Effects of Contact Structure on the Transient Evolution of HIV Virulence

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Abstract

Early in an epidemic, high densities of susceptible hosts select for relatively high parasite virulence; later in the epidemic, lower susceptible densities select for lower virulence. Thus over the course of a typical epidemic the average virulence of parasite strains increases initially, peaks partway through the epidemic, then declines again. However, precise quantitative outcomes, such as the peak virulence reached and its timing, may depend sensitively on epidemiological details. Fraser *et al.* proposed a model for the eco-evolutionary dynamics of HIV that incorporates the tradeoffs between transmission and virulence (mediated by set-point viral load, SPVL) and their heritability between hosts. Their models use implicit equations to capture the effects of partnership dynamics that are at the core of epidemics of sexually transmitted diseases. Our models combine HIV virulence tradeoffs with a range of contact models, modeling partnership formation and dissolution and allowing for individuals to transmit disease outside of partnerships. We assess summary statistics such as the peak virulence (corresponding to the maximum value of population mean $\log_{10}$ SPVL achieved throughout the epidemic) across models for a range of parameters applicable to the HIV

epidemic in sub-Saharan Africa. Although virulence trajectories are broadly similar across models, the timing and magnitude of the virulence peak vary considerably. Previously developed implicit models predicted lower virulence and slower progression at the peak (a maximum of 3.5 $\log_{10}$ SPVL) compared both to more realistic models and to simple random-mixing models with no partnership structure at all (both with a maximum of ≈ 4.7 years to $\log_{10}$ SPVL). In this range of models, the simplest random-mixing structure best approximates the most realistic model; this surprising outcome occurs because the dominance of extra-pair contact in the realistic model swamps the effects of partnership structure.

Author Summary

Pathogens such as HIV can evolve rapidly when the environment changes. Such changes include decreases in the probability that an infectious contact (such as a sneeze for a respiratory disease, or an unprotected sex act for a sexually transmitted disease) encounters an uninfected, susceptible person and thus has a chance to transmit the pathogen. Disease spread during an epidemic reduces the fraction of susceptible people in the population and thus changes the direction of parasite evolution. While researchers have explored these evolutionary dynamics with simulations, their models have neglected important processes such as people entering and leaving sexual partnerships. We compared several evolutionary models that include partnership dynamics and sexual contact outside of stable partnerships. Models of intermediate complexity predicted lower virulence over the course of the epidemic (a maximum of 3.5 $\log_{10}$ SPVL) than either more realistic models or simple models without any partnership structure at all (both approx. 4.7 $\log_{10}$ SPVL), because sexual contact outside of stable partnerships tended to wash out the effects of contact structure. The large effect of epidemiological details on evolutionary dynamics suggests that researchers trying to predict the evolution of pathogens should proceed with caution.

Introduction

The evolution of pathogen virulence has both theoretical and, potentially, practical importance. In general, evolutionary theory suggests that pathogens with higher reproduction numbers ($\mathcal{R}_0$) — that is, the number of secondary infections caused by a single infected host over the course of its infectious period — will tend to increase in prevalence relative to strains with lower reproductive ratios. Pathogens can increase their reproduction numbers either by increasing their transmission rate, the rate (per infected host) at which they infect new hosts, or by decreasing their clearance or disease-induced mortality rate, the rate at which hosts recover or die from disease. The *trade-off theory* [1] postulates that transmission and disease-induced mortality rates are both driven by the rate at which the pathogen exploits host resources for within-host reproduction, and that pathogen evolution will thus strike a balance between the pathogen's rate of transmission to new hosts and its rate of killing its host (or of provoking the host's immune system to eliminate it). Some biologists have criticized the tradeoff theory [2,3], but others have successfully applied it to a variety of host-pathogen systems [4–7].

Fraser *et al.* have applied these ideas to HIV, showing that the virus appears to satisfy the prerequisites of the tradeoff theory. The *set-point viral load* (SPVL: i.e., the characteristic virus load measured in blood during the intermediate stage of infection) is a measurable proxy for the rate of HIV within-host reproduction. Higher viral loads are correlated with shorter progression times (higher virulence). Studies of discordant partnerships — stable sexual partnerships with one infected and one uninfected partner — have shown that SPVL is (1) correlated with faster transmission (the time to infection of the uninfected partner is shorter when their partner has a higher SPVL) and (2) heritable (when the uninfected member of the couple does become infected, their SPVL is similar to their partner's). Furthermore, the rate of transmission increases with increasing SPVL (and hence with decreasing progression time) but with a decreasing slope as progression time decreases, fulfilling the requirements of the tradeoff theory [8]. Subsequent studies [10–12] used these data to parameterize mechanistic models of HIV virulence evolution, suggesting that HIV invading a novel population would initially evolve increased virulence, peaking after approximately 100-200 years and then

declining slightly to a long-stable virulence level.   32

The work of Shirreff *et al.* [10], and particularly the predicted transient peak in HIV   33
virulence midway through the epidemic, highlights the importance of interactions   34
between epidemiological and evolutionary factors [13, 14]. However, despite these   35
studies' attention to detail at the individual or physiological level, the contact structures   36
used in these models are relatively simple.   37

As we discuss in detail below, existing models of HIV eco-evolutionary dynamics   38
either use implicit models that incorporate the average effects of within-couple sexual   39
contact — without representing the explicit dynamics of partnership formation and   40
dissolution or accounting for extra-partnership contact — or use an agent-based   41
formulation with parameters that effectively lead to random mixing among infected and   42
uninfected individuals. Here we explore the effects of incorporating *explicit* contact   43
structure in eco-evolutionary models.   44

Because our main goal is to explore how conclusions about virulence evolution   45
depend on the way in which contact structure is modeled, we consider a series of models   46
with increasing levels of complexity in the contact structure, but simplify some of the   47
other epidemiological processes (such as the within-host life history of HIV). We   48
evaluate our models across a wide range of parameters, using a Latin hypercube design;   49
for each model run, we compute a set of metrics that summarize the evolutionary   50
trajectory of SPVL over the course of the epidemic.   51

Materials and Methods   52

Infection dynamics   53

Our models explicitly track the evolution of the distribution of $\log_{10}$ SPVL (which we   54
denote as α) rather than the rate of progression to AIDS itself (hereafter "virulence"   55
will refer to $\log_{10}$ SPVL). We use a single-stage model of HIV that assumes constant   56
infectivity over the course of an exponentially distributed infectious period; this   57
contrasts with Shirreff *et al.*'s previous model which explicitly tracked three stages of   58
HIV infection (primary, asymptomatic, and AIDS) and used a more realistic   59
Weibull-distributed infectious period; we show below that our results are not overly   60

sensitive to this simplification. Shirreff *et al.* allowed the transmission rate and infection duration to depend on virus load only during the asymptomatic stage. In order to adapt their parameterization to our single-stage model, we used their estimates to compute the SPVL-dependent transmission rate and duration during the asymptomatic stage and then derived the overall duration of the infectious period as the sum of the three stage durations and the average transmission rate as the duration-weighted average of the three stage-specific transmission rates. Thus the within-couple transmission rate, β, for our models is given by:

$$\beta(\alpha) = \frac{D_P \beta_P + D_A(\alpha)\beta_A(\alpha) + D_D \beta_D}{D_P + D_A(\alpha) + D_D}, \tag{1}$$

where the duration of infection (D_P and D_D) and rate of transmission (β_P and β_D) of the Primary and Disease stages of infection are independent of the host's SPVL (Table 1 gives definitions, units, and values for all parameters). . Following Shirreff *et al.*, the duration of infection (D_A) and rate of transmission (β_A) for the Asymptomatic stage are Hill functions of the SPVL:

$$
\begin{aligned}
D_A(\alpha) &= \frac{D_{\max} D_{50}^{D_k}}{V_\alpha^{D_k} + D_{50}^{D_k}}, \\
\beta_A(\alpha) &= \frac{\beta_{\max} V_\alpha^{\beta_k}}{V_\alpha^{\beta_k} + \beta_{50}^{\beta_k}},
\end{aligned}
\tag{2}
$$

where $V_\alpha = 10^\alpha$.

The uncoupled and extra-couple transmission rates (i.e., the rates of transmission among people outside of a stable partnership, or between people inside of a stable partnership and people other than their partner) are scaled by multiplying the within-couple transmission rate β by the contact ratios c_u/c_w and c_e/c_w (see Appendix S1). Simplifying the model of HIV pathogenesis from three stages to a single stage could affect our conclusions about the evolution of virulence (e.g. Kretzschmar and Dietz [17] show that pair formation dynamics and multiple stages of infectivity have interactive effects on $\mathcal{R}_0$). However, our simplified model produces results that are qualitatively similar to those of Shirreff *et al.*'s [10] model; when our model is calibrated to have a similar initial epidemic growth rate r, the peak $\log_{10}$ SPVL occurs at the

Table 1. Parameter ranges/values. Parameters with fixed values are kept constant throughout simulations while other parameter values are taken from Latin hypercube samples using ranges specified in the table. Values of c and ρ are doubled from those given by Champredon *et al.* because we keep track of individuals in the model, while they keep track of couples. Starred (*) parameters (used in Fig 1), and descriptions of Hill function coefficients, are taken from [10].

Notation	Description	Range/Value	Source
ρ	Partnership formation rate	1/10-2/5 per year	[15]
c	Partnership dissolution rate	1/15-1/5 (1.25*) per year	[15]
c_u/c_w	Relative contact rate for uncoupled transmission	1/5-5	Assumption
c_e/c_w	Relative contact rate extra-couple	0.01-1	[15]
β_P	Rate of transmission during primary infection	1.31-5.09 (2.76*) per year	[18]
β_D	Rate of transmission during high transmission disease stage	0.413-1.28 (0.76*) per year	[18]
D_P	Duration of primary infection	1.23/12-6/12 (0.25*) years	[18]
D_D	Duration of high transmission disease stage	4.81/12-14/12 (0.75*) years	[18]
$\beta_{\max}$	Maximum rate of transmission during asymptomatic stage	0.317 per year	[10]
β_{50}	SPVL at which infectiousness is half maximum	13938 copies per ml	[10]
β_k	Hill coefficient: steepness of increase in infectiousness as a function of SPVL	1.02	[10]
$D_{\max}$	Duration of primary infection	25.4 years	[10]
D_{50}	SPVL at which duration of asymptomatic infection is half maximum	3058 copies per ml	[10]
D_k	Hill coefficient: steepness of decrease in duration as a function of SPVL	0.41	[10]
σ_M	Mutation standard deviation of $\log_{10}$ SPVL	0.12	[10]
$\alpha_{\min}$	Minimum $\log_{10}$ SPVL	2	[10]
$\alpha_{\max}$	Maximum $\log_{10}$ SPVL	7	[10]
n	Number of strains	21 (51*)	Assumption
μ	Mean number of non-cohabiting sexual partners	0.103 - 1.206	[19]
κ	Squared coefficient of variation of number of non-cohabiting sexual partners	0.01 - 100	Assumption

same time ($\approx$ 200 years) but slightly higher (4.6 $\log_{10}$ SPVL vs. 4.3 $\log_{10}$ SPVL: Fig 1).   85

Mutation   86

Over the course of infection, mutation occurs within the host. However, we follow   87

Shirreff *et al.* in assuming that SPVL of the strain transmitted by an infected individual   88
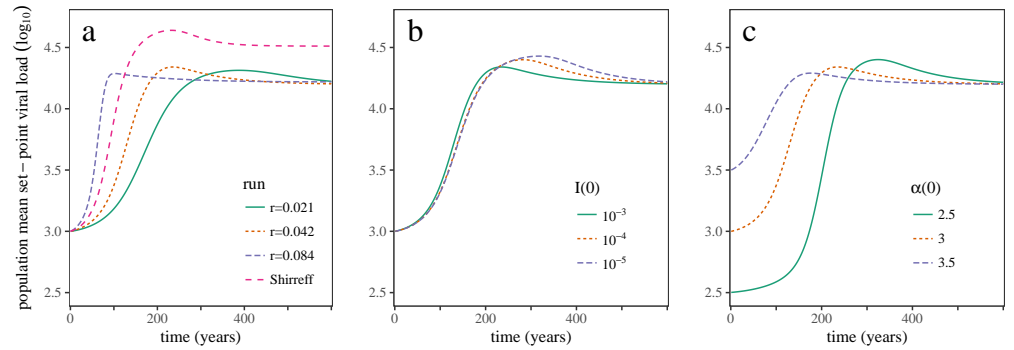
Fig 1. Baseline dynamics. Time series of mean population $\log_{10}$ SPVL using baseline parameters. Each initial condition was varied independently in order to test their effects on transient dynamics of virulence evolution. Note that the initial condition has negligible effect on equilibrium virulence. (a) Contrast between the three-stage Shirreff model and the single-stage model calibrated to varying initial exponential growth rates, r. (b) Effects of varying initial infectious density $I(0)$. (c) Effects of varying initial mean virulence $\alpha(0)$. The middle $r = 0.042$ (orange, dotted) curve in panel (a), calibrated to match the epidemic dynamics of Shirreff et $al.$'s three-stage model [10], shows that our simplified single-stage HIV model can produce similar SPVL trajectories to the original three-stage model; the other r values are chosen to show the effects of doubling or halving the initial epidemic growth rate. The eco-evolutionary dynamics are qualitatively similar across a range of initial conditions (panels b,c).

is determined by the SPVL at the time of infection and is not further affected by within-host mutation. Instead, the mutational effect is modeled as occurring in a single step at the time of transmission. First, the distribution of $\log_{10}$ SPVL is discretized into a vector:

$$\alpha_i = \alpha_{\min} + (\alpha_{\max} - \alpha_{\min})\frac{i-1}{n-1} \qquad i = 1, 2, 3, \ldots n. \tag{3}$$

We have experimented with varying degrees of discretization in the strain distribution (i.e., values of n); in our model runs comparing results with Shirreff et $al.$ [10] (Fig 1) we use $n = 51$ (i.e. a bin width of 0.1 $\log_{10}$ SPVL for α), but reducing n to 21 (bin width = 0.25 $\log_{10}$ SPVL) makes little difference; we use this coarser grid for all other simulations reported.

We construct an n by n mutational matrix, M — which is multiplied with the transmission term — so that M_{ij} is the probability that a newly infected individual will have $\log_{10}$ SPVL of α_j given that the infector has $\log_{10}$ SPVL of α_i. Finally, the probabilities are normalized so that each row sums to 1:

$$M_{ij} = \frac{\Phi(\alpha_j + d/2; i) - \Phi(\alpha_j - d/2; i)}{\Phi(\alpha_{\max} + d/2; i) - \Phi(\alpha_{\min} - d/2; i)}, \tag{4}$$

where $\Phi(x; i)$ is the Gaussian cumulative distribution function with mean α_i and variance of σ_M^2, and $d = (\alpha_{\max} - \alpha_{\min})/(n-1)$. Unlike Shirreff *et al.*, who allowed for variation in the expressed phenotype (SPVL) of each genotype, we use a one-to-one genotype-phenotype map. Thus there is a single value for transmission rate and for progression rate corresponding to each SPVL compartment in the model:

$$
\begin{aligned}
\beta_i &= \beta(\alpha_i), \\
\lambda_i &= \frac{1}{D_P + D_A(\alpha_i) + D_D}.
\end{aligned}
\tag{5}
$$

Contact structure and partnership dynamics

We developed seven multi-strain evolutionary models covering a gamut including Champredon *et al.*'s relatively realistic [15] and Shirreff *et al.*'s relatively simple [10] contact structures, each of which is based on different assumptions regarding contact structure and partnership dynamics. Specifically, we focus on the effects of the assumptions of (1) instantaneous vs. non-instantaneous partnership formation; (2) zero vs. positive extra-partnership sexual contact and transmission; and (3) homogeneous vs. heterogeneous levels of sexual activity on the evolution of mean $\log_{10}$ SPVL.

Our first four models consider explicit partnership dynamics [15]. The first assumes non-instantaneous partnership formation (i.e. individuals spend some time uncoupled, outside of partnerships) and consist of five states that are classified by infection status and partnership status; single (uncoupled) susceptible individuals (S), single infected individuals (I), concordant negative (susceptible-susceptible) couples (SS), discordant (susceptible-infected) couples (SI), and concordant positive (infected-infected) couples (II). The rates of pair formation are based on the numbers of uncoupled susceptible and infected individuals and the pair-formation rate; partnerships can either dissolve into singletons or be transformed into other types of partnerships by infection of one partner. This model also includes extra-partnership contact with both uncoupled individuals and individuals in other partnerships (we denote it "pairform+epc"), so that susceptible uncoupled individuals and susceptible partners in any type of partnership can be infected by infected uncoupled individuals or infected partners in any type of partnership.

DP: check that my description is still correct Specifically, single individuals

(S and I) acquire partners at a rate ρ, and partnerships dissolve at a rate c. Infected individuals in a discordant partnership infect their susceptible partner at a rate β (within-couple transmission rate) and susceptible individuals outside the partnership at a rate c_e (extra-couple transmission rate). Infected individuals in seropositive (II) partnerships can also infect any susceptible individual at rate c_e. Likewise, single infected individuals (I) can infect any susceptible individuals (single individuals S, or susceptible members of SS or SI partnerships) at a rate c_u through uncoupled mixing. This parameterization follows Champredon *et al.*; we have adapted some of the details of their model to a multi-strain scenario, so that we track (for example) a matrix II_{ij} that records the number of concordant, HIV-positive partnerships in which the two partners have $\log_{10}$ SPVL of α_i and α_j.

Our second model ("pairform") only considers within-couple transmission, in which case infection can only occur within a serodiscordant partnership; that is, we set c_e and c_u to zero.

Our third and fourth models, which are intended to bridge the gap between models with fully explicit pair-formation dynamics and the simpler, implicit models used by Shirreff *et al.* [10], assume instantaneous partnership formation ("instswitch"). The compartmental structure thus omits the single states S and I, comprising only the three partnered states: SS, SI, and II. Like the first two models, this pair of models differs in their inclusion of extra-pair contact: the third model ("instswitch+epc") includes extra-partnership contact (now only with individuals in other partnerships, since uncoupled individuals do not exist in this model) while the fourth ("instswitch") only considers within-couple transmission. Although these models can also be implemented by setting the partnership formation rate of the explicit partnership models to a high value (and we have tested that both methods in fact produce same results), we model instantaneous partnership formation models independently in order to avoid scaling of partnership formation rate during model calibration affecting the virulence trajectory.

The fifth and sixth models represent extreme simplifications of sexual partnership dynamics. One ("implicit") is an implicit serial monogamy model based on the epidemiological model used by Shirreff *et al.* [10]. It is actually a random mixing model that explicitly tracks only the total number of susceptible and infected individuals. However, to reflect the effect of partnership structure, it uses an adjusted transmission

rate derived from an approximation of the basic reproduction number of a serial ₁₆₂
monogamy model with instantaneous pair formation [18]. The second model of this pair ₁₆₃
("random") is a simple random-mixing model. ₁₆₄

Lastly, we add a model of heterogeneity in sexual activity to the models. Individuals ₁₆₅
are divided into different risk groups based on the sexual activity level; we scale all ₁₆₆
aspects of sexual activity, assuming that sexual activity level in both within- and ₁₆₇
extra-couple contacts is directly proportional to number of non-cohabiting (extra-couple ₁₆₈
and uncoupled) partners per year [19] (see Appendix S1). We assume random ₁₆₉
activity-weighted mixing between risk groups [20]. (In the main text we focus on the ₁₇₀
model with non-instantaneous pair formation, extra-partnership contact ₁₇₁
("pairform+epc") and heterogeneous sexual activity, which we denote as "hetero"; **give** ₁₇₂
ref in supp material presents results on the effect of adding heterogeneity to other ₁₇₃
model variants.) While this model lacks some important elements, such as ₁₇₄
age-structured mixing patterns, needed for realistic models of HIV transmission in ₁₇₅
sub-Saharan Africa, it represents a first step toward assessing the effects of ₁₇₆
epidemiological complexity. As even the models shown here push the limits of ₁₇₇
compartmental-based models (the heterogeneity model comprises 24530 coupled ₁₇₈
ordinary differential equations), adding further complexity will probably require a shift ₁₇₉
to an agent-based model framework, as well as considerable effort in model ₁₈₀
calibration [11, 21]. ₁₈₁

For simplicity (and following Shirreff *et al.*), all of our base models use an SIS ₁₈₂
(susceptible-infected-susceptible) formulation, where there is no natural mortality (and ₁₈₃
no explicit introduction of newly sexually active individuals into the susceptible pool) ₁₈₄
individuals who die from AIDS are immediately replaced by an individual in the single ₁₈₅
susceptible compartment. While admittedly unrealistic, this approach is reasonable ₁₈₆
given that (1) the natural mortality rate is low relative to the epidemiological dynamics ₁₈₇
and (2) the infectious period is long, so that the overall rates of disease-induced ₁₈₈
mortality and recruitment of newly sexually active individuals would roughly balance. ₁₈₉
We also built models with vital dynamics where individuals dying from AIDS are ₁₉₀
removed from the population, with constant recruitment rates and constant low *per* ₁₉₁
capita natural mortality rates; this additional structure had minor effects on the results. ₁₉₂

Initial conditions

Choosing the initial conditions for the simulations is something of a challenge. In the most common theoretical modeling contexts researchers are primarily interested in equilibria (or other long-term dynamical attractors such as limit cycles) and are exploring models that have a single stable attractor, so initial conditions can be ignored as long as we run models for long enough. In eco-evolutionary dynamics, however, the initial conditions do affect our conclusions. We have no empirical information that would justify a particular quantitative choice of the fraction infected and the mean and variance of the distribution of SPVL at the point when the pandemic strain of HIV-1 entered the human population; in any case, the level of realism of our model does not support such a detailed consideration of the early dynamics of HIV. In most cases, we started with an initial $\log_{10}$ SPVL of 3.0, to match the value used by Shirreff *et al.*. Shirreff *et al.* use an initial $I(0) = 10^{-3}$; we show results for this value in Fig 1. Because we calibrated parameters based on the initial epidemic growth rate (see "Simulation runs" below), we set $I(0)$ to 10^{-4} to ensure that the exponential growth phase lasted long enough for reliable estimation of the initial growth rate.

We ran one small set of sensitivity analyses with baseline values of the epidemiological parameters (Table 1) to test the effects of the initial conditions. Appendix S1 provides further details on initial conditions, such as the initial distribution of SPVL around the mean and the distribution of initial infected density across single people and different partnership types.

Latin hypercube sampling

Despite considerable effort [15, 18], the parameters determining the rate and structure of sexual partnership change and contact are still very uncertain; this led Champredon *et al.* [15] to adopt a Latin hypercube sampling (LHS) strategy [22] that evaluates model outcomes over a range of parameter values. In order to make sure that our comparisons among models apply across the entire space of reasonable parameter values, and in order to evaluate the differential sensitivity of different model structures to parameter values, we follow a similar protocol and perform LHS over a parameter set including both the early- and late-stage transmission and duration parameters (β_P, D_P, β_D, D_D)

and contact/partnership parameters (ρ, c, c_u/c_w, and c_e/c_w). For the heterogeneity model, the mean and squared coefficient of variation (CV) for the number of non-cohabiting partners are sampled as well. We do not allow for uncertainties in parameters that are directly related to the evolutionary process ($\beta_{\max}$, β_{50}, β_k, $D_{\max}$, D_{50}, D_k, σ_M), instead using Shirreff *et al.*'s point estimates throughout [10].

Latin hypercube sampling is done as in Champredon *et al.* [15]. For each parameter, z, its range is divided into $N = 1000$ equal intervals on a log scale:

$$z_i = \exp\left(\log(z_{\min}) + [\log(z_{\max}) - \log(z_{\min})]\frac{i-1}{N-1}\right) \qquad i = 1, 2, 3, \ldots, N. \quad (6)$$

Random permutations of these vectors form columns in a sample parameter matrix; each row contains a different parameter set that is used for one simulation run.

Table 1 gives the ranges of the model parameters used for LHS. Parameter ranges regarding contact and partnership dynamics (ρ, c, and c_e/c_w) are taken from Champredon *et al.* [15], whereas those regarding infection (β_P, D_P, β_D, and D_D) are taken from Hollingsworth *et al.* [18]. The remaining parameters are taken from Shirreff *et al.* [10].

One parameter in our model, the ratio of uncoupled to within-couple transmission c_u/c_w, is needed to more flexibly contrast uncoupled and extra-couple transmission dynamics within multi-strain models (see Appendix S1); it appears neither in either Shirreff *et al.* nor Champredon *et al.*'s models, so we need to pick a reasonable range for it. Champredon *et al.* [15] assume that the effective within-couple contact rate and effective uncoupled contact rate have the same range of 0.05 - 0.25. Given Champredon *et al.*'s parameter range, the possible maximum and minimum values of c_u/c_w are 5 and 1/5. Therefore, we use 1/5-5 as the range for the parameter c_u/c_w. Although this adds more uncertainty to the parameter c_u — Champredon *et al.*'s range implies a 5-fold difference whereas ours gives a 25-fold difference — we consider the wider range appropriate, as little is not much known about the uncoupled transmission rate.

Two parameters, mean and the squared coefficient of variation (CV) of number of non-cohabiting partners, are sampled for heterogeneity in sexual activity. To allow for a wide range of uncertainty, range for the mean number of non-cohabiting partners was taken from unmarried men, as that was the group with the largest variability [19].

Omori *et al.* [19] give a very wide range for the coefficient of variation (≈ 0 - 20, corresponding to squared CV range of 0-400): we narrowed this range for CV^2 to 0.01-100. At the bottom end of the range, estimating that a group behaves perfectly homogeneously ($CV = 0$) is likely to be a sampling artifact; at the upper end, the estimate is also likely to be noisy because of the low mean value among married females (who have the largest range of CV). We assume that the number of non-cohabiting partners follows a Gamma distribution.

Simulation runs

One of the most difficult parts of model comparison is finding parameter sets that are commensurate with many different model structures. For the most part, our models are too complex to easily derive analytical correspondences among them. Given a numerical criterion, such as r (initial exponential growth rate) or $\mathcal{R}_0$ (intrinsic reproductive number), we can adjust one or more parameters by brute force to ensure that all of the models match according to that criterion. While $\mathcal{R}_0$ is often considered the most fundamental property of an epidemic, and might thus seem to be a natural matching criterion, here we focus on matching the initial growth rate r for several reasons. First, our primary interest is in the transient evolutionary dynamics of virulence, which are more strongly affected by r than $\mathcal{R}_0$. Second, r is more directly observable in real epidemics; r can be estimated by fitting an exponential curve to the initial incidence or prevalence curves [23], while $\mathcal{R}_0$ typically requires either (1) knowledge of *all* epidemic parameters or (2) calculations based on r and knowledge of the serial interval or generation interval of the disease [24]. Thus, we scale parameters so that every run has the same initial exponential growth rate in disease incidence.

In order to allow for all models to have equal initial exponential growth rate, r, we need to pick a parameter, s, such that $\lim_{s\to 0} r(s) = 0$ and $\lim_{s\to\infty} r(s) = \infty$. As adjusting either partnership change rate (i.e. partnership formation and dissolution rate) or transmission rate fails this requirement for some of our models, we scaled partnership change rate and dissolution rate by the same factor of γ: $\beta_{\mathrm{adj}} = \gamma\beta_{\mathrm{base}}$, $c_{\mathrm{adj}} = \gamma c_{\mathrm{base}}$, $\rho_{\mathrm{adj}} = \gamma\rho_{\mathrm{base}}$. Since transmission rate is adjusted by the scale of γ, uncoupled and extra-couple transmission rates are adjusted as well. For the

instantaneous-switching and implicit models, none of which track single individuals, only the transmission rate and partnership dissolution rate (in this case equivalent to the partnership change rate) are adjusted.

We run each model for each of 1000 parameter sets chosen by Latin hypercube sampling, with fixed starting conditions of mean $\log_{10}$ SPVL of 3 and epidemic size of 10^{-4}. After each run, initial exponential growth rate is calculated. Then, parameters are scaled so that the initial exponential growth rate is scaled to 0.04, a value that approximates the growth rates of Shirreff *et al.*'s original models. For calibration purposes, we run each model for only 500 years (full simulations are run for 4000 years), which is always long enough to capture the exponential growth phase of the model. We use a 4/5 order Runge-Kutta method (`ode45` from the `deSolve` package [25]) for all simulations. (For the heterogeneous model, approximately 10% of the samples failed due to numerical instability.)

Although each disease strain's core characteristic is its SPVL, the SPVL has one-to-one correspondences (based on eq. 2) with both the expected time to progression to AIDS and with the rate (probability per unit time) of HIV transmission. Because the time to progression (measured in years) is easier to interpret than SPVL (measured in $\log_{10}$ SPVL units), we summarize the virulence trajectories for each model run in terms of time to progression rather than SPVL. Because the time to progression is inversely related to SPVL (increasing SPVL decreases the time to progression), the time to progression is technically measuring inverse virulence rather than virulence (we did not think that reporting virulence as the rate of progression to AIDS, in units of years^{-1}, would help interpretability). For each model we derive the following summary statistics: minimum expected time to progression; time at which this minimum occurs (corresponding to peak virulence — this is also the time at which the maximum rate of progression, maximum SPVL, and maximum transmission rate occur); equilibrium time to progression; and the ratio of progression time at its minimum to the equilibrium value. Equilibrium progression time is calculated after 4000 years of simulated time. Although most simulations reach equilibrium much earlier, we set our time horizon at a much later date as some simulation runs have slow rate of evolution depending on the parameter set and model assumptions.

Knowing the minimum progression time, timing of the minimum progression

time/peak virulence, and equilibrium progression time provide sufficient detail to 314
identify the overall shape of the virulence trajectory. In particular, knowing the timing 315
of the peak virulence (how many years into the epidemic the virulence peaks) can help 316
epidemiologists guess whether the virulence of an emerging pathogen is likely (1) to 317
have peaked early, possibly even before the pathogen is detected spreading in the 318
population, and decline over the remaining course of the epidemic; (2) to increase, peak, 319
and decline over the foreseeable future; or (3) to increase very slowly, peaking only in 320
the far future. To the extent that our simplistic model for HIV reflects reality, we would 321
take the peak time of 150-300 years (Fig 1c) to mean that, in the absence of treatment, 322
the epidemic would probably still be increasing in virulence. 323

Results 324

Our simplifications of Shirreff et $al.$'s model [10] reproduce its qualitative behaviour — 325
in particular, its predictions of virulence dynamics — reasonably well. As we change r 326
from 0.042 to 0.084 (the former value matching the initial rate of increase in prevalence 327
in Shirreff et $al.$'s full model) the initial trajectory of increasing virulence brackets the 328
rate from the original model (Fig 1a). However, our model produces lower peak 329
virulence (≈ 4.3 vs. ≈ 4.6 $\log_{10}$ SPVL) and equilibrium virulence (≈ 4.25 vs. ≈ 4.5 330
$\log_{10}$ SPVL) than Shirreff's, even for matching initial incidence trajectories (i.e., 331
$r = 0.042$ year^{-1}). 332

Changing the initial infectious density ($I(0)$), while it produces the expected changes 333
in the initial epidemic trajectory (Supplementary material), has little effect on the 334
virulence trajectory. Decreasing $I(0)$ makes SPVL peak slightly later and higher, 335
because it allows a longer exponential-growth phase before the transition to endemic 336
dynamics (Fig 1b). Decreasing the initial SPVL also leads to progressively later, higher 337
peaks in SPVL (Fig 1c). In this case the delay in the peak is more pronounced than for 338
low $I(0)$, because the rate of SPVL increase is eventually limited by the mutation rate. 339
The peak SPVL is actually larger for a lower starting SPVL, presumably because lower 340
SPVL also allows for a longer epidemic phase. However, the peaks are similar across the 341
entire range of initial conditions, because even in the most limited (high-$I(0)$, high-$\alpha(0)$) 342
cases HIV is able to evolve most of the way to the SPVL that would be optimal in an 343

indefinitely prolonged growth phase.

Across the entire range of parameters covered by the LHS analysis, all of the classes
of models we considered produce qualitatively similar virulence trajectories, which we
quantify in terms of population mean $\log_{10}$ SPVL (Fig 2: higher population mean $\log_{10}$
SPVL corresponds to higher virulence). Although the speed of virulence evolution
varies, leading to wide variation in the peak SPVL (ranging from 3 to 5.5) because HIV
can evolve farther toward its exponential-phase optimum before the transition to the
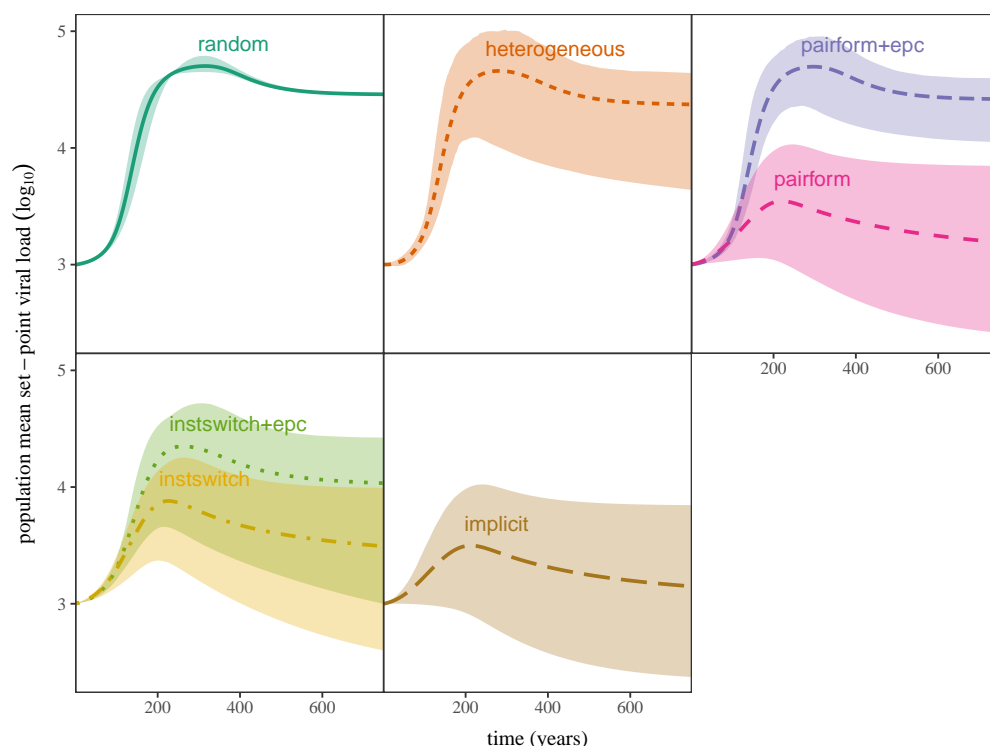endemic phase, virulence peaks in all models between 200 and 300 years.

**Fig 2. Envelopes of virulence trajectories (population mean $\log_{10}$ SPVL)
under all models.** All models were run until $t = 4000$ years using parameters from
1000 Latin hypercube samples to illustrate the range of dynamics each model can
exhibit. Envelopes contain mid 95% trajectories, while lines within the envelopes show
mean trajectories. Truncated series (up to year 800) are shown here.

Our chosen summary statistics (peak time, maximum mean $\log_{10}$ SPVL, equilibrium
mean $\log_{10}$ SPVL, and minimum mean progression time) all vary considerably across
models (Fig 3). We first consider the models of intermediate realism: implicit,
instantaneous-switching with and without extra-pair contact, and pair formation
without extra-pair contact. Some parameter sets for these models lead to low

equilibrium virulence (2.3-3 $\log_{10}$ SPVL). For these data sets, virulence may either increase from its initial value, reaching an early peak (≈ 200 years) between 3 and 4 $\log_{10}$ SPVLand then declining to a lower equilibrium value, or in extreme cases virulence may decline immediately, leading to a peak virulence (as we have defined it) equal to the starting value of $\alpha(0) = 3 \log_{10}$ SPVLat $t = 0$. (Fig 4). At the opposite extreme, parameter sets that produce high equilibrium virulence (4.7 $\log_{10}$ SPVL) also produce late peaks (> 200 years) and high peak virulence (5.6 $\log_{10}$ SPVL).
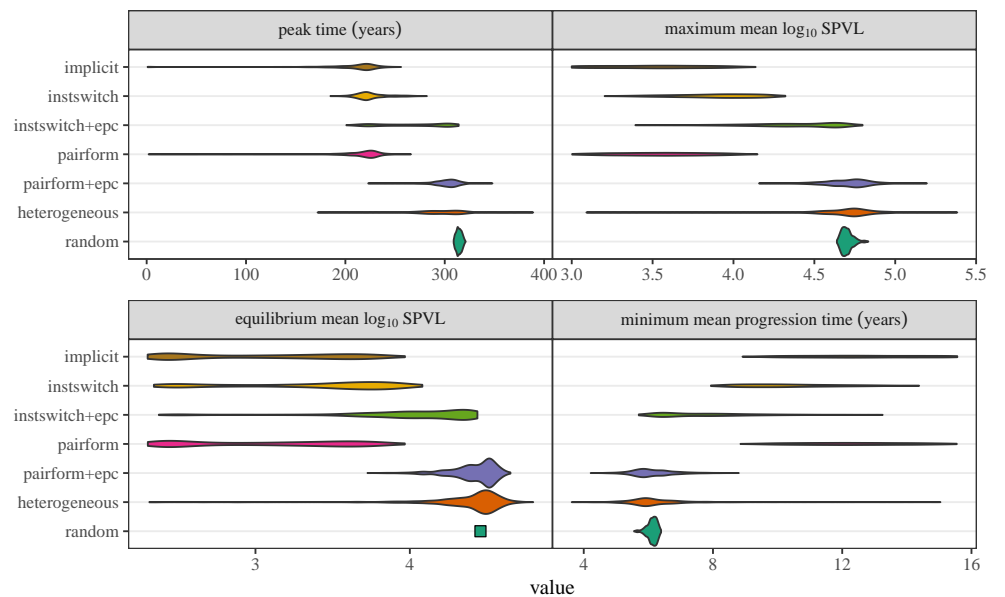

Fig 3. Univariate distributions of summary statistics. For every simulation, three summary statistics were obtained: peak time, maximum mean $\log_{10}$ SPVL, and equilibrium mean $\log_{10}$ SPVL. Peak time is the time at which a virulence trajectory achieves its maximum value (maximum mean $\log_{10}$ SPVL). Equilibrium mean $\log_{10}$ SPVL is taken by taking the mean $\log_{10}$ SPVL value at $t = 4000$. Minimum mean progression time is obtained by applying the hill function to maximum mean $\log_{10}$ SPVL of each run. The distribution of equilibrium mean $\log_{10}$ SPVL (lower left panel) for the random mixing model is very narrow, and has been replaced by a point in order to preserve the vertical axis scaling.

The most striking aspect of the univariate comparisons in Fig 3, (and the bivariate comparisons in Fig 4) is the similarity between the results of the least (random mixing) and the most complex (pair formation with extra-pair contact, pairform+epc with heterogeneity) models. The random-mixing model has the lowest variability, because it is unaffected by uncertainty in pair formation and extra-pair contact parameters, but otherwise the virulence dynamics of these three extreme models are remarkably similar. This phenomenon is driven by the strong effects of extra-pair contact in the model with
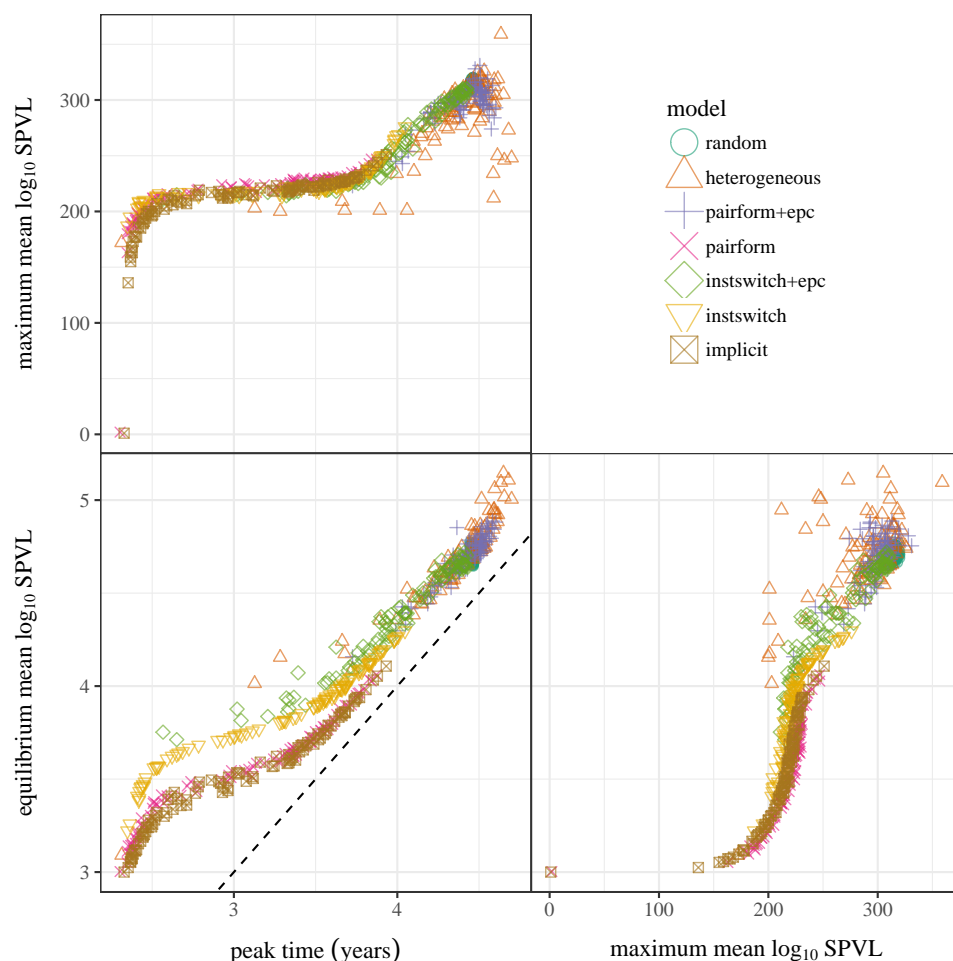
Fig 4. Pairs plot: bivariate relationships among summary statistics for each model structure. Three summary statistics obtained from each simulation have been plotted against each other to visualize the relationship among the summary statistics and to allow for clearer comparison between models. Surprisingly, the implicit model, an approximation for instantaneous partnership formation model (instswitch), shows an almost identical trend with a model that has pair formation dynamics (pairform). Dashed line in equilibrium vs. peak virulence plot shows 1:1 line, where equilibrium and peak virulence are equal. 100 values were sampled from each model to allow for clearer distinction between the models

explicit pair formation and extra-pair contact ("pairform+epc" in Figs 2-5). When   371

individuals spend time uncoupled between partnerships, and when these single   372

individuals can transmit disease to coupled individuals, the resulting unstructured   373

mixing overwhelms the effect of structured mixing within partnerships, leading to   374

mixing that is effectively close to random. Once unstructured mixing is strong, adding   375

realistic heterogeneity of mixing to the model has little effect other than increasing the   376

variability in the outcomes. 377

These differences are practically as well as scientifically important. The 378
random-mixing, pairform+epc, and heterogeneous models all predict high population 379
mean $\log_{10}$ SPVL at the virulence peak (median (95% CI) = 4.7 (4.65-4.79), 4.72 380
(4.37-4.96), 4.72 (4.09-5.03)). In contrast, the implicit model predicts a much lower peak 381
$\log_{10}$ SPVL value: 3.52 (3-4.02) years. In terms of mean time to progression to AIDS, 382
The random-mixing, pairform+epc, and heterogeneous models predict rapid progression 383
to AIDS at the virulence peak (median/95% CI = 6.1 (5.7-6.3), 6.02 (5.04-7.7), 6.03 384
(4.8-9.2)), while the implicit model predicts minimum progression times about twice as 385
long (12.5 (9.6-15.6) years). The corresponding differences in mean within-couple 386
transmission probability at the peak are even more extreme, about a fourfold difference: 387
0.249 (0.24-0.26), 0.252 (0.19-0.28), and 0.252 (0.15-0.28) per year for the random and 388
pairform+epc models vs. 0.059 (0.02-0.13) per year for the implicit model (see 389
Appendix S2 for plots showing univariate summaries of expected progression time to 390
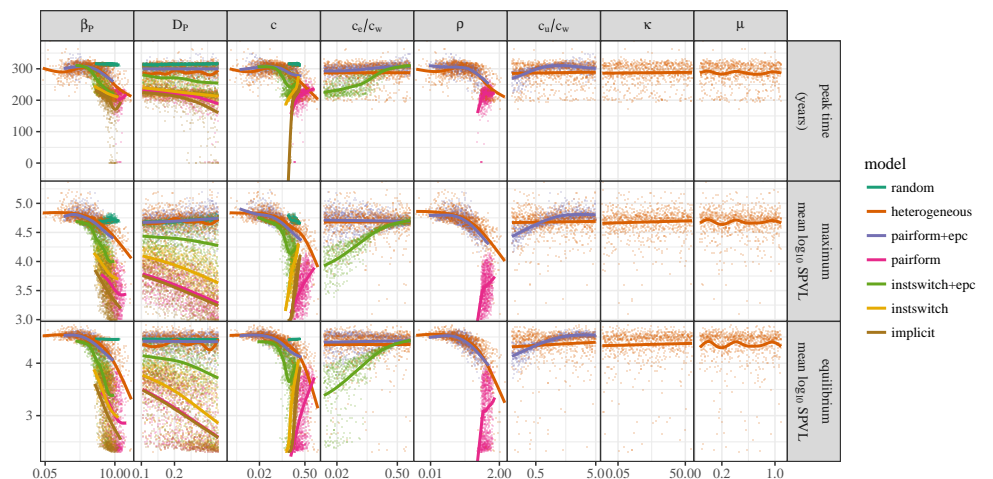AIDS and transmission probability). 391

Fig 5. Sensitivity plot. For most parameters in the Latin hypercube samples, the
figure shows the distribution (points) and trend (smooth line) of the summary statistic
as a function of the parameter value, some of which have adjusted to achieve the
standard initial epidemic growth rate (see Methods).
Opposing trends in summary statistics with respect to partnership dissolution rate, c,
(third column) between the model with and without extra-pair contact illustrates that
similar model with different assumptions may yield opposing predictions.

The bivariate relationships (Fig 4) help distinguish the results of different models 392
with similar univariate dynamical summaries. While the relationship between 393

equilibrium $\log_{10}$ SPVL and peak time is similar for all model structures (top left   394

panel), the other relationships show more variation. In particular, the implicit and   395

pair-formation (without extra-pair contact) are very similar to each other, but distinct   396

from the other models. We still do not have a convincing explanation for this   397

distinction; we would have expected the implicit model to be most similar to the the   398

instantaneous-switching model without extra-pair contact, which most closely matches   399

its derivation. However, we note that the implicit model derivation is based on defining   400

the force of infection to match a scaled version of $\mathcal{R}_0$, and as such would be expected to   401

match the equilibrium behaviour but not necessarily the epidemic-phase behaviour of a   402

model with explicit partnership dynamics.   403

Finally, the sensitivity plot (Fig 5) shows the effects of each parameter on the   404

summary statistics. The most notable difference can be observed by comparing the   405

scaled parameters (e.g. β_P, β_D, c, ρ) with the unscaled parameters (e.g. D_P, D_D,   406

c_e/c_w, c_u/c_w, κ, μ); note that the effects of β_D and D_D are not shown in Fig 5 as their   407

patterns are so similar to β_P and D_P, respectively.   408

One of the distinguishing features of the scaled parameters (in comparison to the   409

unscaled parameters) is that the range of the parameters is compressed (relative to   410

other models) for models without extra-pair contact as those models require parameters   411

to be scaled by a large value in order to achieve a given r of 0.04. Models with   412

extra-pair contact show wide range parameters as they can display a wide range of   413

dynamics depending on c_e/c_w (as well as c_u/c_w for models with uncoupled mixing) and   414

thus require wide range of scaling factors to achieve the target r. Parameter range for   415

random-mixing model is severely compressed because latin hypercube sampling does not   416

affect the prevalence trajectory very much, and scaling factor does not vary much across   417

parameters.   418

For parameters involved in partnership turnover (c and ρ), main distinction is   419

between models with and without extra-pair contact. With extra-pair contact, we get   420

gradual decrease in peak time, maximum $\log_{10}$ SPVL, and equilibrium $\log_{10}$ SPVL with   421

increasing turnover rates; Otherwise we get increase in summary statistics. Although we   422

have not verified this idea analytically, we speculate that increase in turnover rates   423

diminishes the effect of epc (equivalently increasing relative importance of   424

within-partnership contact), therefore selecting for lower $\log_{10}$ SPVL. For models   425

without epc, increased rates of partnership change decrease the level of structured   426

mixing (mimicking epc models), resulting in selection for higher $\log_{10}$ SPVL.   427

We also note that the implicit model and the instantaneous partnership formation   428

model show similar patterns in scaled parameters. In fact, we can see that the effect of   429

partnership dissolution rate, c, on equilibrium $\log_{10}$ SPVL of the two models are almost   430

identical (in Fig 4, they have distinguishing features). Lastly, we note that increase in   431

transmission rates (β_P and β_D) has a decreasing effect on summary statistics for all   432

models except for random mixing model.   433

Surprisingly, once calibration is taken into account, the unscaled parameters have   434

little to no effect overall. Increase in duration (D_P, D_D) in the primary and disease   435

stages generally decrease the equilibrium virulence, peak virulence, and peak time,   436

although the models with uncoupled mixing and random mixing model have high,   437

relatively constant values with respect to these parameters. The ratio of extra-pair to   438

within-pair contact (c_e/c_w) affects summary statistics in the instantaneous-switching   439

+epc model, but not the pair-formation+epc model (probably because the uncoupled   440

individuals present in the pair-formation+epc model make extra-pair contact by coupled   441

individuals less important). Similarly, increasing the ratio of uncoupled to within-pair   442

contact, c_u/c_w, increases peak and equilibrium $\log_{10}$ SPVL and delays peak time of the   443

pair-formation+epc model but has almost no effect on the heterogeneous model.   444

Neither the uncoupled contact rate nor the mean (μ) or CV^2 of the number of   445

non-cohabiting sexual partners has much systematic effect in the heterogeneous model.   446

Discussion   447

All models must simplify the world. Many constraints — among them data availability,   448

computation time, and code complexity — drive the need for parsimony, with different   449

constraints applying in different contexts. The critical question that modelers must ask   450

is whether the simplified model gives adequate answers, or whether the simplifications   451

lead to qualitative or quantitative errors. This question is especially important for   452

modelers who are hoping that their conclusions will guide management decisions.   453

In the particular example of HIV virulence eco-evolutionary dynamics and the   454

complexity of contact structures we reach the slightly ironic conclusion that the effort   455

put into building a more realistic model essentially cancels out, putting us back where   456
we started when used a naive random-mixing contact model. However, we are not quite   457
back where we started, as the complex models lead to wider, presumably more realistic   458
confidence intervals on the predictions. In general, unstructured mixing — whether   459
occurring through purely random mixing, or through extra-pair contact and contact   460
among people outside of stable partnerships — tends to drive faster virulence evolution,   461
leading to higher peak virulence and lower times to progression at the peak time.   462

Taking further steps to make the model even more realistic might add further   463
structure, making the random-mixing model predictions less accurate. For example, our   464
model forms partnerships randomly, and assumes that extra-pair contact is randomly   465
mixing across the population; one could instead model extra-pair contact as arising   466
from multiple concurrent partnerships (some, such as contact with sex workers, of very   467
short duration) and/or more structured partnership formation (by age, ethnicity, or   468
behaviour group). The effects of other realistic complications such as explicit modeling   469
of two sexes (both in contact structure and differential transmission probabilities),   470
temporal and spatial variation in epidemic processes, or presence of genetic variation in   471
hosts are harder to predict.   472

Parameterization is one of the biggest challenges of epidemiological modeling. In   473
addition to following Champredon *et al.* [15] by doing Latin hypercube sampling across   474
a wide range of epidemiological parameters, we calibrated each set of parameters to the   475
same initial epidemic growth rate, chosen to match the results of previous models [10].   476
Previous models in this area have drawn their parameters from cohort studies from the   477
1990s [18, 26] rather than doing any explicit calibration to epidemic curves, but they   478
give reasonable order-of-magnitude growth rates (≈ 0.04 year^{-1}) for the early stages of   479
the HIV epidemic (although considerably lower than estimates of $\approx 0.07 - 0.1$ year^{-1} 480
based on population genetic reconstructions [27]). However, our reason for calibrating   481
was not to match any specific observed epidemic, but rather to make sure that we were   482
making meaningful comparisons across a range of models with radically different   483
contact structures, and hence involving different interpretations of the same   484
quantitative parameters. For example, in models with instantaneous switching the   485
partnership dissolution rate c is identical to the partnership formation rate; in models   486
with explicit partnership formation, the partnership formation rate is also c at   487

equilibrium, but might vary over the course of an epidemic. It is not obvious whether   488
models with equal parameters but different structures should be directly compared;   489
calibration solves this problem.   490

More generally, any model that wants to be taken seriously for management and   491
forecasting purposes should be calibrated to *all* available data, using informative priors   492
to incorporate both realistic distributions of uncertainty for all parameters from   493
independent measurements [28] and calibration from population-level observations of   494
epidemic trajectories. Such a procedure would also be an improvement on the common   495
— although not universal — practice, which we have followed here, of assessing   496
uncertainty over uniform ranges rather than using distributions that allow more   497
continuous variation in support over the range of a parameter.   498

Researchers have documented that HIV virulence and set-point viral load are   499
changing, on time scales comparable to those portrayed here (e.g., compare Fig 2 to   500
Herbeck *et al.*'s estimated rate of change of 1.3 $\log_{10}$ SPVL per century [95% CI -0.1 to   501
3] [29]), and have begun to build relatively realistic models that attempt to describe   502
how interventions such as mass antiretroviral therapy (ART) can be expected to change   503
the trajectory of virulence evolution [12, 30, 31]. While these efforts are well-intentioned,   504
we caution that structural details that are currently omitted from these models could   505
significantly change their conclusions.   506

Acknowledgements   507

Supporting Information   512

Appendix S1: Model Details   513

Appendix S2: Dynamics of Transmission and Virulence   514

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