior (and subsequently, potentially their HIV service utilization) during the COVID pandemic.
- seed.behav.changer: Parameter to turn on/off assigning behavior changers. The default is FALSE, then change to TRUE during the COVID pandemic (or when we want there to be behavior changers). If set to TRUE and pr.behav.changer is a non-zero probability (like 0.2), then this will set the proportion of behavior changers to pr.behav.changer. Once set, people can remain as behavior changers but the effect of behavior changers can be stopped (for example, at the end of the COVID pandemic) by changing the behavior changer effect parameters (such as behav.modifier.tests) back to their no-effect/null values.
- behav.modifier.casual: Modifier of sexual act rate of casual partnerships for behavior changers.

- behav.modifier.oo: Modifier of sexual act rate of one-time partnerships for behavior changers.
- behav.modifier.tests: Modifier of HIV testing rate for behavior changers (i.e., if set to 0.7, then expect testing to be 0.7 of what it was for these people, the behavior changers, before COVID).
- behav.modifier.prep: Modifier of PrEP initiation for behavior changers (includes general PrEP initiation indication and identified partners indication). I.e., If set to 0.25, then expect PrEP initiation to be 0.25 of what it was for these people (the behavior changers) before COVID; if set to 0.25, expect that 75% of behavior changers will NOT initiate PrEP.
- acts.modifier.mc: Modifier of sexual act rate for persistent partnerships (main and casual). This precedes and is separate from modification of sexual act rate related to behavior changers.
- acts.modifier.oo: Modifier of sexual act rate for one-time partnerships. This precedes and is separate from modification of one-time sexual acts related to behavior changers.

9.2 Addition of COVID-Era Intervention Parameters

Additional new model parameters were created to allow for the home-based HIV testing and PrEP retention interventions used in Aim 3, in addition to those added in the preceding section. is a list of the new intervention-related model parameters with their descriptions.

- prep.interv.cov: The proportion of those eligible to start the PrEP retention intervention that will enter the intervention.
- prep.discont.rate.interv: The rate of spontaneous discontinuation from PrEP per time step for Black/Hispanic/White MSM in the PrEP intervention. The effect of the intervention is changing the PrEP discontinuation rate from prep.discont.rate.young

prep.discont.rate.old (the default rate for those not on the intervention) to prep.discont.rate.interv.

- prep.interv.dropoff: The rate of drop-off from the PrEP retention intervention per time step for those in the intervention.
- hiv.test.interv.cov: The proportion of those eligible for the HIV testing intervention that become enrolled in the intervention (the coverage of the HIV testing intervention).
- hiv.test.rate.interv: The updated HIV testing rate for Black/Hispanic/White MSM for those in the HIV testing intervention.
- hiv.test.interv.dropoff: The rate of drop-off from the HIV testing intervention per time step for those in the HIV testing intervention.

9.3 Parameterization of COVID-Era Parameters

COVID-era sexual behavior and clinical service model parameters were set using data from a variety of sources. The Supplemental Table A.14 below explains the model parameters, data sources, and parameter calculations and related assumptions, where applicable, for these parameters.

Supplemental Table A.14. Model Parameters, Data Sources, and Parameter Calculations and Related Assumptions, Where Applicable, for Parameters.

<table>
<tr><th>Model Parameter</th><th>Estimate/ Modifier and Time Information</th><th colspan="4">Information/Justification</th><th>Source</th></tr>
<tr><td rowspan="5">behav.modifier.casual</td><td rowspan="5">April–May 2020:

Casual: 0.11 (0.11-0.77)

November 2020–January 2021:</td><td>L&S Question</td><td></td><td>All</td><td>Behavior Changers Only</td><td rowspan="5">Stephenson et al 2021;[264] Stephenson et al 2022[165]; Weiss et al 2020[218]</td></tr>
<tr><td rowspan="2">April–May 2020: How many sex partners in 3 months before COVID19?</td><td>Mean</td><td>4.26</td><td>5.96</td></tr>
<tr><td>Median</td><td>2</td><td>5</td></tr>
<tr><td rowspan="2">April–May 2020: How many times anal sex in 3</td><td>Mean</td><td>8.29</td><td>6.57</td></tr>
<tr><td>Median</td><td>4</td><td>5</td></tr>
</table>

Casual: 1.0 (0.95-1.0)

Between May and November 2020: Gradual slope

between time steps 4026–4045 (the last week of May and first week of October 2020) and then 4056 and 4069 (January–March 2021)

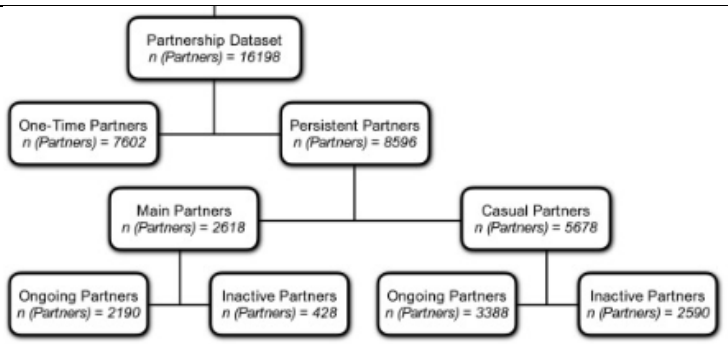
A gradual slope approach was also utilized for behav.modifier, acts, and condom use weekly parameters between time steps 4026–4045 (last week of May and first week of October 2020) and then 4056 and 4069 (January 2021 through March 2021).

months before COVID19?			
April–May 2020: How many sex partners during COVID19 pandemic?	Mean	1.83	1.50
	Median	1	1
April–May 2020: How many times anal sex during COVID19?	Mean	6.99	3.81
	Median	3	2
November 2020–January 2021: How many sex partners in past 3 months?	Mean	2.55	4.07
	Median	1	3
November 2020–January 2021: How many times anal sex in past 3 months?	Mean	8.45	8.15
	Median	4	5

In Love & Sex in the Time of COVID (L&S) dataset, in April–May 2020, the median number of sex partners for behavior changers decreases from 5 (pre-COVID) to 1 (COVID); the average decreases from 6.0 to 1.5). In L&S dataset, in November 2020–January 2021, the median number of sex partners for behavior changers decreases from 5 (pre-COVID) to 3 (COVID); the average decreases from 6.0 to 4.1. From this, we make the following calculations:

Network degree and partnership type data, from Weiss et al 2020:[218]

		Casual Degree				Marginal Summary	
		0	*1*	*2*	*3*	Frequency	Mean Casual Degree
Main Degree	*0*	1432	719	320	338	57%	0.84
	1	1463	271	136	130	41%	0.47
	2	48	19	21	7	2 %	0.86
Marginal Summary	Frequency	60 %	21 %	10 %	10 %		
	Mean Main Degree	0.53	0.31	0.37	0.30		



Before COVID, the median number of sex partners is 5.

From distribution of partner types from ARTnet, then:

$$5\ median\ partners * \left(\frac{2618}{2618+5678+7602}\right) = 5 * 0.165 = 0.82\ main$$
$$5 * 0.357 = 1.79\ casual\ partners$$
$$5 * 0.478 = 2.39\ oo\ partners$$

For April/May 2020:

Reduces to 1 partner.
If we assume main partners are not affected and one-time are 100% reduced (most likely scenario):

$$0.82\ main\ partners\ (0\%\ reduction)$$
$$1 - 0.82 = 0.18\ casual \rightarrow \left(\frac{1.79-0.18}{1.79}\right) = 89.9\%\ reduction$$
$$0\ oo\ (100\%\ reduction)$$

If we assume there is an even split between main and casual partner reduction, and one-time (oo) are 100% reduced:

$$\frac{2618}{2618+5678} * 1\ median\ partner = 0.316\ main\ partners \rightarrow \left(\frac{0.82-0}{0.82}\right.$$
$$\frac{5678}{2618+5678} * 1 = 0.684\ casual \rightarrow \left(\frac{1.79-0.684}{1.79}\right) = 61.8$$
$$0\ oo \rightarrow (100\%\ reduction)$$

If assume even split between main, casual, and one-time partner reduction:

$$\left(\frac{2618}{2618+5678+7602}\right) * 1 = 0.165\ main\ partners \rightarrow \left(\frac{0.82-0.165}{0.82}\right) =$$
$$\left(\frac{5678}{2618+5678+7602}\right) * 1 = 0.357\ casual \rightarrow \left(\frac{1.79-0.357}{1.79}\right) = 80$$
$$\left(\frac{7602}{2618+5678+7602}\right) * 1 = 0.478\ oo \rightarrow \left(\frac{2.39-0.478}{2.39}\right) = 80.0$$

All experience 80% reduction. But this is unlikely to be what is actually happening.

It is not logical to assume that all changes are in casual partnerships (and none in one-time partnerships).

		For November 2020–January 2021: Reduces to 3 partners. If we assume main partners are not affected and one-time are 100% reduced, this would result in an increase in casual partners (2.18 casual partners vs 1.79 pre-COVID). So instead, we assume that main partners are not affected, casual are not affected, and one-time partnership absorb the decrease: $0.82\ main\ partners\ (0\%\ reduction)$ $1.79\ casual\ (0\%\ reduction)$ $3 - 0.82 - 1.79 = 0.39\ oo \rightarrow \left(\frac{2.39 - 0.39}{2.39}\right) = 83.7\%\ reduction$ If we assume there is a even split between casual and one-time partner reduction, and main partners are not affected, then both experience a 40% reduction. <u>Ranges for April/May 2020 (from partner numbers):</u> Main: Decrease by 0%-80% = modifier of 0.2-1.0; 1.0 most likely Casual: Decrease by 61%-89%; modifier of 0.11-0.39; 0.11 most likely OO: Decrease by 80%-100%=modifier of 0.0-0.2; 0.0 most likely <u>Ranges for November 2020–January 2021 (from partner numbers):</u> Main: Decrease by 0%; modifier of 1.0; 1.0 most likely Casual: Decrease by 0%-40%; modifier of 1.0 most likely OO: Decrease by 40%-83.7%-100%; modifier of 0.16 most likely However, the number of causal partners ≠ number of casual acts. To translate from partners to acts, we could assume that the change in number of partners directly approximates the change in number of acts (that is, assume the act rate is the same for each persistent partner an individual has). If assuming all changes are within one-off partnerships, the maximum modifier for both main and casual could be 1.0. Or, alternatively, can use act rate data: Before COVID, the median number of sexual acts is 5. From distribution of partner types from ARTnet, then: $5\ median\ acts * \left(\frac{2618}{2618 + 5678 + 7602}\right) = 5 * 0.165 = 0.82\ acts\ with\ p$ $5 * 0.357 = 1.79\ acts\ with\ casual\ partners$ $5 * 0.478 = 2.39\ acts\ with\ oo\ partners$	

		For April/May 2020: Reduces to 2 acts. If assume main partner acts are not affected and one-time are 100% reduced: $$0.82\ main\ partner\ acts \rightarrow (0\%\ reduction)$$ $$2\ acts - 0.82 = 1.18\ casual\ acts \rightarrow \left(\frac{1.79 - 1.18}{1.79}\right) = 34.0\%\ reduction$$ $$0\ oo\ acts \rightarrow\ (100\%\ reduction)$$ If assume even split between main and casual partner reduction, and one-time are 100% reduced: $$\frac{2618}{2618+5678} * 2\ median\ acts = 0.631\ main\ partner\ acts \rightarrow \left(\frac{0.82-0.631}{0.82}\right) =$$ $$\frac{5678}{2618+5678} * 2 = 1.37\ casual\ acts \rightarrow \left(\frac{1.79-1.37}{1.79}\right) = 23.5\%\ redu$$ $$0\ oo \rightarrow (100\%\ reduction)$$ If assume even split between main, casual, and one-time acts reduction: $$\left(\frac{2618}{2618 + 5678 + 7602}\right) * 2 = 0.329\ main\ partners\ acts \rightarrow \left(\frac{0.82 - 0.3}{0.82}\right.$$ $$\left(\frac{5678}{2618 + 5678 + 7602}\right) * 2 = 0.714\ casual\ acts \rightarrow \left(\frac{1.79 - 0.714}{1.79}\right)$$ $$\left(\frac{7602}{2618 + 5678 + 7602}\right) * 2 = 0.956\ oo \rightarrow \left(\frac{2.39 - 0.956}{2.39}\right) = 60$$ All experience 60% reduction. **For November 2020–January 2021:** Maintains at 5 acts=modifier of 1.0 for all (if assuming that all 5 acts weren't shifted to main partner, for example). We could also assume, for example, that there were 3 one-time partners and 1 persistent partner with 2 acts (because 3 partners reported). This is unlikely however, though not impossible. <u>Ranges for April/May 2020 (from acts):</u> Main: Decrease by 0%-60% = modifier of 0.4-1.0; 1.0 most likely Casual: Decrease by 23%-60%=modifier of 0.4-0.77; 0.66 most likely OO: Decrease by 60%-100%=modifier of 0.0-0.2; 0.0 most likely <u>Ranges for November 2020–January 2021 (from acts):</u> All: 1.0; but with uncertainty	

<table>
<tr>
<td></td>
<td></td>
<td><u>Overall ranges for April/May 2020 (combining partner and act approach):</u>

Main: 1.0 (0.2-1.0)
Casual: 0.11 (0.11-0.77)
OO: 0.0 (0.0-0.2)

<u>Overall ranges for November 2020–January 2021 (combining partner and act approach):</u>

Main: 1.0 (0.95-1.0); 0.95 to introduce uncertainty
Casual: 1.0 (0.95-1.0); 0.95 to introduce uncertainty
OO: 0.16 (0.0-1.0)

Modifiers are then applied to weekly rates.</td>
<td></td>
</tr>
<tr>
<td>behav.modifier.oo</td>
<td>April–May 2020:

OO: 0.0 (0.0-0.2)

November 2020–January 2021:

OO: 0.16 (0.0-1.0)</td>
<td>See above for calculations.</td>
<td>Stephenson et al 2021;[264] Stephenson et al 2022[165]; Weiss et al 2020[218]</td>
</tr>
<tr>
<td>acts.modifier.mc</td>
<td>April–May 2020:

Main: 1.0 (0.5-1.0)
Casual: 0.94 (0.5-1.0)

November 2020–January 2021:

Main: 1.0 (0.5-1.0)
Casual: 0.94 (0.5-1.0)</td>
<td>
<table>
<tr><th>L&S Question</th><th></th><th>All</th><th>Behavior Changers Only</th></tr>
<tr><td rowspan="2">April–May 2020: How many sex partners in 3 months before COVID19?</td><td>Mean</td><td>4.26</td><td>5.96</td></tr>
<tr><td>Median</td><td>2</td><td>5</td></tr>
<tr><td rowspan="2">April–May 2020: How many times anal sex in 3 months before COVID19?</td><td>Mean</td><td>8.29</td><td>6.57</td></tr>
<tr><td>Median</td><td>4</td><td>5</td></tr>
<tr><td rowspan="2">April–May 2020: How many sex partners during COVID19 pandemic?</td><td>Mean</td><td>1.83</td><td>1.50</td></tr>
<tr><td>Median</td><td>1</td><td>1</td></tr>
<tr><td rowspan="2">April–May 2020: How many times anal sex during COVID19?</td><td>Mean</td><td>6.99</td><td>3.81</td></tr>
<tr><td>Median</td><td>3</td><td>2</td></tr>
<tr><td rowspan="2">November 2020–January 2021: How many sex partners in past 3 months?</td><td>Mean</td><td>2.55</td><td>4.07</td></tr>
<tr><td>Median</td><td>1</td><td>3</td></tr>
<tr><td rowspan="2">November 2020–January 2021:</td><td>Mean</td><td>8.45</td><td>8.15</td></tr>
<tr><td>Median</td><td>4</td><td>5</td></tr>
</table>
</td>
<td>Stephenson et al 2021;[264] Stephenson et al 2022[165]; Weiss et al 2020[218]</td>
</tr>
</table>

How many times anal sex in past 3 months?				

In Love & Sex in the Time of COVID (L&S) dataset, in April–May 2020, the median number of sex partners for decreases from 2 (pre-COVID) to 1 (COVID). In L&S dataset, in November 2020–January 2021, the median number of sex partners also decreases from 2 (pre-COVID) to 1 (COVID). From this, we make the following calculations:

Before COVID, the median number of sex partners is 2.

From distribution of partner types from ARTnet, then:

$$2\ median\ partners * \left(\frac{2618}{2618+5678+7602}\right) = 0.329\ main\ partners$$
$$2 * 0.357 = 0.714\ casual\ partners$$
$$2 * 0.478 = 0.956\ oo\ partners$$

For April–May 2020:

Reduces to 1 partner.
If we assume main partners are not affected and one-time are 100% reduced (most likely scenario):

$$0.329\ main\ partners\ (0\%\ reduction)$$
$$1 - 0.329 = 0.671\ casual \rightarrow \left(\frac{0.714-0.671}{0.714}\right) = 6.0\%\ reduction$$
$$0\ oo\ (100\%\ reduction)$$

If we assume there is an even split between main and casual partner reduction, and one-time are 100% reduced:

$$\frac{2618}{2618+5678} * 1\ median\ partner = 0.316\ main\ partners \rightarrow \left(\frac{0.329-}{0.32}\right.$$
$$\frac{5678}{2618+5678} * 1 = 0.684\ casual \rightarrow \left(\frac{0.714-0.684}{0.714}\right) = 4.2$$
$$0\ oo \rightarrow (100\%\ reduction)$$

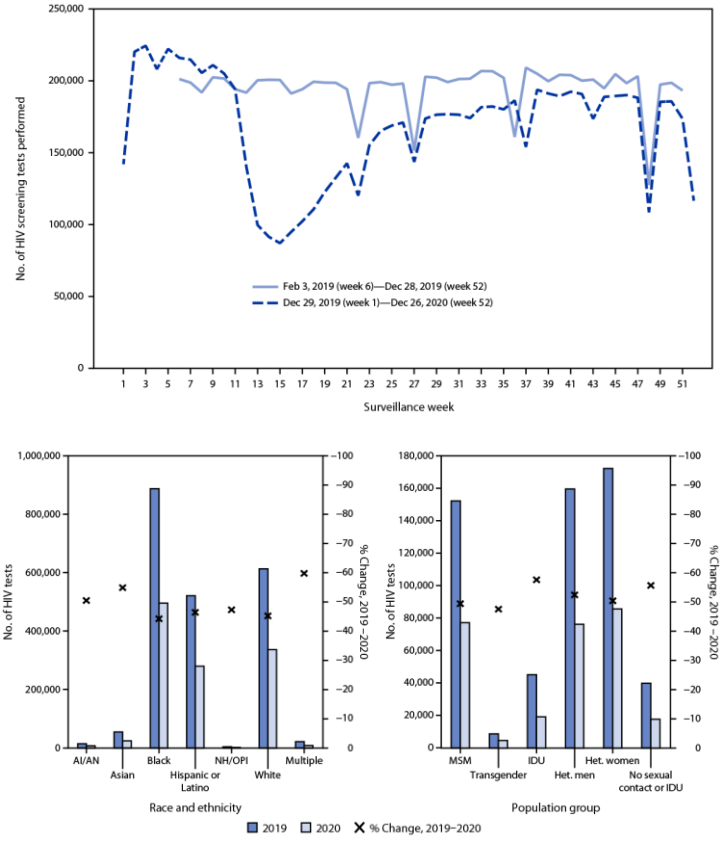
If assume weighted split between main, casual, and one-time partner reduction:

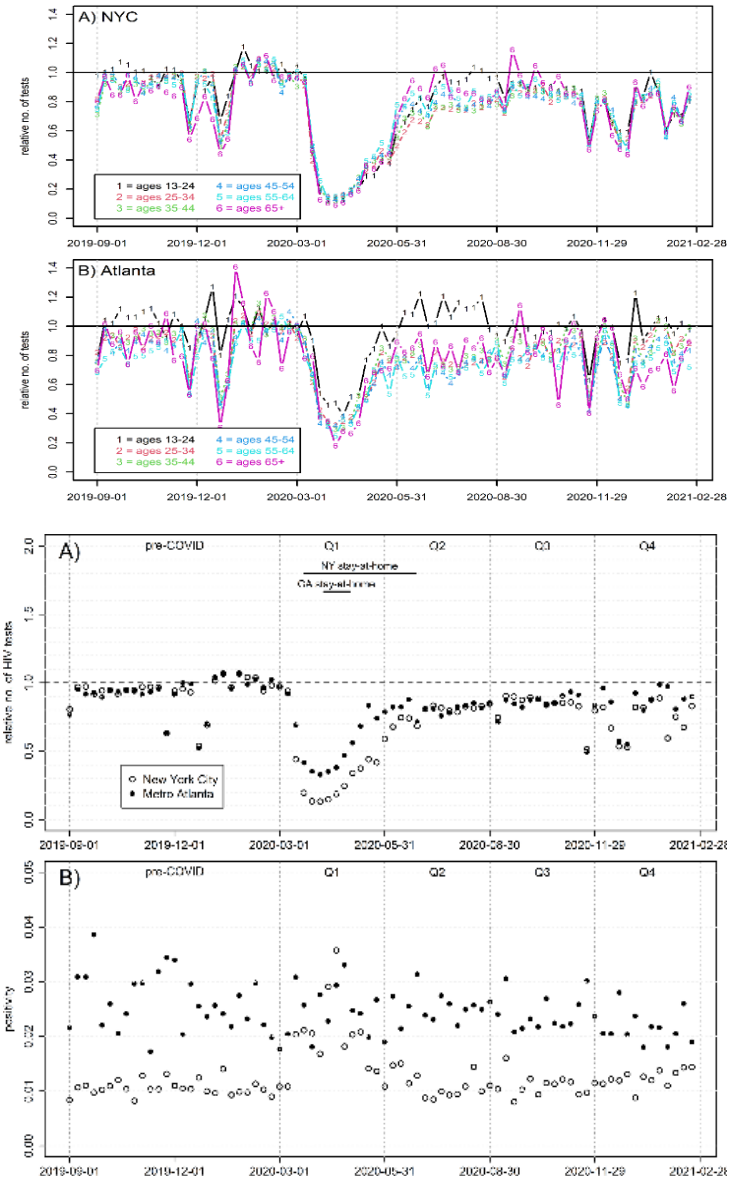
$$\left(\frac{2618}{2618+5678+7602}\right) * 1 = 0.165\ main\ partners \rightarrow \left(\frac{0.329-0.165}{0.329}\right)$$
$$\left(\frac{5678}{2618+5678+7602}\right) * 1 = 0.357\ casual \rightarrow \left(\frac{0.714-0.357}{0.714}\right) = 5$$
$$\left(\frac{7602}{2618+5678+7602}\right) * 1 = 0.478\ oo \rightarrow \left(\frac{0.956-0.478}{0.956}\right) = 50.$$

In this approach, all experience 50% reduction. But this doesn't really make sense.

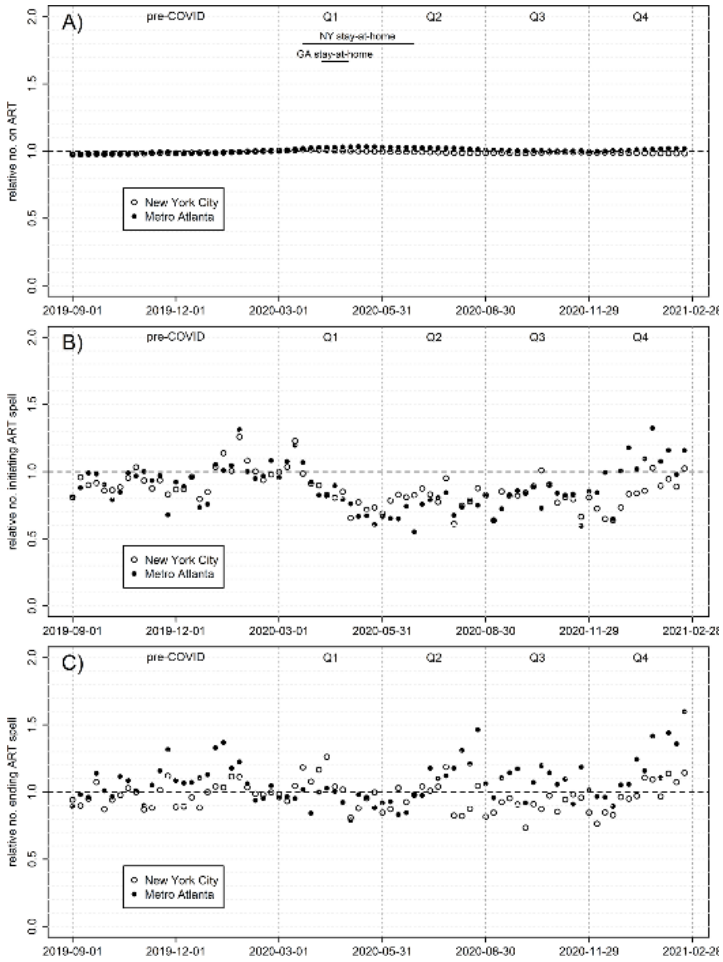
		It is not logical to assume that all changes are in casual (and none in one-time partnerships). **For November 2020–January 2021:** Also reduces to 1 partner. So same calculations as April/May can be used. <u>Ranges for April–May 2020and November 2020–January 2021 (from partner numbers):</u> Main: Decrease by 0%-50% = modifier of 0.5-1.0; 1.0 most likely Casual: Decrease by 4%-50%; modifier of 0.5-0.96; 0.94 most likely OO: Decrease by 50%-100%=modifier of 0.0-0.5; 0.0 most likely However, the number of causal partners ≠ number of casual acts. To translate from partners to acts, we could assume that the change in number of partners directly approximates the change in number of acts (that is, assume the act rate is the same for each persistent partner an individual has). If assuming all changes are within one-off partnerships, the maximum modifier for both main and casual could be 1.0. Alternatively, using act rate data: Before COVID, the median number of sexual acts is 4. From distribution of partner types from ARTnet, then: $4\ median\ acts * \left(\frac{2618}{2618+5678+7602}\right) = 0.659\ acts\ with\ main\ partn$ $4 * 0.357 = 1.428\ acts\ with\ casual\ partners$ $4 * 0.478 = 1.912\ acts\ with\ oo\ partners$ **For April–May 2020:** Reduces to 3 acts If we assume main partner acts are not affected and one-time are 100% reduced, this would result in an increase in casual partner acts. So instead, we assume that main partner acts are not affected, casual acts are not affected, and one-time partnership acts absorb the decrease: $0.66\ main\ partner\ acts\ (0\%\ reduction)$ $1.43\ casual\ acts\ (0\%\ reduction)$ $3 - 0.66 - 1.43 = 0.91\ oo \rightarrow \left(\frac{1.912-0.91}{1.912}\right) = 52.4\%\ reduction$ **For November 2020–January 2021:** Maintains at 4 acts=modifier of 1.0 for all <u>Ranges for April-May (from acts):</u>	

		Main: Decrease by 0% = modifier of 1.0 most likely Casual: Decrease by 0% = modifier of 1.0 most likely OO: Decrease by 52.4%=modifier of 0.48 most likely <u>Ranges for November 2020–January 2021 (from acts):</u> All: 1.0; but with uncertainty <u>*Overall ranges for April–May 2020 (combining partner and act approach):*</u> *Main: 1.0 (0.5-1.0)* *Casual: 0.94 (0.5-1.0)* *OO: 0.0 (0.0-0.48)* <u>*Overall ranges for November 2020–January 2021 (combining partner and act approach):*</u> *Main: 1.0 (0.5-1.0)* *Casual: 0.94 (0.5-1.0)* *OO: 0.5 (0.0-1.0)*	
acts.modifier.oo	April–May 2020: OO: 0.0 (0.0-0.48) November 2020–January 2021: OO: 0.5 (0.0-1.0)	See above for calculations.	Stephenson et al 2021;[264] Stephenson et al 2022[165]; Weiss et al 2020[218]
cond.modifier.mc	April 2020: 0.95 (0.93-1.0) September–December 2020: 0.93 (0.92-1.0)	In AMIS, in April and July, 94% of participants reported no change in condom use; 4-5% reported decrease in use. In September–December 2020, this changed to 92% and 5%, respectively, with 2% reporting increased use. We assume this is same for main & causal and one-time partners (though with decreases in one-time rate, this will have less of an effect there). For calculating, we looked at distribution of increase/decrease/no change. Since majority was no change we used these values.	Sanchez et al 2020;[265] Mann et al 2023[161]
cond.modifier.oo	April 2020: 0.95 (0.93-1.0) September–December 2020: 0.93 (0.92-1.0)	In AMIS, in April and July 2020, 94% of participants reported no change in condom use; 4-5% reported decrease in use. In September–December 2020, this changed to 92% and 5%, respectively, with 2% reporting increased use. We assume this is same for main & causal and one-time partners (though with decreases in one-time rate, this will have less of an effect there). For calculating, we looked at distribution of increase/decrease/no change. Since majority was no change we used these values.	Sanchez et al 2020;[265] Mann et al 2023[161]
pr.behav.changer	0.185	L&S: In April–May 2020, 18.5% of people stopped PrEP and reduced sexual partners.	Sanchez et al 2020;[265] Mann et

		AMIS: In April, 11.4% decreased sexual partners and decreased HIV testing (no PrEP stoppage data in AMIS COVID survey). We will keep the parameter at 0.185 the whole time, but dilute the behavior changer modifier parameters over time since we see less behavior changers over time (to weaken its effect). We cannot really change the rate (create a range) without re-calibrating model (given that the probability is set at initialization and arrivals), so we will keep the value at 0.185.	al 2023;[161] Stephenson et al 2021[264]
hiv.test.rate.young_1 hiv.test.rate.young_2 hiv.test.rate.young_3 hiv.test.rate.old_1 hiv.test.rate.old_2 hiv.test.rate.old_3	Week- and race- specific modifiers	The number of HIV screening tests, from DiNenno et al 2022:[175]  	DiNenno et al 2022;[175] Goodreau et al 2023[177]

		The number of HIV tests in NYC and Atlanta, from Goodreau et al 2023:[177]  Data on weekly HIV screening tests reported by two commercial laboratories from the National Syndromic Surveillance Program were used to estimate the weekly decrease in HIV testing between 2019 and 2020. A week-specific modifier was created that was adjusted for by race: In 2020, the total number of HIV tests funded by CDC that were distributed in health care and non–health care settings decreased by 44.1% for Black individuals, 46.3% for Hispanic individuals, and 45.1% for White individuals. For example, the week-specific Black modifier was calculated by month-specific modifier*(1-0.441))/(1-0.451)=week-specific modifier for Black individuals. The COVID-era data stop in December 2020, so these modifiers were generated through December 2020.	

		We are not stratifying by young/old age category because data are very similar, especially when splitting into two binary categories (<30, ≥30 years); the differences more so are in very old, very young, but are lost in the large binary categories. Also no weekly HIV screening data divided by age are available the time of this analysis.	
behav.modifier.tests	0.0	We don't know the number of HIV tests for behavior changers in AMIS, just that they experienced a decrease in their HIV testing. Since the average HIV testing interval is already >1 year, we will assume if behavior modifiers are changing their testing this means they will not have any tests in COVID period, so modify their testing by 100% (modifier of 0).	Sanchez et al 2020;[265] Mann et al 2023[161]
tx.init.rate.young_1 tx.init.rate.young_2 tx.init.rate.young_3 tx.init.rate.old__1 tx.init.rate.old__2 tx.init.rate.old__3	Same as base	There was no change in HIV treatment linkage from 2019 to 2020 (there was actually an increase), so we assume no change in treatment initiation rate. Linkage to HIV Medical Care in 30 days in 2019 (CDC-funded HIV testing and linkage to HIV medical care among persons newly diagnosed with HIV, 60 jurisdictions in the United States, Puerto Rico, and the U.S. Virgin Islands, 2019): 71.4%. For Black: 68.3%, for Hispanic: 76.3%, for White: 72.9%. Linkage to HIV Medical Care in 30 days in 2020: 76.4%. For Black: 74.2%, for Hispanic: 82.4%, for White: 73.9%.	CDC 2019;[266] CDC 2020[267]
tx.halt.partial.rate.young_1 tx.halt.partial.rate.young_2 tx.halt.partial.rate.young_3 tx.halt.partial.rate.old_1 tx.halt.partial.rate.old_2 tx.halt.partial.rate.old_3	Same as base	No significant difference in results between 2019 and 2020 for the following: ART adherence in the past 30 days: How many days did you miss at least 1 dose of any of your HIV medicines? How well did you do at taking your HIV medicines in the way you were supposed to? How often did you take your HIV medicines in the way you were supposed to? ART outcomes for NYC and Atlanta, from Goodreau et al 2023:[177]	CDC 2021;[268] CDC 2022;[204] Goodreau et al 2023[177]

		 Also, when looking at ART data in New York City and Atlanta, we do not see notable changes in adherence:	
tx.halt.full.or.young_1 tx.halt.full.or.young_2 tx.halt.full.or.young_3 tx.halt.full.or.old_1 tx.halt.full.or.old_2 tx.halt.full.or.old_3	Same as base	No significant difference in results between 2019 and 2020 for the following: ART adherence in the past 30 days: How many days did you miss at least 1 dose of any of your HIV medicines? How well did you do at taking your HIV medicines in the way you were supposed to? How often did you take your HIV medicines in the way you were supposed to? Also, when looking at ART data in New York City and Atlanta, we do not see notable changes in adherence.	CDC 2021;[268] CDC 2022;[204] Goodreau et al 2023[177]

tx.halt.durable.or.young_1 tx.halt.durable.or.young_2 tx.halt.durable.or.young_3 tx.halt.durable.or.old_1 tx.halt.durable.or.old_2 tx.halt.durable.or.old_3	Same as base	No significant difference in results between 2019 and 2020 for the following: ART adherence in the past 30 days: How many days did you miss at least 1 dose of any of your HIV medicines? How well did you do at taking your HIV medicines in the way you were supposed to? How often did you take your HIV medicines in the way you were supposed to? Also, when looking at ART data in New York City and Atlanta, we do not see meaningful changes in adherence.	CDC 2021;[268] CDC 2022;[204] Goodreau et al 2023[177]
tx.reinit.partial.rate.young_1 tx.reinit.partial.rate.young_2 tx.reinit.partial.rate.young_3 tx.reinit.partial.rate.old_1 tx.reinit.partial.rate.old_2 tx.reinit.partial.rate.old_3	Same as base	No significant difference in results between 2019 and 2020 for the following: ART adherence in the past 30 days: How many days did you miss at least 1 dose of any of your HIV medicines? How well did you do at taking your HIV medicines in the way you were supposed to? How often did you take your HIV medicines in the way you were supposed to? Also, when looking at ART data in New York City and Atlanta, we do not see notable changes in adherence.	CDC 2021;[268] CDC 2022;[204] Goodreau et al 2023[177]
tx.reinit.full.or.young_1 tx.reinit.full.or.young_2 tx.reinit.full.or.young_3 tx.reinit.full.or.old_1 tx.reinit.full.or.old_2 tx.reinit.full.or.old_3	Same as base	No significant difference in results between 2019 and 2020 for the following: ART adherence in the past 30 days: How many days did you miss at least 1 dose of any of your HIV medicines? How well did you do at taking your HIV medicines in the way you were supposed to? How often did you take your HIV medicines in the way you were supposed to? Also, when looking at ART data in New York City and Atlanta, we do not see notable changes in adherence.	CDC 2021;[268] CDC 2022;[204] Goodreau et al 2023[177]

tx.reinit.durable.or.young_1 tx.reinit.durable.or.young_2 tx.reinit.durable.or.young_3 tx.reinit.durable.or.old_1 tx.reinit.durable.or.old_2 tx.reinit.durable.or.old_3	Same as base	No significant difference in results between 2019 and 2020 for the following: ART adherence in the past 30 days: How many days did you miss at least 1 dose of any of your HIV medicines? How well did you do at taking your HIV medicines in the way you were supposed to? How often did you take your HIV medicines in the way you were supposed to? Also, when looking at ART data in New York City and Atlanta, we do not see notable changes in adherence.	CDC 2021;[268] CDC 2022;[204] Goodreau et al 2023[177]
part.tx.init.rate.young_1 part.tx.init.rate.young_2 part.tx.init.rate.young_3 part.tx.init.rate.old_1 part.tx.init.rate.old_2 part.tx.init.rate.old_3	Same as base	There was no change in HIV treatment linkage from 2019 to 2020 (there was actually an increase), so we assume no change in treatment initiation rate. Linkage to HIV Medical Care in 30 days in 2019 (CDC-funded HIV testing and linkage to HIV medical care among persons newly diagnosed with HIV, 60 jurisdictions in the United States, Puerto Rico, and the U.S. Virgin Islands, 2019): 71.4%. For Black: 68.3%, for Hispanic: 76.3%, for White: 72.9%. Linkage to HIV Medical Care in 30 days in 2020: 76.4%. For Black: 74.2%, for Hispanic: 82.4%, for White: 73.9%.	CDC 2019;[266] CDC 2020[267]
part.tx.reinit.rate.young_1 part.tx.reinit.rate.young_2 part.tx.reinit.rate.young_3 part.tx.reinit.rate.old_1 part.tx.reinit.rate.old_2 part.tx.reinit.rate.old_3	Same as base	No significant difference in results between 2019 and 2020 for the following: ART adherence in the past 30 days: How many days did you miss at least 1 dose of any of your HIV medicines? How well did you do at taking your HIV medicines in the way you were supposed to? How often did you take your HIV medicines in the way you were supposed to? Also, when looking at ART data in New York City and Atlanta, we do not see notable changes in adherence.	CDC 2021;[268] CDC 2022;[204] Goodreau et al 2023[177]

prep.start.prob.young_1 prep.start.prob.young_2 prep.start.prob.young_3 prep.start.prob.old_1 prep.start.prob.old_2 prep.start.prob.old_3	Month- and race- specific modifiers	Calculated from monthly data on new PrEP users. Data are from a national pharmacy database from January 2017 through March 2021, and from an interrupted time-series model that predicted PrEP prescriptions and new PrEP users had the pandemic not occurred.	Huang et al 2022[174]

PrEP prescriptions, from Huang et al 2022:[174]

Table 1.

Observed and Expected Number of PrEP Prescriptions and New PrEP Users and Predicted Percentage Reduction by Month

	PrEP Prescriptions				New PrEP Users			
	Observed No.	Expected No.	% Reduction	95% CI	Observed No.	Expected No.	% Reduction	95% CI
Total	825 239	1 058 162	22.0	19.1–24.8	125 793	167 720	25.0	20.9–28.9
Month								
15–31 March 2020	31 151	32 545	4.3	−0.8 to 8.8	4550	5668	19.7	13.6–25.1
April 2020	68 502	85 587	20.0	15.5–24.0	8452	13 960	39.5	34.5–43.7
May 2020	53 878	69 344	22.3	17.9–26.3	7062	10 740	34.2	28.8–38.9
June 2020	58 442	70 747	17.4	12.7–21.6	9266	11 098	16.5	9.6–22.4
July 2020	70 520	91 338	22.8	18.4–26.7	11 291	15 434	26.8	20.9–32.0
August 2020	58 477	74 572	21.6	17.2–25.5	9859	12 778	22.8	16.7–28.2
September 2020	58 971	76 951	23.4	19.1–27.2	9588	12 622	24.0	18.0–29.3
October 2020	80 256	99 207	19.1	14.5–23.2	12 790	15 344	16.6	9.8–22.5
November 2020	63 448	79 510	20.2	15.7–24.2	8499	11 669	27.2	21.2–32.3
December 2020	74 199	99 625	25.5	21.4–29.2	10 161	14 697	30.9	25.2–35.7
January 2021	64 991	82 923	21.6	17.2–25.6	10 209	12 935	21.1	14.6–26.6
February 2021	63 782	86 357	26.1	21.9–29.9	11 115	13 919	20.1	13.6–25.8
March 2021	78 622	109 457	28.2	23.9–32.0	12 951	16 857	23.2	16.5–28.9

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Table 2.
Observed and Expected Number of PrEP Prescriptions and New PrEP Users and Predicted Percentage Reduction From 1
<table>
<tr><th rowspan="2">Characteristics</th><th colspan="4">PrEP Prescriptions</th><th colspan="4">New PrEP Users</th></tr>
<tr><th>Observed No.</th><th>Expected No.</th><th>% Reduction</th><th>95% CI</th><th>Observed No.</th><th>Expected No.</th><th>% Reduction</th><th>95% CI</th></tr>
<tr><td>Total</td><td>825 239</td><td>1 058 162</td><td>22.0</td><td>19.1–24.8</td><td>125 793</td><td>167 720</td><td>25.0</td><td>20.9–28.9</td></tr>
<tr><td>Sex</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Male</td><td>777 508</td><td>997 928</td><td>22.1</td><td>19.2–24.9</td><td>110 327</td><td>146 369</td><td>24.6</td><td>20.4–28.6</td></tr>
<tr><td>Female</td><td>47 412</td><td>59 958</td><td>20.9</td><td>17.2–24.5</td><td>15 202</td><td>21 599</td><td>29.6</td><td>25.2–33.8</td></tr>
<tr><td>Age group (years)</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>16–29</td><td>228 206</td><td>294 897</td><td>22.6</td><td>18.0–27.0</td><td>51 145</td><td>70 623</td><td>27.6</td><td>22.6–32.2</td></tr>
<tr><td>30–39</td><td>297 576</td><td>387 818</td><td>23.3</td><td>20.5–26.0</td><td>40 113</td><td>54 126</td><td>25.9</td><td>21.5–30.0</td></tr>
<tr><td>40–49</td><td>152 494</td><td>188 931</td><td>19.3</td><td>16.3–22.2</td><td>17 199</td><td>21 945</td><td>21.6</td><td>17.0–26.0</td></tr>
<tr><td>50+</td><td>146 963</td><td>186 800</td><td>21.3</td><td>18.2–24.3</td><td>17 336</td><td>21 279</td><td>18.5</td><td>13.7–23.1</td></tr>
<tr><td>Race/ethnicity</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>White</td><td>202 283</td><td>253 142</td><td>20.1</td><td>17.3–22.8</td><td>21 724</td><td>30 418</td><td>28.6</td><td>24.9–32.1</td></tr>
<tr><td>Black</td><td>40 074</td><td>47 967</td><td>16.5</td><td>13.1–19.7</td><td>6383</td><td>8274</td><td>22.9</td><td>17.7–27.6</td></tr>
<tr><td>Hispanic</td><td>48 115</td><td>59 726</td><td>19.4</td><td>16.1–22.6</td><td>6665</td><td>8775</td><td>24.0</td><td>19.2–28.6</td></tr>
<tr><td>Other</td><td>12 195</td><td>15 738</td><td>22.5</td><td>18.7–26.2</td><td>1352</td><td>1916</td><td>29.4</td><td>22.3–36.0</td></tr>
<tr><td>Unknown</td><td>522 572</td><td>681 756</td><td>23.3</td><td>20.3–26.2</td><td>89 669</td><td>118 455</td><td>24.3</td><td>19.8–28.6</td></tr>
<tr><td>Payer type</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Commercial</td><td>456 859</td><td>597 358</td><td>23.5</td><td>20.7–26.3</td><td>52 494</td><td>74 090</td><td>29.1</td><td>25.0–33.1</td></tr>
<tr><td>Public</td><td>106 426</td><td>125 232</td><td>15.0</td><td>11.5–18.4</td><td>19 048</td><td>26 534</td><td>28.2</td><td>23.5–32.6</td></tr>
<tr><td>Cash</td><td>13 876</td><td>15 900</td><td>12.7</td><td>6.8–18.3</td><td>4923</td><td>6336</td><td>22.3</td><td>15.8–28.3</td></tr>
<tr><td>Other</td><td>110 287</td><td>137 718</td><td>19.9</td><td>15.7–23.9</td><td>28 213</td><td>31 606</td><td>10.7</td><td>5.0–16.1</td></tr>
<tr><td>Region</td><td></td><td></td><td></td><td></td><td></td><td></td><td></td><td></td></tr>
<tr><td>Northwest</td><td>177 115</td><td>245 188</td><td>27.8</td><td>25.1–30.3</td><td>22 188</td><td>33 579</td><td>33.9</td><td>29.5–38.0</td></tr>
<tr><td>Midwest</td><td>124 985</td><td>160 258</td><td>22.0</td><td>18.8–25.1</td><td>15 533</td><td>23 925</td><td>35.1</td><td>30.7–39.2</td></tr>
<tr><td>South</td><td>298 094</td><td>360 993</td><td>17.4</td><td>14.1–20.6</td><td>57 032</td><td>66 619</td><td>14.4</td><td>9.5–19.1</td></tr>
<tr><td>West</td><td>223 347</td><td>295 562</td><td>24.4</td><td>21.4–27.4</td><td>30 787</td><td>44 556</td><td>30.9</td><td>26.6–34.9</td></tr>
</table>

To calculate the time- and race-specific modifier, first a month-specific modifier was generated from the percent reduction in new PrEP users. Then, these modifiers were adjusted for race (for example, the month-specific Black modifier was calculated by month-specific modifier*(1-0.229))/(1-0.2584)=month-specific modifier for Black individuals.

The COVID-era data stop in March 2021, so these modifiers were generated through March 2021.
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<tr>
<td>part.prep.start.prob.young_1

part.prep.start.prob.young_2

part.prep.start.prob.young_3</td>
<td>Same as base/</td>
<td>We are not modifying partner starts and instead focusing on other PrEP initiation.</td>
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</tr>
</table>

part.prep.start.prob.old_1 part.prep.start.prob.old_2 part.prep.start.prob.old_3			
prep.adhr.dist_1 prep.adhr.dist_2 prep.adhr.dist_3	Same as base	Not focusing on adherence but instead persistence/discontinuation. Adherence trajectory has been found to be closely associated with PrEP continuation, and retention may be a bigger challenge with more impact on PrEP effectiveness than adherence.	Jin et al 2021;[269] Chan et al 2016[270]
prep.discont.rate.young_1 prep.discont.rate.young_2 prep.discont.rate.young_3 prep.discont.rate.old_1 prep.discont.rate.old_2 prep.discont.rate.old_3	Month- and race- specific modifiers	Calculated from monthly data on PrEP prescriptions. This assumes PrEP prescriptions approximates PrEP discontinuation. Data are from a national pharmacy database from January 2017 through March 2021, and from an interrupted time-series model that predicted PrEP prescriptions and new PrEP users had the pandemic not occurred. To calculate the time- and race-specific modifier, first a month-specific modifier was generated from the percent reduction in PrEP prescriptions. For example, a reduction by 4% translated to a modifier of 1.04. Then, these modifiers were adjusted for race (for example, the month-specific Black modifier was calculated by month-specific modifier*(1.165))/(1.1867)=month-specific modifier for Black individuals. The COVID-era data stop in March 2021, so these modifiers were generated through March 2021.	Sanchez et al 2020;[265] Mann et al 2023;[161] Stephenson et al 2021[264]
behav.modifier.prep	0.0	By our definition (and set from L&S and AMIS data), these represent people that discontinue PrEP alongside sexual behavior change. It is illogical for them to have PrEP initiation, so we can assume the modifier is 0.	Sanchez et al 2020;[265] Stephenson et al 2021[264]

10 Model Calibration

This section describes the methods for executing the simulations and conducting the data analysis on the outcomes in further detail.

Even though our model uses around 20 parameters with uncertain values, most of them have a monotonic direct relationship with a single target. (e.g. HIV test rate and proportion of the HIV positive being diagnosed).

Our calibration methodology employs a two-step process, utilizing various techniques to optimize the model parameters based on target statistics. In the initial step, we focused on calibrating the model to accurately reproduce the target statistics pertaining to the HIV care continuum and HIV diagnosis rates. To achieve this, we conducted simulations of the model over a 60-year period.

We did not include STIs in our models.

To calibrate the model, we employed polynomial regression surrogates to optimize the parameters. Through the process of fitting these regression models, we obtained the most optimal estimates for each parameter. Subsequently, we conducted additional simulations, narrowing down the parameter range to values centered around the estimated optimal values. This iterative process continued until further improvement in the surrogate's prediction was no longer observed, signifying the successful calibration of the parameters.

The selection of the polynomial regression degree, the rate at which the parameter range was reduced, and the improvement threshold were determined as hyperparameters, tuned to enhance the calibration process.

Given that certain parameters exhibited conditional dependencies on the values of other parameters, they were calibrated in a subsequent step. For example, the HIV prevalence parameter relied on a fixed value of the HIV test rate.

For the HIV prevalence, 3 transmission scale parameters govern 3 race stratified HIV prevalence target. In this case, we employed a shrinking grid search approach, aiming to minimize the root mean squared error (RMSE). At each iteration, the search space was narrowed down to the parameter space of the top-performing P simulations. Calibration concluded once we attained N simulations wherein the target statistics deviated from the desired targets by less than a threshold T. The calibrated values were determined by computing the median of each parameter among the qualifying simulations.

Once the HIV care continuum calibration was complete, we simulated 20,000 replicates of the fitted model and selected the single simulation with values of the target statistics closest to the targets (with total absolute deviance).

In the second step of our calibration process, we conducted additional model simulations over a 5-year period to introduce entropy into the system. Subsequently, we extended the simulation for an additional 10 years to incorporate the PrEP continuum.

Similar to the first step, the parameters in this stage were optimized using a polynomial regression surrogate. We then calibrated the PrEP parameters.

For each candidate parameter, θ, to be estimated, we:

1. Sampled a candidate θ^i from a prior distribution $\pi(\theta)$
2. Simulated the epidemic model with candidate value, θ^i.
3. Tested if a distance statistic, d (e.g., the difference between observed HIV diagnosis rate and model simulated diagnosis rate) was greater than a tolerance threshold, ϵ.
    a. If $d > \epsilon$ then discard
    b. If $d < \epsilon$ then add the candidate θ^i to the posterior distribution of θ.
4. Sample the next sequential candidate, θ^{i+1}, either independently from $\pi(\theta)$ (if 3a) or from θ^i plus a perturbation kernel with a weight based on the current posterior distribution (if 3b).

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