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Modeling the Impact of Post-Diagnosis Behavior Change on HIV Prevalence in Southern California Men who have Sex with Men (MSM)

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Abstract

Our objective here is to demonstrate the population-level effects of individual-level post-diagnosis behavior change (PDBC) in Southern Californian men who have sex with men (MSM), recently diagnosed with HIV. While PDBC has been empirically documented, the population-level effects of such behavior change are largely unknown. To examine these effects, we develop network models derived from the exponential random graph model (ERGM) family. We parameterize our models using behavioral data from the Southern California Acute Infection and Early Disease Research Program (AIEDRP), and biological data from a number of published sources. Our models incorporate vital demographic processes, biology, treatment and behavior. We find that without PDBC, HIV prevalence among MSM would be significantly higher at any reasonable frequency of testing. We also demonstrate that higher levels of HIV risk behavior among HIV-positive men relative to HIV-negative men observed in some cross-sectional studies are consistent with individual-level PDBC.

Keywords

Post-Diagnosis Behavior Change; Men who have Sex with Men (MSM); HIV Modeling; Exponential Random Graph Models (ERGMs)

Introduction

Men who have sex with men (MSM) form one of the highest risk groups for HIV in the United States, with roughly half of new infections occurring in this population [1]. The Centers for Disease Control and Prevention (CDC) estimate the prevalence of HIV in the MSM community nationally at about 19% [2]. Recent longitudinal studies have found that many MSM reduce risky sexual activity upon HIV diagnosis [3, 4, 5], a phenomenon we term “post-diagnosis behavior change” (PDBC).

One likely cause of PDBC is a desire among some MSM to protect one's partners, and such “community-initiated” strategies may have much potential for prevention of new infections [4, 6]. These modifications include reducing the number of sexual partners, especially casual ones, reducing unprotected anal sex within partnerships, and choosing partners with the same HIV status (serosorting) [3, 4]. Since transmission of HIV is more probable when the infected partner is insertive rather than receptive [7], modifying sexual role in partnerships (sero-positioning) is another behavioral strategy MSM adopt to reduce transmission events [3, 4]. MSM have multiple types of sexual contacts, ranging from stable main partnerships to casual, one-time contacts [3, 8]; levels and patterns of PDBC appear to vary by partnership type [5], as may be expected, since the desire to protect one's partner would reasonably vary with levels of emotional intimacy.

In contrast, a review of cross-sectional studies found that MSM diagnosed as HIV-infected average a high level of risky sexual activity [9]. Another cross-sectional study found an increase in condom use and/or abstinence among MSM at diagnosis, but that a high proportion of those who reported anal intercourse still reported no condom use [10]. Given the cross-sectional nature of the latter study and those in the review, it is difficult to assess from them the change in level of risky sexual activity that occurred upon diagnosis.

The timing, extent and durability of PDBC, as well as the levels of heterogeneity in all of these measures, are not well understood. However, even short-term reductions among recently HIV diagnosed individuals may be highly effective in reducing onward transmission events, since recently diagnosed individuals are more likely than others to be in (or not far removed from) the stage of acute infection when viral loads are very high and patients are likely to be highly infectious [11]. If behavior change to reduce risk of onward transmission occurs when individuals are most infectious, its preventive potential may be maximized. The effectiveness of risk-reduction approaches that MSM undertake, however, continues to be debated [12].

In this paper, we use mathematical models to demonstrate the impact of PDBC of recently diagnosed MSM on overall HIV prevalence in MSM. Our models are parameterized using data from the longitudinal Acute Infection and Early Disease Research Program (AIEDRP), a multi-center investigation of newly diagnosed MSM. We use behavioral data from, and focus our model on, Southern California [3, 5]. This populous and racially diverse area of the United States includes the major urban areas of Los Angeles and San Diego, and is home to a large HIV epidemic in which MSM comprise approximately 70-80% of new and prevalent infections [13, 14, 15]. We also consider how a cross-sectional sample of

diagnosed and undiagnosed MSM drawn from our dynamically simulated population would compare in their behavior, in order to interpret our results in light of previous cross-sectional studies [9]. Finally, we present estimates of the proportion of individuals who are diagnosed within the first 180 days of infection ("early diagnosis"), the period during which PDBC is expected to have its greatest effect.

Methods

Overview

We create a dynamic, stochastic network simulation based in the exponential random graph modeling (ERGM) framework, parameterized using biological, behavioral and demographic data. The model structure closely follows that developed for the Prevention Umbrella for MSM in the Americas (PUMA) project, as do many of the biological parameters [16]. Our model incorporates births, deaths, aging, treatment, circumcision status, testing behavior, methamphetamine use, diagnosis status, post-diagnosis behavior change (PDBC), partnership types, viral load, and sexual role.

Extensive detail on each component is included in the appendix; summary data are below. The behavioral data are primarily from a sub-study of the Southern California Acute Infection and Early Disease Research Program (AIEDRP) study. Complete details on the AIEDRP sub-study are elsewhere [3, 5]. In summary, newly diagnosed HIV positive men completed behavioral questionnaires at baseline, including information on their overall sexual behavior and behaviors with individual partners in the months prior to diagnosis (the latter commonly called "egocentric" network data). Follow-up information was collected at interviews every 3 months after initial enrollment, up to 12 months. A total of 193 respondents completed the baseline and at least one follow-up survey. At baseline, respondents provided detailed information on their three most recent partners, and at follow-up, on the most recent partner, yielding a total of 1011 partner reports. Although the survey included seven options for partnership type, for simplicity we dichotomize these as "main" and "non-main"; the former includes the survey option "main", while the latter category includes all others (unknown, one-time, acquaintance, friend, regular, trade).

We use these data to create network models constructed using extensions to the exponential random graph model framework (ERGMs, also called p^* in the literature). In their basic form, ERGMs allow us to simulate cross-sectional networks, maintaining an arbitrary set of network features (within stochastic variation). These features are described in the form of statistics that may include various forms of dependence in the ties in the network. This capability to include statistical dependence among partnerships (e.g. as in the case of two or more partnerships overlapping in time [17], a major behavioral feature in the models we develop here) is a major strength of the applicability of the ERGM framework to the modeling of sexual partnerships, since classical compartmental methods for modeling HIV transmission cannot capture such dependence [18]. As in compartmental models, we are also able to account for various selection forces such as assortative mixing based on age, race and knowledge of HIV status. Separable-temporal ERGMs (known as STERGMs) [19], are an extension of ERGMs to the case of dynamic networks, allowing us to model

stochastically evolving networks with relational dependence in a statistically principled fashion.

Our models employ both cross-sectional ERGMs and dynamic STERGMs, as explained below. Both are implemented using the statnet suite of packages programmed in the R programming language [20].

Non-Main Networks: Specification and Estimation

We model UAI contacts in non-main partnerships in our population as a series of cross-sectional networks. The specific features of the network structure that we capture are the mean number of partnerships per person cross-sectionally, assortative mixing by age and race, general heterogeneity in UAI propensities, and additional heterogeneity in these propensities between methamphetamine users and non-users. In this network, PDBC is modeled by considering two network features: a reduction in total UAI with non-main partners by diagnosed individuals and selective mixing by diagnosis status so that the number of ties between individuals of the same diagnosis status is greater than would be expected by chance.

Data for all of these features (except race mixing and methamphetamine use) are obtained from the AIEDRP study [3, 5]. While the AIEDRP study reports data on race mixing in MSM, these data were too sparse to adequately parameterize our models; we therefore use a larger study of MSM from elsewhere in the same state (San Francisco) [21]. Note that we are not assuming that the race composition of San Francisco and Southern California are the same, but rather, that the patterns of within- and across-race mixing in the two settings are the same, conditional on the local composition.

The proportion of methamphetamine users in the AIEDRP sample is extremely high, presumably because this is a sample of recent seroconverters. To use estimates more reflective of methamphetamine use in our population of interest, we use data from a separate study that reports 11% of MSM recently diagnosed with AIDS in Los Angeles County have used methamphetamines in the past 12 months [22].

Main Network: Specification and Estimation

The main network incorporates partnership duration information in addition to information on network statistics measurable from our egocentric cross-sectional data. Therefore, we use the STERGM class of models [19]. This approach preserves the following features stochastically: the proportion of individuals who report 0, 1, or 2 ongoing main partnerships at a given time, and age and race mixing. As in the non-main networks, all statistics except race mixing are from AIEDRP, and race mixing is from the same study of MSM in San Francisco [21].

We model transmission of infection in the main network through UAI acts within ongoing partnerships that occur on a given day (more details below). PDBC in the main network is modeled by considering a reduction in the daily probability of UAI in main partnerships that are discordant by diagnosis status. For main partnerships, the daily probability of UAI was

not directly estimable from AIEDRP; therefore, we used this estimate as given in PUMA [16].

Testing

We assume that everyone who has not previously been diagnosed as HIV-positive has the same daily probability of testing. Our base model parameterizes testing frequency using studies containing self-reports of the time since last test for negative men from a study of MSM in clinics in four major US cities [23]. The study reports a median inter-test interval of 243 days [23]. If we assume a simple exponential waiting time distribution for the time until test, this statistic corresponds to a mean inter-test interval of 351 days. We conduct sensitivity analyses on this parameter (discussed below).

Treatment

Since treatment is an important component of HIV epidemiology in United States MSM, we adopted a basic model of treatment that estimates timing of treatment initiation in terms of time since infection, disaggregated by race in accordance with clinical data from Swindells et al. [24] and as presented in PUMA [16]. We also match epidemiological data on the proportion of HIV-infected and diagnosed individuals on treatment at any given point of time, as well as the percent of those who are virally suppressed, as presented in PUMA [16]; details are in the appendix.

Components of Simulation

We create an initial population of 5,000 MSM using a simulated annealing algorithm that approximates the network structural statistics estimated from our behavioral data sources. We randomly infect 19% of our population in accordance with recent estimates of HIV prevalence in United States MSM [2]. We then simulate our model forward in daily time steps, with each of the following steps:

1. Arrivals: Men enter our population at age 18, when they are untested for HIV, and are HIV-negative. We set the number of arrivals to have a population that grows slightly given a stable HIV epidemic.
2. Deaths/Departures: Non-HIV deaths follow US age-specific mortality rates derived from CDC life-tables [16]. AIDS-related deaths occur as a function of time since infection, treatment, and suppression history (see below). Individuals leave the population of interest at 65 years of age (the general upper limit for available behavioral data).
3. UAI in non-main partnerships: In the non-main network, partnerships are defined as UAI contacts on a particular day. We simulate a random draw from our ERGM model to identify the pairs having non-main UAI.
4. UAI in main partnerships: UAI events occur with a given probability on a particular day in accordance with parameters used in PUMA, since these parameters are not directly estimable from AIEDRP. This daily probability is based on the diagnosis statuses of the two partners.

5. Transmission in main and non-main partnerships: HIV transmission occurs probabilistically in partnerships on days containing UAI events. This probability is a function of the viral load and circumcision status of the infected partner. We consider transmission only due to UAI, and ignore transmission due to other events such as oral intercourse, or needle sharing.

6. Formation and dissolution of main partnerships: We model this process using our current population as a base from which to simulate a single time step from our STERGM model.

7. Changes in other attributes: We update temporal attributes such as age and time since infection. We then update viral load, treatment status and infectivity, each as a complex function of multiple attributes including time since infection.

We repeat all steps over a 50 year period to allow the epidemic trajectory sufficient time to equilibrate. (For our purposes here, we consider our prevalence to have equilibrated if prevalence changes by less than 0.05% in absolute value over 1000 time units, and if this trend is maintained over the last 3000 time steps of the simulation; recall that one time step equals one day here.) We then re-run each scenario 10 times to obtain a measure of the stochastic variation within scenarios.

Modeling Post Diagnosis Behavior Change (PDBC)

We model the following mechanisms of PDBC:

1. Reduction in total number of non-main partnerships: We model a 25.6% reduction in mean number of non-main partnerships upon diagnosis in accordance with AIEDRP data, as seen in Figure 1 of Gorbach et al., where the mean number of non-main partners is 8.37 in the three months prior to diagnosis, and 6.23 post-diagnosis, taking the mean over the four follow-up periods [5].

2. Selection of non-main partners by diagnosis status: AIEDRP data classify the HIV status of partners as positive, negative or unknown. We reclassify the unknown partners as positive or negative according to the proportion of HIV positives in the population nationally. We then model, in accordance with AIEDRP, an average reduction of 40% in the proportion of discordant non-main ties compared to the number expected if there was proportional mixing by diagnosis status.

3. UAI in Main Partnerships: Within main partnerships, we model a reduction in daily probability of UAI from 0.156 to 0.109. As explained above, the former is obtained from AIEDRP data and the latter from PUMA [16].

In this work, we do not model sero-positioning as a risk reduction strategy.

Counter-Factual Models

We explore counter-factual models that vary from the baseline models by removing all behavioral change as a result of diagnosis. That is, we model no reduction in total number of non-main partners upon diagnosis, proportional mixing by diagnosis status in non-main

partnerships, and the same daily probability of UAI within main partnerships that are diagnosed serodiscordant as those that are not.

Parameters from the AIEDRP follow-up data represent the behavior of diagnosed men. Therefore, our base scenario that models PDBC includes parameters from both baseline and follow-up data-sets. The counterfactual that does not incorporate PDBC includes information only collected at baseline to capture the behavior of undiagnosed men.

Sensitivity Analysis

Our baseline model was parameterized using reported data on testing frequency [23]. Other studies have reported different summary metrics on testing and awareness, e.g. the proportion of HIV-positive men in a given setting who are aware of their status. For instance, the CDCs NHBS study reported that only about 56% of infected MSM nationally are aware of their status [2]. In contrast, initial runs of our baseline model suggested that at our selected level of testing, about 95% of infected MSM would be aware of their status at a given point in time. To obtain the 56% figure, we set the mean inter-test interval at 4000 days (10.9 years) in our model.

These numbers are thus difficult to reconcile within our model. One obvious solution would be if there were a large proportion of men who never tested at all, something our model does not consider. However, the same NHBS study suggests that only about 9.1% of MSM have never tested [2]. Multiple additional potential explanations exist (see the discussion). Since we cannot ascertain which explanation is correct, we conduct a sensitivity analysis in which we vary the mean testing frequency, which in turn leads to different proportions of the HIV-positive population being aware of their status in the long run. We experimented with two main scenarios:

1. "Testing Frequency" (Baseline Models): In this setting we assume that men test once every 351 days on average in accordance with clinical data from Helms et al. [23].
2. "Level of Awareness": Here we assume that the proportion of HIV-positive MSM who are aware of their status as reported by the CDC (56%) is correct [2]. We experiment with scenarios iteratively to obtain the mean testing frequency that yields level of diagnosis of approximately 55-60% awareness of infection among HIV-positive men. Given the large computing time per experimental run, we simulated a set of testing intervals and selected the one with the resulting level of awareness that came closest to the estimated value of 56%. As mentioned previously, this average testing interval is 4000 days (approximately 10.9 years).

We then run additional simulations in between these values, considering average testing rates of 2, 4, 6, 8, and 10 tests every ten years. In each case, we model the scenario with PDBC and the counterfactual without it. We also present the proportion of individuals who are diagnosed "early" (within 180 days of infection) at these testing rates, and interpret these results in light of current needs for public health planning.

Results

Figure 1 shows a comparison of prevalence trajectories in the baseline testing frequency models with and without PDBC. We see that mean prevalence at the end of our simulation when PDBC is accounted for is 31.9%, and 41.7% when there is no PDBC. Thus, prevalence would be higher by close to a third (30.6%) without PDBC given our baseline models. With testing at this frequency, our model suggests that approximately 94.8% of HIV-positive men would be aware of their status at the steady state. Note that the prevalences we see in this paper are higher than national estimates for MSM, since our baseline model is parameterized by the behavior of men just before diagnosis. We discuss implications below.

In contrast, under the level-of-awareness model (Figure 2), the effects of PDBC are much smaller: the mean equilibrium prevalence with and without PDBC is 44.5% and 45.3% respectively, a mere 1.8% increase. Recall that to reduce the level of awareness, we had to assume that the average testing frequency in this model is about once every 10.9 years. The mean proportions of those infected who are aware of their infection status in the cases with and without PDBC are 62.3% and 62.9% respectively.

Figure 3 shows the percent rise from the PDBC scenario to the no-PDBC scenario for each of the intermediate testing frequency models. We see that a large effect for PDBC (approximately 30% higher prevalence without it than with) persists through testing averages as infrequent as 6 per 10 years (slightly more than once every two years). Even at an average of only two tests every ten years, the equilibrium prevalence without PDBC is 15.2% higher than when PDBC is accounted for.

In Figure 4, we compare the cross-sectional mean number of non-main partners per person of diagnosed and undiagnosed men; the latter category includes truly negative and positive but undiagnosed men. We see that both the testing frequency and level-of-awareness models show diagnosed individuals having a greater number of non-main partners per individual cross-sectionally than undiagnosed individuals, despite the existence of PDBC. The initial level of heterogeneity in HIV risk behavior in our population (derived from data), combined with the fact that those with most risk selectively become positive, leads to the counter-intuitive pattern where diagnosed positives have more partners than other men, despite having reduced their partner numbers at diagnosis.

In Table I, we present the proportion of infected individuals who are diagnosed early for all models that we consider. As expected, the average rate of testing and the proportion of infected men diagnosed early are positively correlated.

Discussion

In this paper, we demonstrated the population-level effects of the individual-level behavior change of recently diagnosed HIV-positive MSM. Our baseline scenario (“testing frequency”), based on clinical data from Helms et al. [23], shows that without PDBC, HIV prevalence in the MSM community would be higher by about 30.6% than with PDBC. Our second scenario (“level of awareness”), created to match NHBS data [2], show that without

PDBC, equilibrium prevalence would be higher by only about 1.8% relative to models that incorporate PDBC.

We interpret our two scenarios as providing bounds on high and low rates of testing among MSM. Our analyses indicate that under some intermediate testing frequencies, prevalence among MSM would be higher by up to 30% if men did not practice observed levels of PDBC. Furthermore, even with testing as infrequent as twice every ten years on average, prevalence among MSM would still be higher by about 15% in the absence of observed levels of PDBC.

We also observe that in the testing frequency scenario the proportion of individuals diagnosed early is about 30%, and approximately 3% in the level-of-awareness scenario. Not surprisingly, the proportion of early diagnoses and the average frequency of testing are positively correlated (as seen in Table 3). At average testing rates as low as two tests per 10 years, we see about 6.9% early diagnoses; this proportion rises to about 18% at average testing frequencies of five tests per ten years (or one test every two years).

We also found that even when we account for PDBC in the population, diagnosed individuals have more partners cross-sectionally (per person) than undiagnosed individuals. More longitudinal studies are needed to capture the true extent of PDBC; cross-sectional measures of levels of sexual activity among diagnosed and undiagnosed individuals are not suggestive of the extent to which PDBC exists, and potentially impacts the HIV epidemic, in a population.

This study is not an attempt to model the historical trajectory of the epidemic. Therefore, readers should not interpret Figures 1 and 2 as a prediction of HIV prevalence over the next 50 years. Rather, the purpose of this paper is to model HIV prevalence trajectories given current data on the sexual behavior of Southern California MSM and demonstrate how much higher prevalence could be if PDBC were not present, and the potential for behavior change to impact the course of the epidemic.

The different sampling mechanisms may be one possible reason for the large difference in proportion of diagnosed individuals in the clinical data reported by Helms et al. [23] and the NHBS [2]; the former reports data on MSM testing at clinics, and the latter samples MSM frequenting venues popular in the community. Some venues where NHBS data are collected (bars, clubs) tend to have an over-representation of young MSM, who are particularly likely to not be diagnosed. Thus the low infection awareness in the NHBS data is likely an artifact of the interplay of various sampling factors, and less representative of the real infection awareness in the MSM population.

Another possible reason why the clinical and NHBS data sources differ widely in proportion of infected MSM who are diagnosed is that stigma and social desirability can influence accurate reporting of knowledge of HIV status. A recent study reports that fear of judgment and timing of the interview (relative to time of diagnosis) are factors that may influence both, the reporting of test results and the reporting of testing history [25]. It is likely that the truth on awareness of infection lies somewhere between what the clinical and NHBS data show, and it is helpful to interpret the results of our study in this light.

We also do not include MSM who never test in our models, and it is possible the testing frequency and the level-of-awareness scenarios would not be as different if the models did include non-testers. One might argue that including non-testers in our model is hence necessary. However, data from NHBS 2008 reveal that only a small proportion (about 9.1%) of MSM in their sample are non-testers, while about 58.3% tested in the last year (the rest tested more than a year ago) [2]. Given that the proportion of individuals who never test is so low, it is unlikely that simply including a group of non-testers in the model will explain the apparent gap between the clinical and NHBS data.

The prevalence values we see in this paper are somewhat higher than the national estimates of 20-25% in MSM because the baseline components of these data come from a group of recently HIV-diagnosed individuals. Since our sample consists of recently diagnosed men (with a likely disproportionately high number of recent seroconverters), on average, the behavior of these men with regards to HIV acquisition is potentially more risky than a typical member of the MSM population. It is also likely that the follow-up data show more reduction in behaviors directly related to HIV acquisition than typically occur because these men are participants in the follow-up components of the study and are therefore likely more conscious of their behavior upon diagnosis than a typical member of the population. Therefore, our work provides an upper bound on the extent to PDBC potentially mitigates the epidemic – under the assumption that diagnosed individuals reduce their sexual activity with regards to the three mechanisms we model. The extent of variability around this estimate can be quantified by a sensitivity analysis, which we leave for future modeling work on testing strategies and PDBC.

In the AIEDRP data, respondents report on their last three partners at baseline, and only their last partner at follow-up. However, we were not limited to these partners in identifying the total numbers of partners that individuals had, which was also reported. For additional partners beyond these, however, we did not have information on whether they were a main or non-main partner, and we assigned all to non-main. It is possible that we may have misclassified some partners who were actually main. However, since the desire to protect a main partner through condom use or by replacing anal with oral sex is likely to be greater than the desire to protect a non-main partner, any effect of this misclassification would likely underestimate the effect of PDBC.

Gorbach et al. [5] found evidence for behavioral rebound towards more potentially transmitting sex acts around month 12 after diagnosis; their metric of interest was the proportion of partners of unknown HIV status with whom the respondents had recent UAI. Our model was parameterized in terms of temporal frequency of UAI with main and casual partners of different perceived serostatuses, a metric that includes that of Gorbach et al. [5] plus additional information about overall coital frequency and numbers of partners by perceived serostatus. In this combined metric, the appearance of rebound at month 12 was less clear, and we hence did not include such an effect in our model.

Rebound effects would clearly reduce the degree to which PDBC has lowered HIV burden in this population relative to the counterfactual of no PDBC. The extent to which our results would change is unclear, although we note that all rebound would occur long after the end of

the acute phase, when infectiousness has declined. More information on the situations under which rebound does or does not occur, as well as its magnitude and durability, is needed. Our research team is currently running a longitudinal prospective cohort study of newly diagnosed men, which should help clarify many of these issues, and we hope that future modeling work will revisit this question with the new data.

Given the importance of treatment in the HIV epidemiology of MSM in the United States, we adopted a basic model of treatment that accounts for race differentials as measured by the waiting time between onset of infection and commencement of treatment in accordance with a clinical study in PUMA [16]. However, the landscape of treatment is constantly evolving, and future work on the subject should account for changes in such treatment patterns. Furthermore, although treatment is included in our model, and diagnosis was a necessary but not sufficient condition to begin treatment, our model did not consider explicit treatment-as-prevention interventions, as these have received considerable modeling focus [26, 27, 28, 29]. Such benefits of treatment-as-prevention strategies would occur in addition to the benefits accruing from behavioral change that we document here.

We also presented the positive correlation between average rate of testing and proportion of early diagnoses. This information is helpful in understanding the importance of diagnosing people when they are likely still in (or not far removed from) acute infection. We are currently conducting additional modeling work to consider the potential impact of various approaches to instituting tests capable of detecting HIV earlier than those currently in wide use, and/or increasing the frequency of testing among MSM.

Our findings suggest that PDBC retains a significant role in altering the future course of HIV epidemics among MSM. This role is in addition to benefits that may come from diagnosis in terms of earlier treatment and subsequent prevention of transmission through reduced viral load. As other studies [30, 31] have pointed out, and as has been highlighted in the international press [32], even with the introduction of new biomedical methods of HIV prevention, it is recognized that the HIV epidemic cannot be fully contained without significant behavioral changes along with the adoption of (and adherence to) biomedical interventions that reduce overall transmission rates.

Supplementary Material

Refer to Web version on PubMed Central for supplementary material.

Acknowledgments

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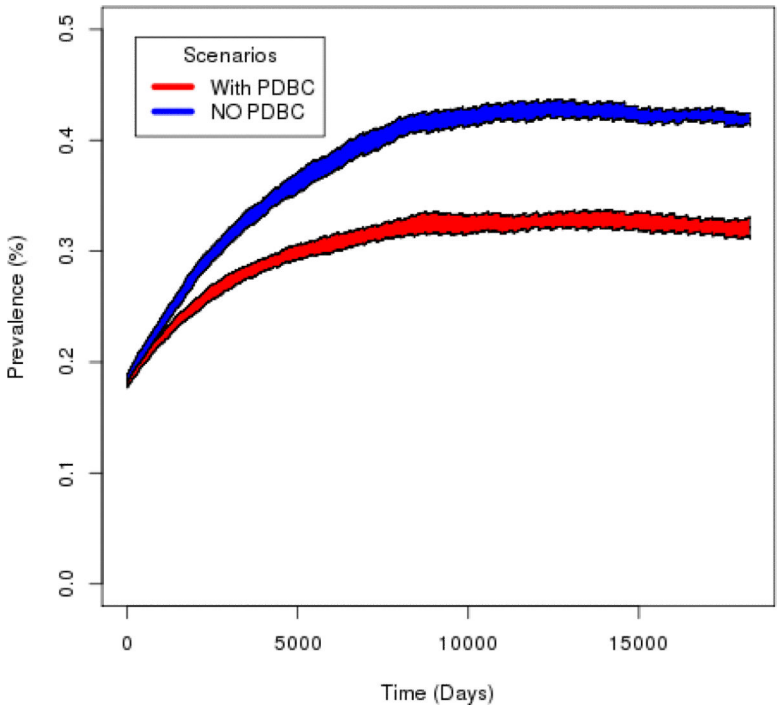

Figure 1.

HIV prevalence with and without post-diagnosis behavior change (PDBC) in the baseline "testing-frequency" models. The shaded areas corresponds to 95% confidence regions.

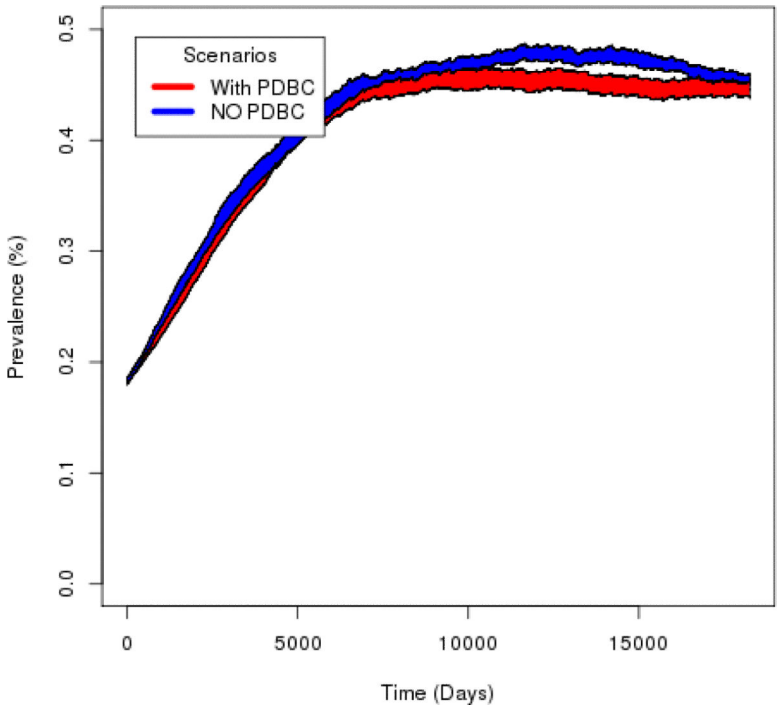

Figure 2.

HIV prevalence with and without post-diagnosis behavior change (PDBC) in the "level-of-awareness" models. The shaded area corresponds to 95% confidence regions.

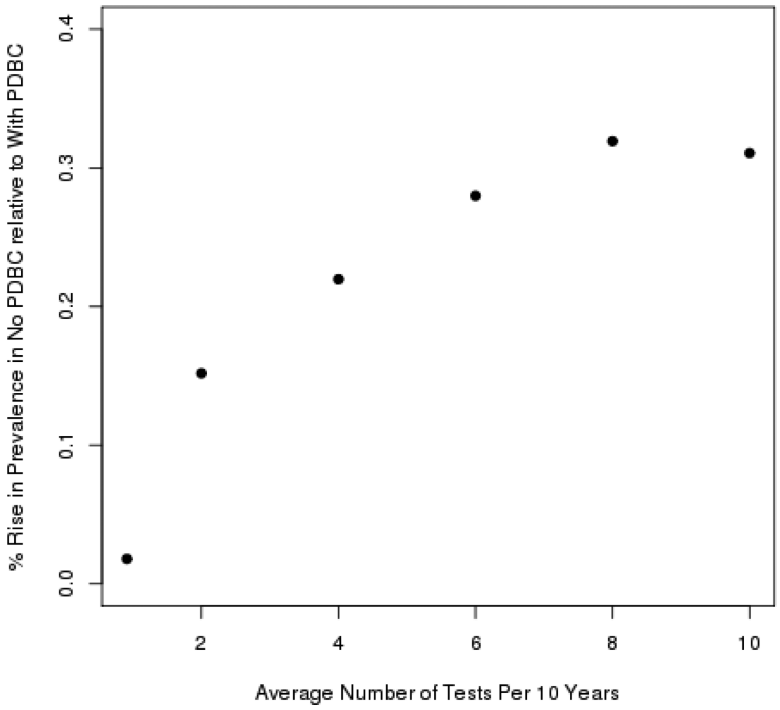

Figure 3.

Increase in equilibrium prevalence in the scenario without post-diagnosis behavior change (PDBC), relative to the scenario with PDBC, at different mean testing frequencies.

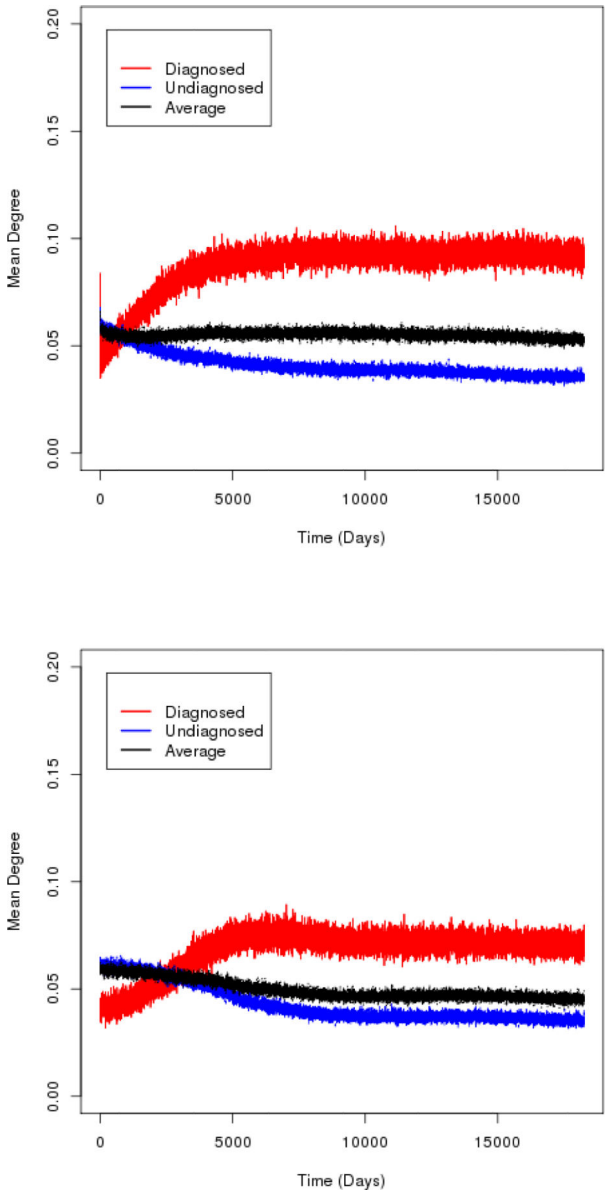

Figure 4.

Mean number of non-main partners, overall and for diagnosed and undiagnosed men, in the "testing frequency" (top figure) and "level-of-awareness" (bottom figure) cases when we account for PDBC. The undiagnosed category includes men who are truly HIV negative, and men who are HIV positive but undiagnosed.

Table I

Proportion of infected individuals who are diagnosed early (within 180 days of infection) for all models with and without PDBC.

Scenario	Average Rate of Testing (mean # of tests per 10 years)	With PDBC	No PDBC
Level-of-Awareness	0.9	3.3%	3.7%
Intermediate Cases	2	6.9%	7.3%
	4	13.7%	13.6%
	6	18.3%	19.4%
	8	24.1%	24.3%
Testing Frequency	10.4	31.6%	30.5%