Title: Beyond instantaneous partnerships: re-examining assumptions and a new model for partnership duration in compartmental models of HIV transmission

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Abstract

Highlights

- We review assumptions and limitations of current models of the force of infection
- We develop a new force of infection model to accurately represent repeated contacts
- We apply current and proposed models to HIV transmission in Eswatini
- We illustrate key differences in inferred drivers of transmission under each model

1 Introduction

The force of infection — or incidence — equation defines the rate of new infections among a susceptible population. As the core of most transmission models, this equation specifies the assumed mechanistic relationships between incidence and factors of interest, such as contact rates or the probability of transmission. The assumptions underpinning a force of infection equation are therefore key determinants of the modelled transmission dynamics, and ultimately evidence generated by the model.

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2 Current Models of the Force of Infection

⟨**1**⟩ **Binomial Per-Partnership:** Perhaps the most common model for the force of infection in HIV transmission models is currently:

$$\lambda_i^{\langle 1\rangle}(t) = \sum_{jhk} Q_{ijk}\left(1-(1-\beta_{hk})^{A_k}\right)\frac{I_{jh}(t)}{N_j} \tag{1}$$

where: β_{hk} is the per-contact (sex act) probability of transmission from individuals in infection stage h via partnership type k; Q_{ijk} is the rate of type-k partnership formation by individuals in group i with those in group j (includes "mixing" between groups); A_k is the number of contacts per type-k partnership; and $I_{jh}(t)/N_j$ is the proportion of group j who are in infection stage h (prevalence).[1]

The term $1-(1-\beta)^A$ represents the probability of transmission per-partnership, which we denote B (Figure 1a, purple). This probability is derived from the binomial distribution for n transmissions after A independent, equal probability contacts:

$$P(n) = \binom{A}{n}\beta^n(1-\beta)^{A-n} \tag{2}$$

Since transmission can only occur once, B is defined via the probability of "escaping" infection:

$$\begin{aligned} B &= 1-P(n=0) \\ &= 1-\binom{A}{0}\beta^0(1-\beta)^A \\ &= 1-(1-\beta)^A \end{aligned} \tag{3}$$

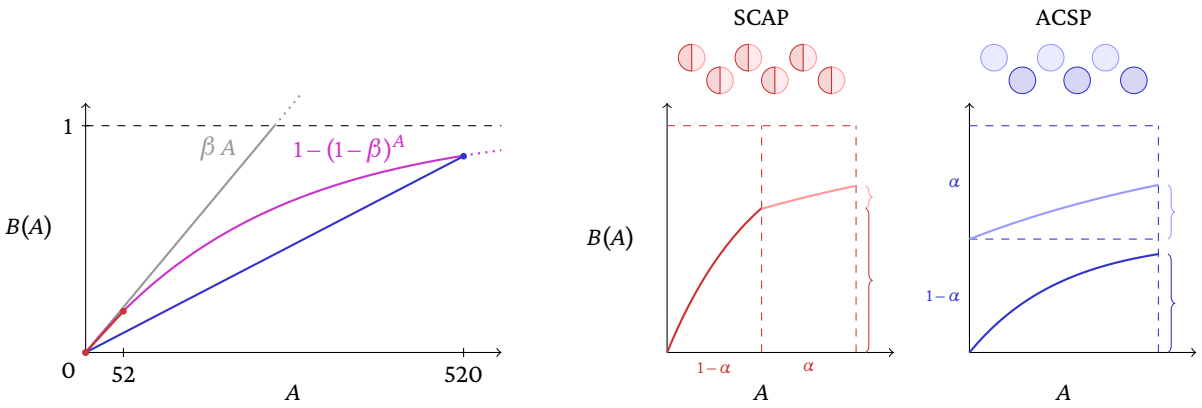
⟨**1b**⟩ **Binomial Per-Partnership-Year:** Many applications of model ⟨1⟩ define the probability of transmission B per-partnership-year, and thus effectively choose partnership duration $\delta = 1$ year, total contacts $A = F$ (yearly contact frequency per-partnership), and partnership formation rate $Q \geq 1$, even for long-duration partnerships. We denote the model allowing $\delta > 1$ as ⟨1a⟩ and that with $\delta = 1$ as ⟨1b⟩, which appears to be more common. As the "true" values of δ, F, and/or β increase, model ⟨1b⟩ can be substantially different from ⟨1a⟩. Figure 1a further illustrates two tangents, whose slope represents the applied yearly transmission rate QB for $\delta = 1$ (red) vs 10 (blue) year partnership durations, with $\beta = 0.34\%$ [3] and contact frequency $F = 52$ per-year. The yearly transmission rate for $\delta = 1$ is nearly double the rate for $\delta = 10$, and the binomial adjustment has almost no effect over 1 year: $B(A \mid \delta = 1) \approx \beta A$.

Transmission Modifiers: Factors that alter the probability of infection, such as condom use, circumcision, and STI co-infection, are usually added to (3) assuming a relative probability R and constant proportion of contacts affected α. For multiple modifiers, B is often defined as:

$$B = 1-\prod_m (1-R_m\beta)^{\alpha_m A} \tag{4}$$

where: $\sum_m \alpha_m = 1$; some R_m may represent the product of multiple factors; and a dummy term $R_m = 1$ can apply to the proportion of contacts without any modifier. In (4), factors are modelled as "some

[1] Table A.1 summarizes the notation used throughout the paper.



(a) Models of probability of transmission: linear vs binomial and per-partnership vs per-partnership-year

(b) Transmission modifier affecting: some contacts in all partnerships vs all contacts in some partnerships

Figure 1: Probability of transmission B vs number of contacts (sex acts) A. (a) Illustrates linear (grey) vs binomial (purple) models for B, and compares the applied yearly *rate* of transmission QB (tangents) for $\delta = 1$ (red) vs $\delta = 10$ (blue) year partnership durations, with fixed contact frequency $F = 52$ per-year, and $\beta = 0.34\%$ from [3]. (b) Compares interpretation of a transmission modifier with $R = 0.3$ effect and $\alpha = 0.5$ coverage as: some contacts in all partnerships (SCAP, red) from (4) vs all contacts in some partnerships (ACSP, blue) from (5); sum of brace heights gives the modelled B.

contacts in all partnerships" (SCAP), *not* "all contacts in some partnerships" (ACSP). To model ASCP, B may be defined instead as:

$$B = \sum_m \alpha_m \left(1 - (1 - R_m\beta)^A\right) \tag{5}$$

which is effectively a weighted average. It can be shown that SCAP (4) $\geq$ ACSP (5), because any large probability of transmission has disproportionate influence on (4), even for a small proportion of contacts affected (α or $1-\alpha$), whereas this influence is bounded by α or $1-\alpha$ in (5), as shown in Figure 1b. Figure A.1 explores the conditions under which differences between SCAP and ACSP are greatest. These conditions can be summarized as: when $R < 1$, $0.5 < \alpha < 1$, and A is large; or when $R > 1$, $0 < \alpha < 0.5$, and A is large, but not too large. Although differences rarely exceeded 20% in our analyses, the more appropriate equation should likely be selected based on a factor's interpretation.

⟨**2**⟩ **Binomial Time Interval:** Another model for the force of infection further generalizes the idea of escaping infection to consider risk from all partnerships simultaneously:

$$\lambda_i^{\langle 2\rangle}(\Delta_t) = 1 - \prod_k \left(1 - \sum_{jh} \left(1 - (1 - \beta_{hk})^{Q_{ijk}A_k\Delta_t}\right) \frac{I_{jh}(t)}{N_j}\right) \tag{6}$$

which is technically a probability ≤ 1, not a rate as in ⟨1⟩. A simple version of this model was introduced in [4], where the dependence on time period Δ_t was explicitly noted. In principle, this model is more precise than ⟨1⟩, provided that Δ_t is matched to the timestep of the numerical solver. However, and the added precision may be insignificant as Δ_t is usually small. Moreover, much like ⟨1⟩, subsequent adaptations of this model have used a period of $\Delta_t = 1$ year, and then applied the

resulting λ_i as a rate over smaller timesteps.[2] This adaptation then reduces transmission vs ⟨1b⟩, since all contacts across all partnership-years are considered in one binomial model.

In (6), the prevalence of infection I_{jh}/N_j is modelled as ACSP, not SCAP, reflecting "homogeneous" partnerships with a heterogeneous pool of partners, rather than "heterogeneous" partnerships with a homogeneous pool of partners. As with transmission modifiers, this distinction is often ignored, and using SCAP allows the following simplification of (6):

$$\lambda_i^{\langle 2\rangle}(\Delta_t) = 1 - \prod_{jhk} (1-\beta_{hk})^{Q_{ijk}A_k\Delta_t \frac{I_{jh}(t)}{N_j}} \tag{7}$$

A further adaptation of (7) first computes a weighted average per-contact transmission probability β_{hk} given the prevalence of each infection stage among partners:

$$\lambda_i^{\langle 2\rangle}(\Delta_t) = 1 - \prod_{hk} \left(1 - \sum_j \beta_{hk} \frac{I_{jh}(t)}{N_j}\right)^{Q_{ijk}A_k\Delta_t} \tag{8}$$

which often yields almost identical results to (7) (< 1% difference in our exploration). We refer to the ACSP model in (6) as ⟨2a⟩, and the SCAP model in (8) as ⟨2b⟩. We have not seen ⟨2a⟩ used in the literature.

⟨**3**⟩ **Pure Rate:** As shown in Figure 1a, the binomial adjustment in models ⟨1-2⟩ has negligible effect when β, A, and/or Δ_t are sufficiently small, at which point $B(A) \approx \beta A$. For completeness, and since it will be useful later, we define a final model ⟨3⟩ with exactly $B(A) = \beta A$:

$$\lambda_i^{\langle 3\rangle}(t) = \sum_{jhk} Q_{ijk}A_k\beta_{hk}\frac{I_{jh}(t)}{N_j} \tag{9}$$

which effectively ignores partnership duration δ.

We further introduce an alternate parameterization to QA. Whereas QA reflects the partnership formation *rate* Q and *number* of contacts per-partnership A, we introduce CF, reflecting the *number* of concurrent partnerships C and contact *frequency* per-partnership F. For a given partnership duration δ, we have $F = A/\delta$, and $C = \delta Q$; thus, the total contact rate in both parameterizations is the same: $QA = CF$.

Limitations of Models ⟨1-3⟩: Models ⟨1-3⟩ span a continuum of trade-offs. At one extreme, model ⟨1a⟩ appropriately reduces the proportion of infections transmitted via long-duration partnerships; however, in doing so, the reduced rate of transmission QB effectively *delays* transmission in such partnerships. At the other extreme, model ⟨3⟩ ignores partnership duration, and thus likely overestimates the proportion of infections transmitted via long-duration partnerships; however, no transmission is delayed by binomial adjustment. In the middle, models ⟨1b⟩, ⟨2a⟩, and ⟨2b⟩ include a small reduction in proportion of transmission via long-duration partnerships and a small delay in transmission. Furthermore, as noted above, applying model ⟨2⟩ as a rate over smaller timesteps but using $\Delta_t = 1$ can substantially underestimate incidence among higher risk groups, due to the probability constraint: (6–8) ≤ 1.

[2] One possible reason that Δ_t in (6) has not been used correctly could be that: most numerical solvers for systems of ordinary differential equations pass only t (not Δ_t) to the derivative computing function, and may use adaptive Δ_t for precision while solving — including: `scipy.integrate.odeint` in Python, `deSolve::lsoda` in R, and `ode45` in MATLAB.

A final and critical limitation affecting all models ⟨1-3⟩ is that partnerships are "instantaneous". As such, newly infected individuals may immediately transmit infection in the same partnership by which they were infected — to an evidently already infected partner. This transmission is possible because, with instantaneous partnerships, the infection status of partners is averaged across the pool of available partners, so a "fraction" of even one single partner is always susceptible (Figure 2a). In other words, incidence is always proportional to prevalence. In reality, infections transmitted via long-duration partnerships become "trapped", unless individuals have additional partners, or the partnership ends. Thus, prevalence immediately increases, but incidence may not increase proportionally until some time later, or ever.

3 Proposed Model

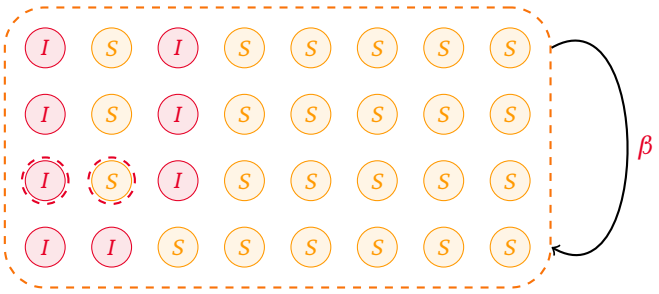
We propose a new model for the force of infection in compartmental transmission models of HIV, that overcomes the limitations of models ⟨1-3⟩. Below we describe the conceptual basis for the model, followed by the equations.

3.1 Conceptual Development

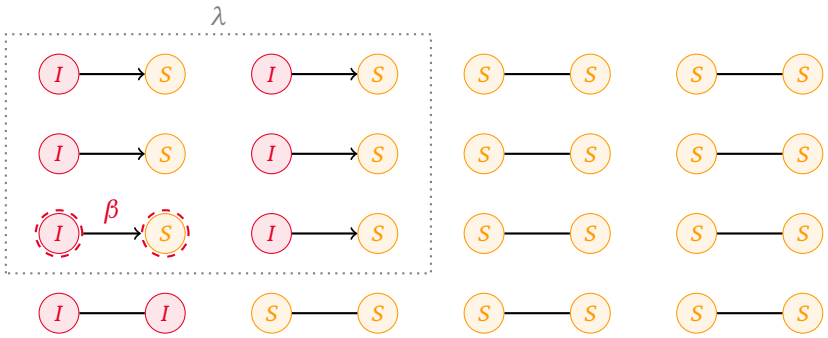
Consider a population of 32 individuals in 16 partnerships with 25% infection prevalence, at the moment of one transmission (Figure 2b). Initially, infection prevalence among partners of susceptible S (6/24) and infectious I (2/8) individuals are equal. Immediately after transmission, the prevalence decreases to 5/23 among partners of S but increases to 4/9 among partners of I, reducing incidence. Next, two events are possible: a) another transmission among the remaining discordant partnerships, yielding 4/22 prevalence among partners of S and 6/10 among partners of I, further reducing incidence; or b) the partnership from the first transmission ends and both individuals form new partnerships at random, yielding prevalence 9/32 among partners of both S and I (on average), increasing incidence. Effectively, models ⟨1-3⟩ all assume that (b) occurs first, but this assumption may be invalid, especially for long-duration partnerships. Other partnerships may begin/end too before (a) or (b), but the proportions of discordant partnerships would remain unchanged, on average.

This scenario highlights how any partnership where transmission has occurred should be "removed" from the force of infection. In a compartmental (non-pair-based) model, these partnerships can be tracked as proportions of individuals: namely, all recently infected individuals *and* all recently transmitting individuals. If individuals have multiple concurrent partnerships ($C_i > 1$), then these individuals should not be removed entirely, but their effective numbers of partners should be reduced by 1. If multiple types of partners are considered, then only the type involved in transmission should be reduced. This adjustment can then be applied until the individuals change partners — an expected period of δ_k. However, during this period, these individuals should be modelled to progress as usual through different stages of infection, aging, etc.

Using this conceptual basis, we propose a new stratification of modelled population, denoted $\bar{k}$. The stratum $\bar{k} = 0$ corresponds to no recent transmission, or all "new" (potentially discordant) partners. Other strata $\bar{k} > 0$ correspond to recent transmission via (to or from) partnership type k. Figure 3 illustrates the new stratification for an system with 5 modelled infection stages. Following infection, all individuals enter a stratum $\bar{k} > 0$ corresponding to the partnership type k by which they were infected. Thus, the rate of entry (from S_i) is λ_{ik}. Individuals may then transition from $\bar{k} > 0$ to $\bar{k} = 0$ upon forming a new partnership, at a rate δ_k^{-1}. Finally, individuals may re-enter any stratum $\bar{k} > 0$ if



(a) Frequentist approximation



(b) Pair-wise reality

Figure 2: Illustration of 32 individuals in a population with 25% infection prevalence, at the moment of one transmission (β)

Notation. S: susceptible; I: infectious; β: transmission event.

they transmit infection via partnership type k. We denote the corresponding rate as λ'_{ik}, representing the per-person rate of *transmission*, not *acquisition* as in λ_{ik}. This rate λ'_{ik} is not usually defined, but we develop the equations to do so below.

3.2 Equations

Since partnership duration is now considered separately, we start from the pure rate model ⟨3⟩. We adapt (9) to: integrate the changes to mixing due to changes in numbers of partners available; and track the rate of transmission *from* risk groups j and infection stages h.

We begin by defining M_{ijk} as the absolute (not per-person) number of type-k partnerships between group i and group j. We assume that M_{ijk} can be defined by an arbitrary function f, with inputs M_{ik}, M_{jk}, and some parameter(s) θ_{ijk} specifying mixing patterns:[3]

$$M_{ijk} = f(M_{ik}, M_{jk}, \theta_{ijk}) \tag{10}$$

[3] A popular simple method to specify mixing is given in [5], although other more interesting approaches are possible [6].

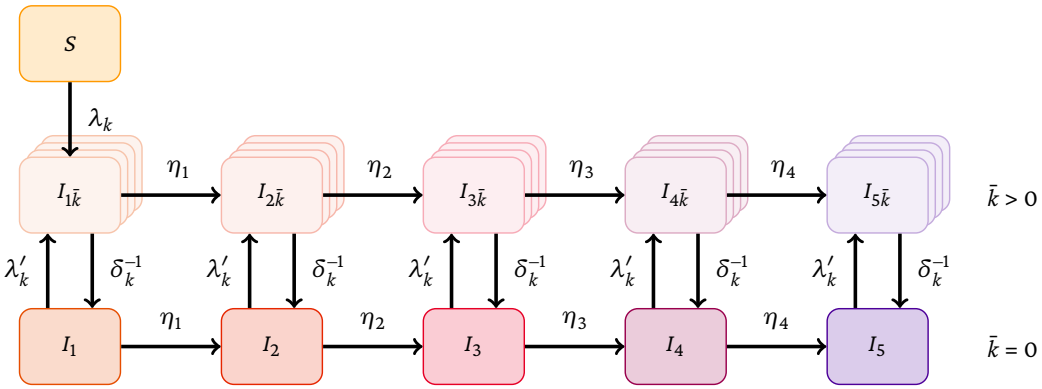


Figure 3: Illustration of a new stratification $\bar{k}$ to track proportions of individuals in partnerships where transmission has already occurred.

Notation. S: susceptible; I_h: infectious in stage h; k: partnership type; $\bar{k}$: new stratification; λ: force of infection to susceptible; λ': force of infection from infectious; η: rate of progression between infection stages; δ: duration of partnership.

We define M_{ik} (and likewise M_{jk}) as the total numbers of type-k partnerships "offered" by group i, across both susceptible and infected individuals in each infection stage h:

$$M_{ik} = M_{S,ik} + \sum_h M_{I,ihk} \tag{11}$$

We define $M_{S,ik}$ and $M_{I,ihk}$ as follows:

$$M_{S,ik} = S_i C_{ik} \tag{12a}$$
$$M_{I,ihk} = I_{ih,\bar{k}=k}(C_{ik} - 1) + \textstyle\sum_{\bar{k}\neq k} I_{ih,\bar{k}} C_{ik} \tag{12b}$$

Equation (12a) is the total number of partnerships "offered" by susceptible individuals, while (12b) is the equivalent sum of partnerships offered across states $\bar{k}$, where the partnership numbers C_{ik} of infected individuals in state $\bar{k} = k$ are reduced by 1.

Next, drawing loosely on (9) with the *CF* parameterization, we define the absolute (not per-person) rate of transmission from group j and infection stage h to group i via type-k partnerships as:

$$\Lambda_{ijhk} = F_k \beta_{hk} M_{ijk} \frac{M_{S,ik}}{M_{ik}} \frac{M_{I,jhk}}{M_{jk}} \tag{13}$$

where the two fractions represent the proportions of all partnerships (M_{ijk}) formed by susceptible individuals in group i ($M_{S,ik}$) with infectious individuals in group j and infection stage h ($M_{I,jhk}$). Finally, we define the per-person transmission rates to i and from jh as follows:

$$\lambda_{ik} = \sum_{jh} \frac{\Lambda_{ijhk}(t)}{S_i} \tag{14}$$

$$\lambda'_{jhk} = \sum_i \frac{\Lambda_{ijhk}(t)}{I_{jh}} \tag{15}$$

For the purposes of solving the model, we can even skip division by S_i and I_{jh} in (14) and (15), since λ'_{ik} and λ'_{jhk} are immediately multiplied by S_i and I_{jh}, respectively, in the system of differential equations.

3.3 Transmission via Multiple Partnerships

In the proposed approach, we do not explicitly model the proportion of infected individuals who recently transmitted or acquired infection via two *different* partnership types, (or two partnerships of the same type). If we did, the required size of the new dimension $\bar{k}$ would be at least 2^K, not $K+1$ — an exponential relationship that is related to the challenge of specifying all combinations of partnership states in pair-based models [7]. However, under frequentist assumptions, we can equivalently model two transmissions by one individual as one transmission each by two individuals, and thus allocate two proportions of $I_{jh\bar{k}=0}$ to $I_{jh\bar{k}=k_1}$ and $I_{jh\bar{k}=k_2}$ (one each), instead of just one proportion to $I_{jh\bar{k}=\text{“}k_1k_2\text{”}}$. In fact, $I_{jh\bar{k}=0}$ can be *negative*, because the dimension $\bar{k}$ is only relevant to (12b), and in all other contexts and equations, we first sum $I_{jh\bar{k}}$ across $\bar{k}$ to yield I_{hj}, which must be positive. Moreover, we can also have $I_{jh\bar{k}} > I_{jh}$, provided that $I_{jh\bar{k}} \leq I_{jh}C_{jk}$, reflecting the situation when 100% of I_{jh} have recently transmitted or acquired infection via at least one type-k partnership, or 50% via at least two, etc. This situation can therefore only arise in the context of concurrent type-k partnerships, $C_{jk} > 1$. In this case $I_{jh\bar{k}=0}$ *must* be negative, but it can be shown that (12b) still yields the correct value of $M_{I,ihk}$. With this perspective, the constraint $I_{jh\bar{k}} \leq I_{jh}C_{jk}$ may be intuitive, and it should be possible to guarantee for small enough timesteps, because $M_{I,ihk}$ approaches zero as $I_{jh\bar{k}}$ approaches $I_{jh}C_{jk}$ — i.e. all partnerships become concordant, and no more transmission can occur before partners change.

4 Experiment

We integrated the two most common force of infection models, ⟨1a⟩, ⟨1b⟩, and ⟨2b⟩, plus the proposed model, denoted ⟨4*⟩, into an existing model of heterosexual HIV transmission in Eswatini [**TBD**]. Models ⟨2a⟩ and ⟨3⟩ were omitted as we could not find any example of their use in the literature. Full details of the transmission model are given in [**TBD**], and key details are given in Appendix B. Briefly, the model includes: five stages of HIV infection, stratified by CD4 count; five states of connection to antiretroviral treatment (ART); two sexes and four risk strata, including higher and lower risk female sex workers (FSW) and their clients. Risk groups have different numbers and mixing of partners, prevalence of STI symptoms, and rates of testing, ART initiation, and ART failure/discontinuation. Four types of partnership are modelled, with different durations, sex frequency, and levels of anal sex and condom use.

Using the Eswatini HIV transmission model, we examined the influence of each force of infection model on the: 1) epidemic dynamics with equal parameters; 2) modelled proportion of transmission attributed to different risk groups and/or partnership types throughout the epidemic; and 3) transmission population attributable fraction [8] of different risk groups and partnership types.

4.1 Equal Parameters

First, to explore fundamental differences in epidemic dynamics under each model, we simulated the Eswatini HIV epidemic under each model with identical parameter values. Parameter values were taken from the top 1000 of 100,000 model ⟨4*⟩ fits (highest likelihood). Since models ⟨1-2⟩ use the *QA* parameterization, not *CF*, we defined $Q_{ijk} = C_{ijk}/\delta_k$, $A_k = F_k\delta_k$ for ⟨1a⟩, and $Q_{ijk} = C_{ijk}$, $A_k = F_k$ for ⟨1b⟩ and ⟨2b⟩. Figure 4 illustrates HIV incidence under each model, stratified by: FSW, their clients, and everyone else ("wider population"); Figure A.2 illustrates prevalence.

In the early epidemic, model ⟨4*⟩ (yellow) consistently yielded higher incidence vs models ⟨1b⟩ (blue) and ⟨2b⟩ (green), because incidence in ⟨4*⟩ is linear before any seroconcordant HIV+ partnerships emerge — i.e. while states $\bar{k} > 0$ are empty. By contrast, models ⟨1a⟩, ⟨1b⟩, and ⟨2b⟩ all reduce incidence from the outset as an adjustment for repeated contacts, some of which effectively reflect *future* contacts. Early incidence under ⟨1a⟩ (purple) was also greater than ⟨1b⟩ and ⟨2b⟩, which may seem counterintuitive because ⟨1a⟩ uses $A = F\delta$ and $Q = C/\delta$, reducing transmission via longer duration partnerships. However, for shorter duration partnerships ($\delta < 1$) that dominate early transmission, model ⟨1a⟩ results in more partnerships ($Q > C$) with fewer contacts ($A < F$), and thus less influence of the binomial adjustment as compared to models ⟨1b⟩ and ⟨2b⟩. Early incidence was similar under models ⟨4*⟩ and ⟨1a⟩, but higher in ⟨1a⟩ under conditions (model fits) where regular sex work partnership durations were shorter and individual clients bought less sex (results not shown). Such conditions result in less binomial adjustment for sex work partnerships in ⟨1a⟩, and faster "saturation" of partnerships among client in ⟨4*⟩. Finally, ⟨2b⟩ yielded the lowest incidence of all, due to the application of the binomial adjustment to all yearly contacts per-person, rather than just per-partnership as in ⟨1a⟩ and ⟨1b⟩.

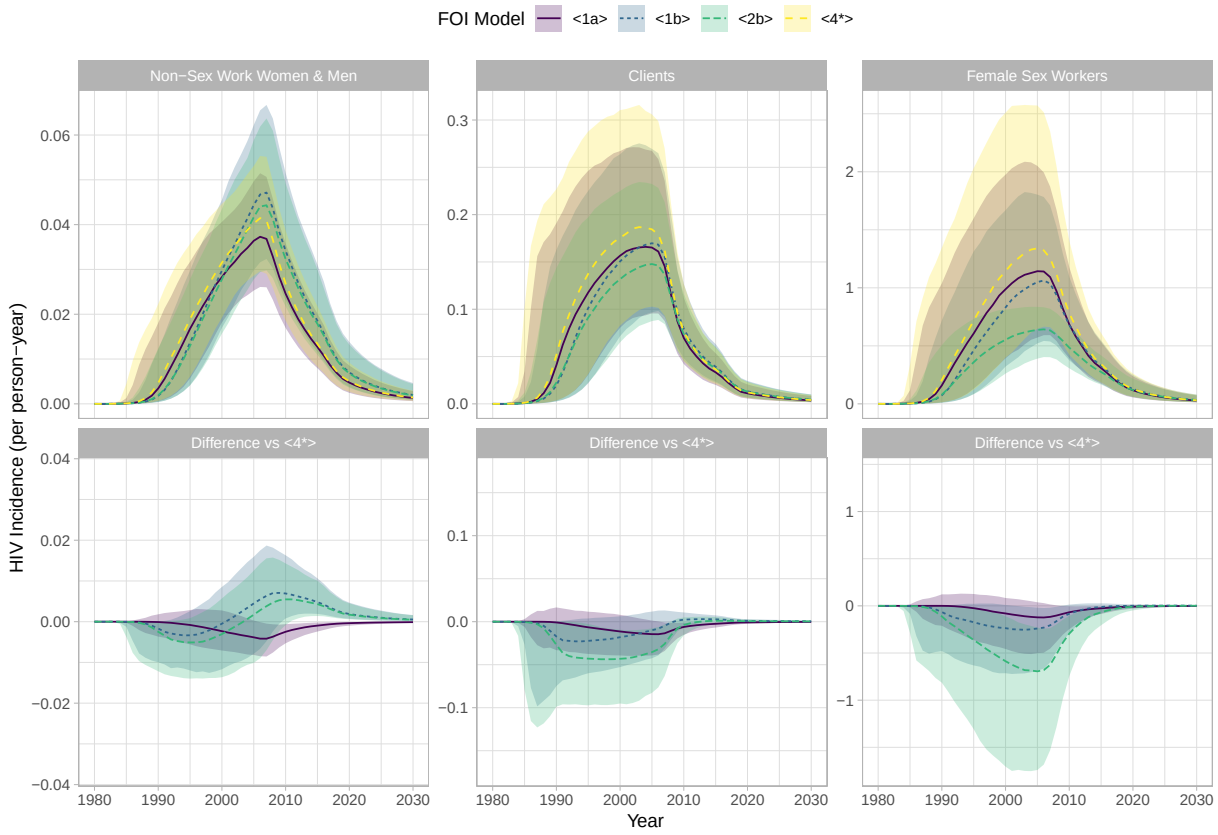


Figure 4: Comparison of modelled incidence under force of infection models ⟨1a⟩, ⟨1b⟩, ⟨2b⟩, and ⟨4*⟩ with equal parameters

FOI Model names: ⟨1a⟩ binomial per-partnership; ⟨1b⟩ binomial per-partnership-year; ⟨2b⟩ binomial per-year; ⟨4*⟩ partnership exclusion (proposed). Parameter values taken from the ⟨4*⟩ model fit with highest likelihood; for ⟨1a⟩: $Q_{ijk} = C_{ijk}/\delta_k$, $A_k = F_k\,\delta_k$; for ⟨1b⟩ and ⟨2b⟩: $Q_{ijk} = C_{ijk}$, $A_k = F_k$. Lines show median values and transparent ribbons show 90% confidence intervals from top 1000 of 100,000 ⟨4*⟩ model fits.

4.2 Distribution of Infections

Next, to explore differences in transmission networks under each model, we computed the distributions of yearly infections after calibrating each model to the same targets. As before, the top 1000 of 100,000 model fits were used in each case. Figure 5 illustrates the proportions of yearly infections transmitted via each partnership type under each calibrated model; Figure A.3a stratifies by the transmitting risk group, Figure A.3a by the acquiring group, and Figure A.4 by all three factors (model ⟨4*⟩ only).

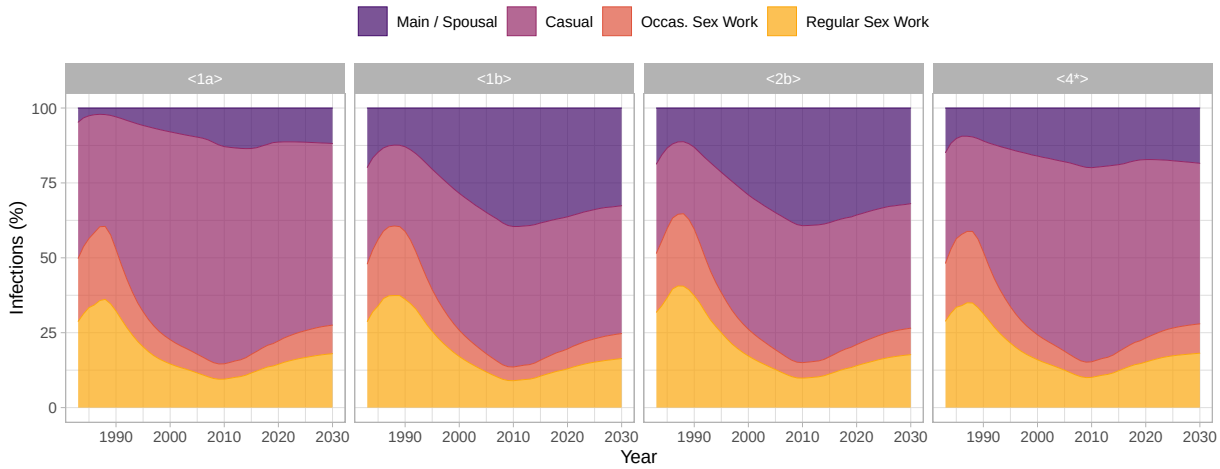


Figure 5: Comparison of the distribution of yearly infections by partnership type under calibrated force of infection models ⟨1a⟩, ⟨1b⟩, ⟨2b⟩, and ⟨4*⟩

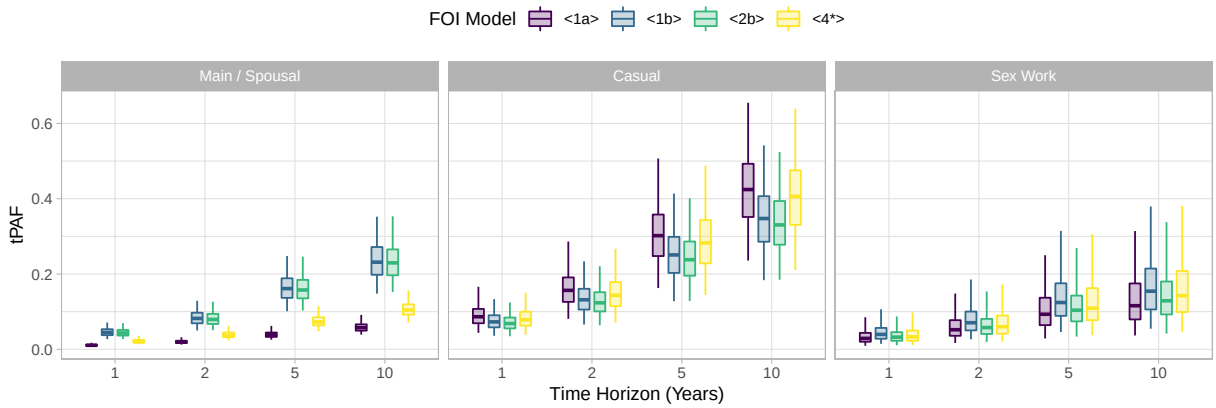
FOI Model names: ⟨1a⟩ binomial per-partnership; ⟨1b⟩ binomial per-partnership-year; ⟨2b⟩ binomial per-year; ⟨4*⟩ partnership exclusion (proposed). Parameters were re-calibrated for each FOI model, and infections reflect the median value from the top 1000 of 100,000 model fits in each case.

After calibration, the proportions of infections transmitted via occasional and regular sex work partnerships were roughly consistent across models (Figure 5). Conversely, we found large differences between models in yearly infections transmitted via main/spousal vs casual partnerships. Specifically, main/spousal partnerships never contributed more than 15% of infections under ⟨1a⟩ or 20% under ⟨4*⟩, but contributed up to 40% of infections under ⟨1b⟩ and ⟨2b⟩; and casual partnerships contributed over 70% under ⟨1a⟩ and 65% under ⟨4*⟩, but never more than 50% under ⟨1b⟩ or ⟨2b⟩. Most differences in who transmitted infection (Figure A.3a) were minimal, as were differences in who acquired infection (Figure A.3b). The only notable difference was that the lowest risk women and men transmitted fewer infections under models ⟨1a⟩ and ⟨4*⟩ vs under ⟨1b⟩ and ⟨2b⟩.

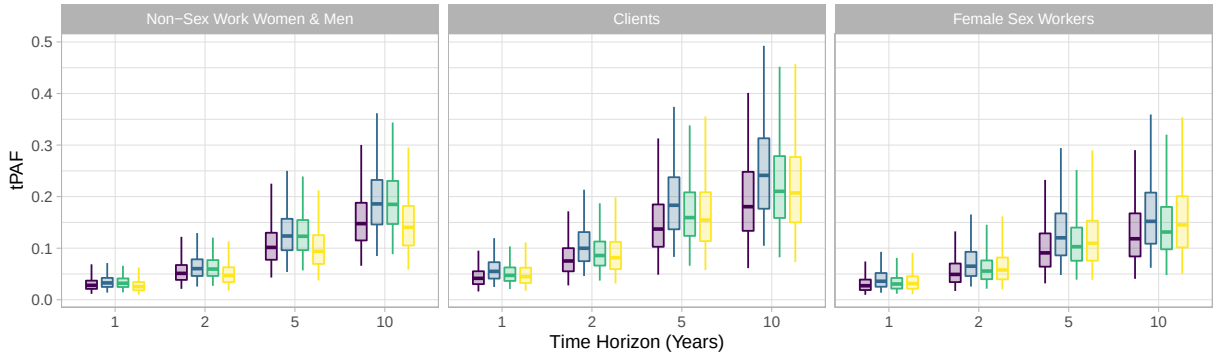
4.3 Transmission Population Attributable Fractions

Finally, to explore differences in epidemic drivers under each model, we computed the transmission population attributable fraction (tPAF) [8] for different partnership types and risk groups, and compared across calibrated models. Each tPAF reflects the proportion of all future infections attributable to unmet prevention needs of risk groups or partnership types, considering nonlinear benefits of

preventing onward transmission. We computed tPAFs over 1, 2, 5, and 10-year time horizons from t_o = 2000. Figure 6 illustrates the tPAFs of partnership types (a) and risk groups (b) under each model. Relative differences between models were similar across other t_o (Figures A.5 and A.6).



(a) Partnership types



(b) Acquisition among risk groups

Figure 6: Comparison of tPAFs of different partnership types and risk groups under calibrated force of infection models ⟨1a⟩, ⟨1b⟩, ⟨2b⟩, and ⟨4*⟩

tPAF: transmission population attributable fraction [8], from t_o = 2000 onward. FOI Model names: ⟨1a⟩ binomial per-partnership; ⟨1b⟩ binomial per-partnership-year; ⟨2b⟩ binomial per-year; ⟨4*⟩ partnership exclusion (proposed). Parameters were re-calibrated for each FOI model, and box plots reflect the median (horizontal bar), plus 90% (whiskers) and 50% (box) confidence intervals from the top 1000 of 100,000 model fits in each case.

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APPENDIX

Title: Beyond instantaneous partnerships: re-examining assumptions and a new model for partnership duration in compartmental models of HIV transmission

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A Supplemental Results

Table A.1: Notation

Symbol	Definition
λ	Rate of infection per susceptible person
λ'	Rate of transmission per infectious person
Λ	Rate of all new infections in the population
β	Probability of transmission per contact (sex act)
A	Total contacts per partnership
B	Probability of transmission per partnership
Q	Rate of partnership formation
F	Rate (frequency) of contacts per partnership
C	Number of concurrent partnerships
R	Relative probability of transmission per contact
α	Proportion of contacts per partnership affected
Δ_t	Time period

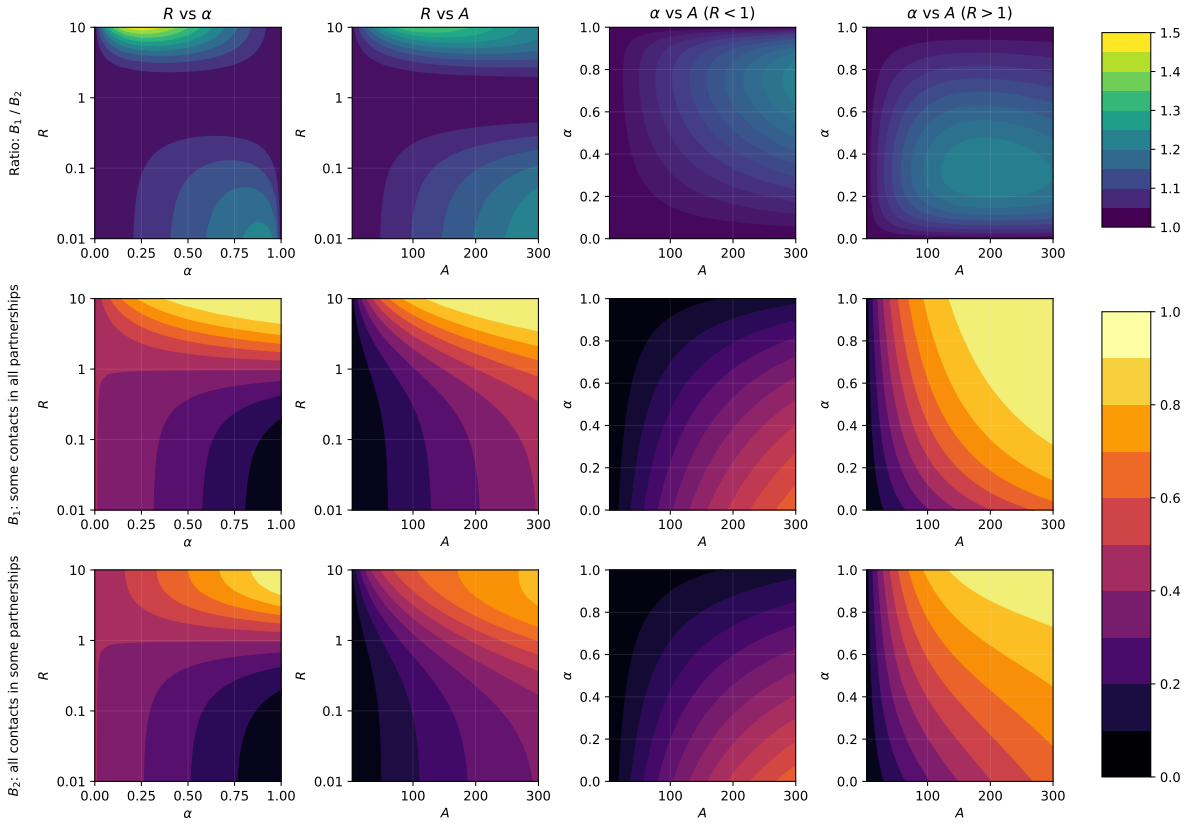


Figure A.1: Per-partnership probability of transmission B, in the presence of a transmission modifier R, calculated assuming either: B_1: α proportion of contacts in all partnerships modified; or B_2: all contacts in α proportion of partnerships modified. We observe $B_1 \geq B_2$.

β = 0.34% throughout [1]. For R vs α, A = 152; for R vs A, α = 0.5; for α vs A, (R < 1) = 0.1, (R > 1) = 5. For 0.1 < R < 3, the ratio $B_1/B_2 \approx 1$. When R < 1, then B_1/B_2 is maximized with $A \to \infty$ and 0.5 < α < 1. When R > 1, then B_1/B_2 is maximized with 1 < A < ∞ and 0 < α < 0.5.

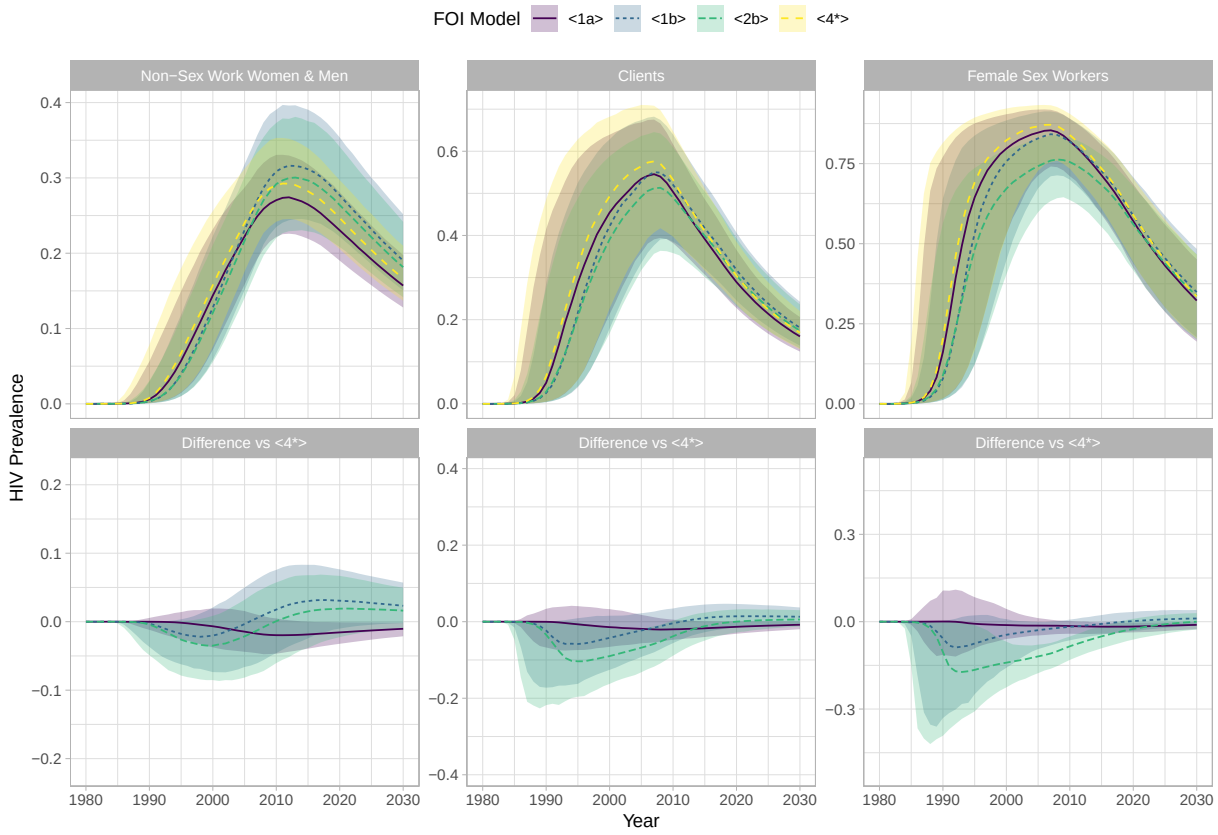
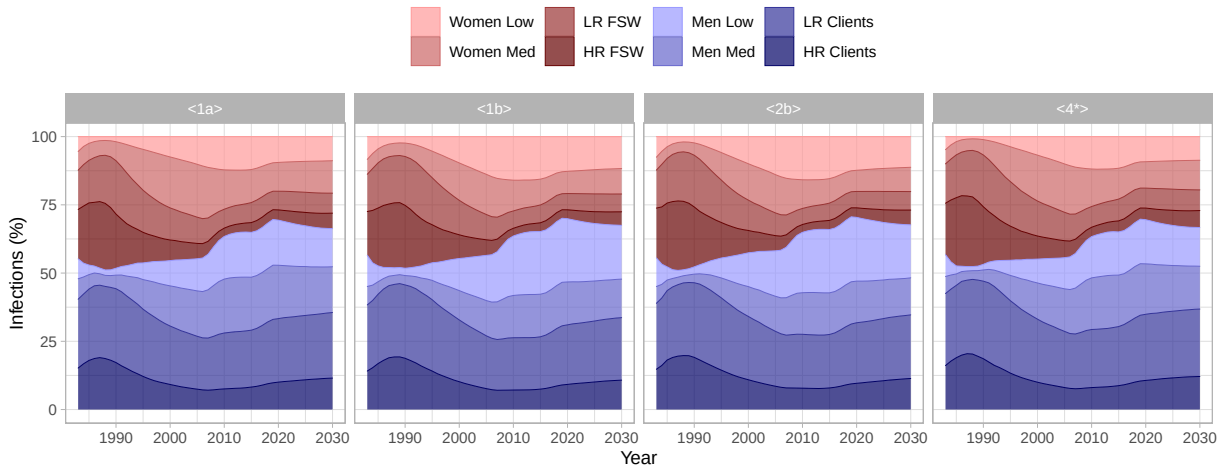
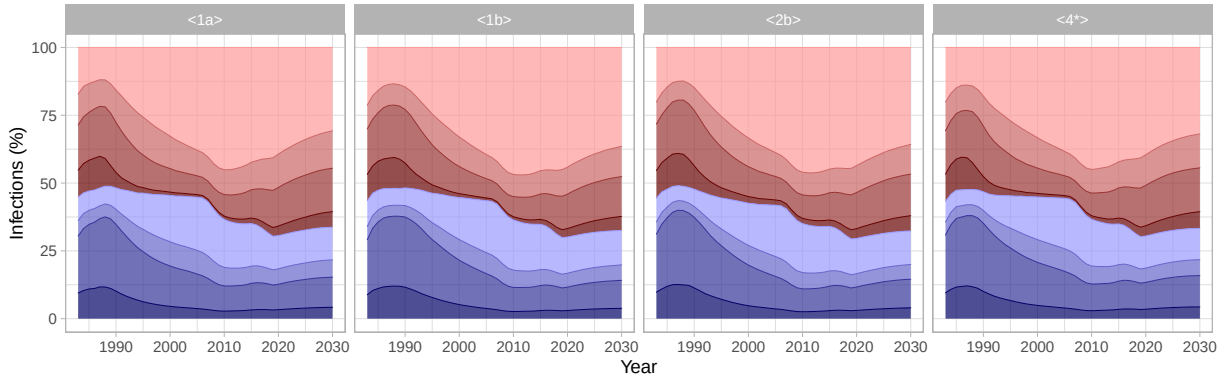


Figure A.2: Comparison of modelled prevalence under force of infection models ⟨1a⟩, ⟨1b⟩, ⟨2b⟩, and ⟨4*⟩ with equal parameters

Model names: ⟨1a⟩ binomial per-partnership; ⟨1b⟩ binomial per-partnership-year; ⟨2b⟩ binomial per-year; ⟨4*⟩ partnership exclusion (proposed). Parameter values taken from the ⟨4*⟩ model fit with highest likelihood; for ⟨1a⟩: $Q_{ijk} = C_{ijk}/\delta_k, A_k = F_k\delta_k$; for ⟨1b⟩ and ⟨2b⟩: $Q_{ijk} = C_{ijk}, A_k = F_k$. Lines show median values and transparent ribbons show 90% confidence intervals from top 1000 of 100,000 ⟨4*⟩ model fits.



(a) From whom (transmitted)



(b) To whom (acquired)

Figure A.3: Comparison of the distribution of yearly infections by transmitting and acquiring risk groups under calibrated force of infection models ⟨1a⟩, ⟨1b⟩, ⟨2b⟩, and ⟨4*⟩

FOI Model names: ⟨1a⟩ binomial per-partnership; ⟨1b⟩ binomial per-partnership-year; ⟨2b⟩ binomial per-year; ⟨4*⟩ partnership exclusion (proposed). Parameters were re-calibrated for each FOI model, and infections reflect the median value from the top 1000 of 100,000 model fits in each case. Risk groups definitions: Low: 0-1 partners in past 12 months (p12m); Med: 2+ partners p12m but no sex work; FSW: female sex workers; Clients: of FSW; LR / HR: lower risk (80%) / higher risk (20%).

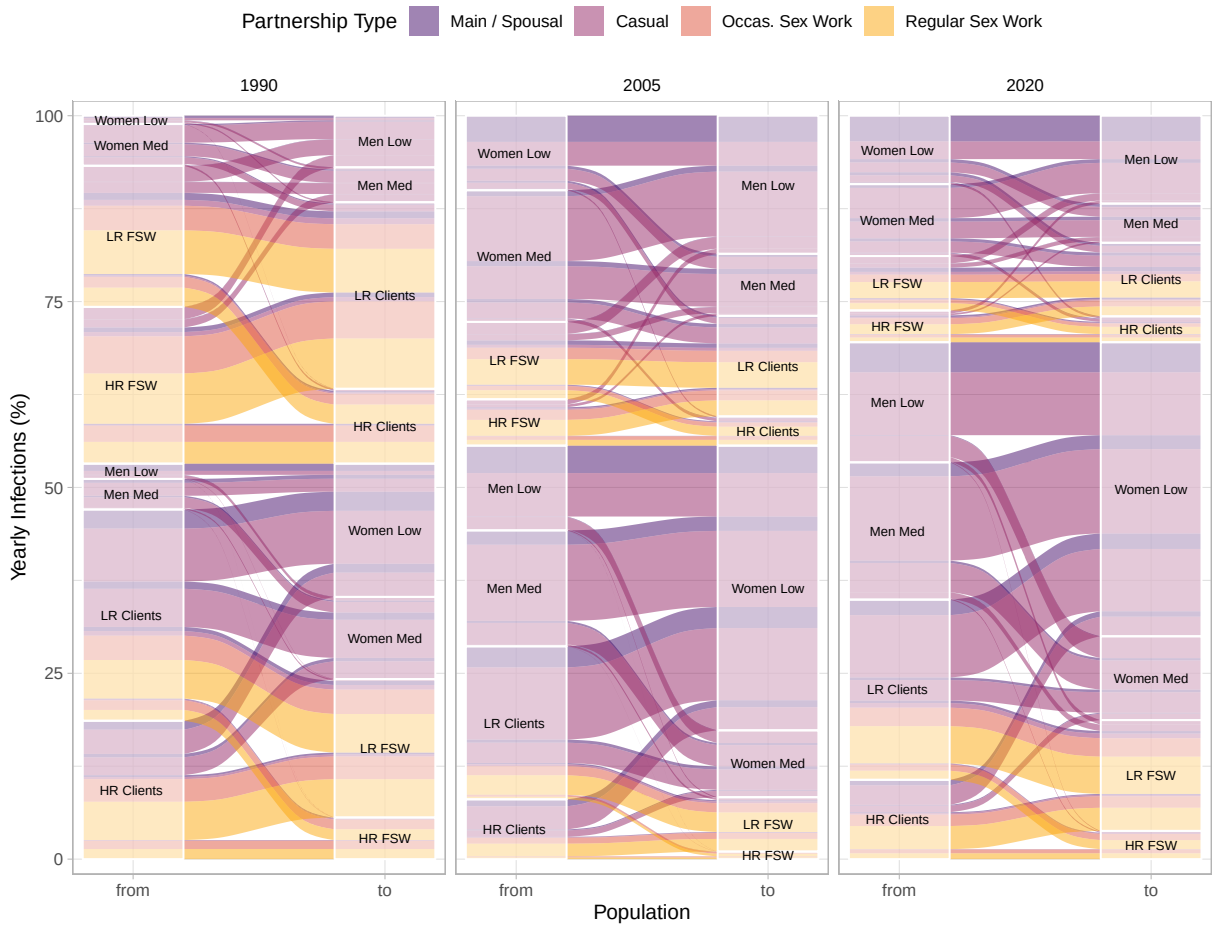


Figure A.4: Distribution of yearly infections by partnership type and transmitting / acquiring risk groups under calibrated model ⟨4*⟩ in 1990, 2005, and 2020

Infections reflect the median value from the top 1000 of 100,000 model ⟨4*⟩ fits. Risk groups definitions: Low: 0-1 partners in past 12 months (p12m); Med: 2+ partners p12m but no sex work; FSW: female sex workers; Clients: of FSW; LR / HR: lower risk (80%) / higher risk (20%).

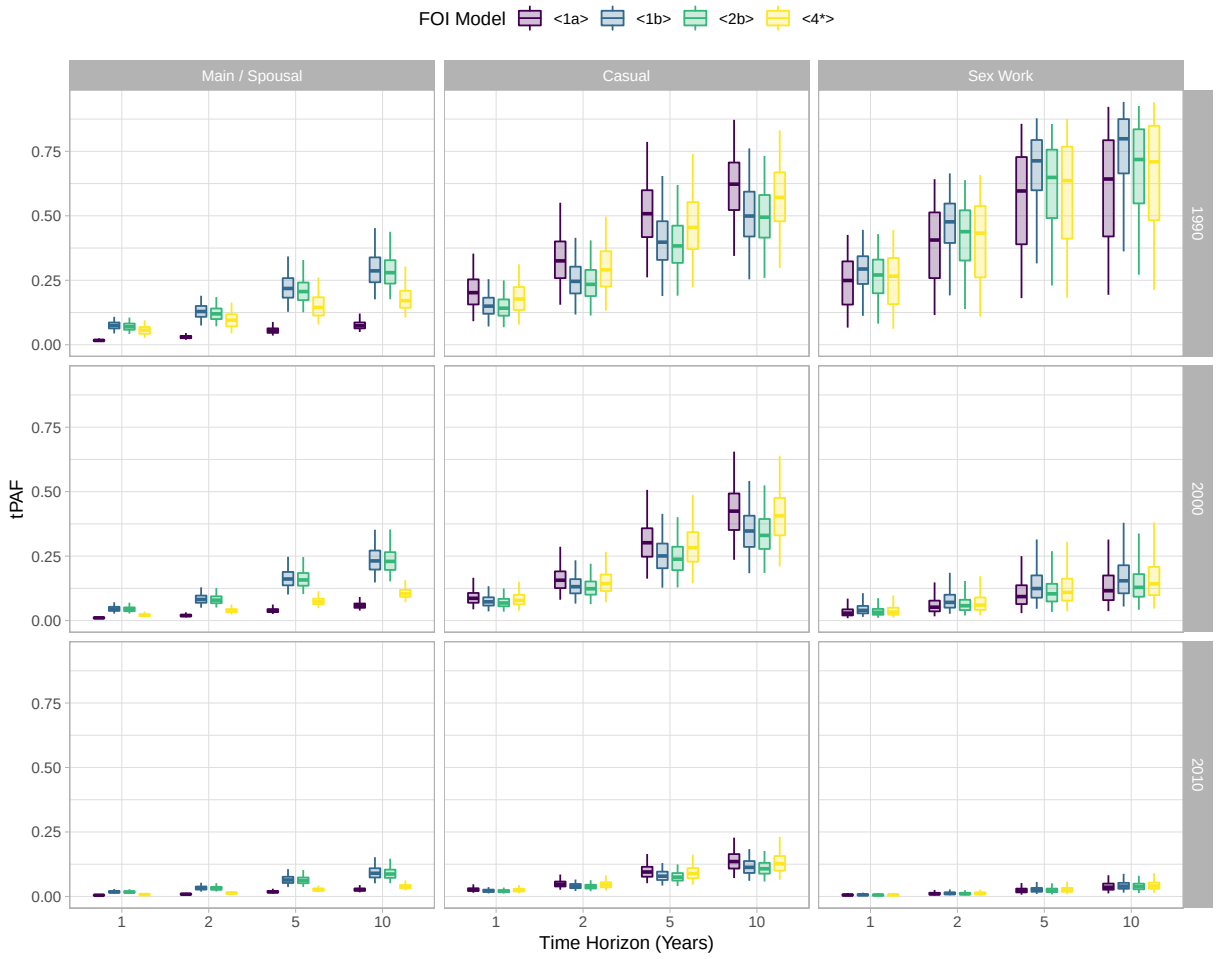


Figure A.5: Comparison of tPAFs of different partnership types under calibrated force of infection models ⟨1a⟩, ⟨1b⟩, ⟨2b⟩, and ⟨4*⟩

tPAF: transmission population attributable fraction [2], from t_o = 1990, 2000, and 2010 onward. FOI Model names: ⟨1a⟩ binomial per-partnership; ⟨1b⟩ binomial per-partnership-year; ⟨2b⟩ binomial per-year; ⟨4*⟩ partnership exclusion (proposed). Parameters were re-calibrated for each FOI model, and box plots reflect the median (horizontal bar), plus 90% (whiskers) and 50% (box) confidence intervals from the top 1000 of 100,000 model fits in each case.

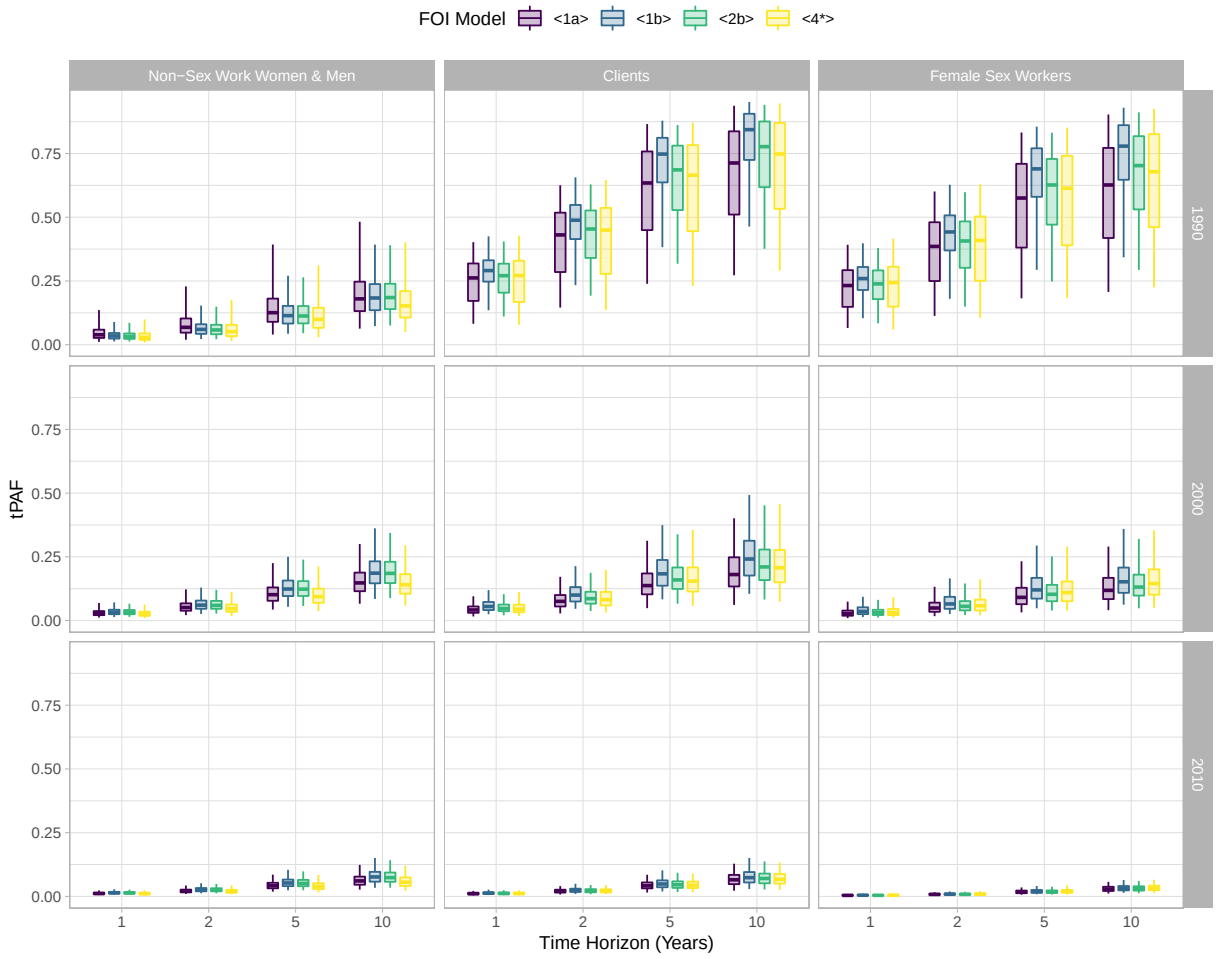


Figure A.6: Comparison of tPAFs of different risk groups (acquisition) under calibrated force of infection models ⟨1a⟩, ⟨1b⟩, ⟨2b⟩, and ⟨4*⟩

tPAF: transmission population attributable fraction [2], from t_o = 1990, 2000, and 2010 onward. FOI Model names: ⟨1a⟩ binomial per-partnership; ⟨1b⟩ binomial per-partnership-year; ⟨2b⟩ binomial per-year; ⟨4*⟩ partnership exclusion (proposed). Parameters were re-calibrated for each FOI model, and box plots reflect the median (horizontal bar), plus 90% (whiskers) and 50% (box) confidence intervals from the top 1000 of 100,000 model fits in each case.

B HIV Transmission Model

References

[1] M. C. Boily, R. F. Baggaley, L. Wang, et al. “Heterosexual risk of HIV-1 infection per sexual act: systematic review and meta-analysis of observational studies”. In: *The Lancet Infectious Diseases* 9.2 (Feb. 2009), pp. 118–129.

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