



In Silico Evaluation of HIV Short-cycle Therapies with Dynamical Models

Mélanie ´ Prague, Daniel Commenges, Rodolphe Thiébaut

► To cite this version:

Mélanie ´ Prague, Daniel Commenges, Rodolphe Thiébaut. In Silico Evaluation of HIV Short-cycle Therapies with Dynamical Models. Keystone Symposium, Aug 2017, Este Park, United States. hal-01579070

HAL Id: hal-01579070

<https://inria.hal.science/hal-01579070>

Submitted on 30 Aug 2017

HAL is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.

Mélanie Prague^{1,2,3}, Daniel Commenges^{1,2,3} and Rodolphe Thiébaut^{1,2,3}

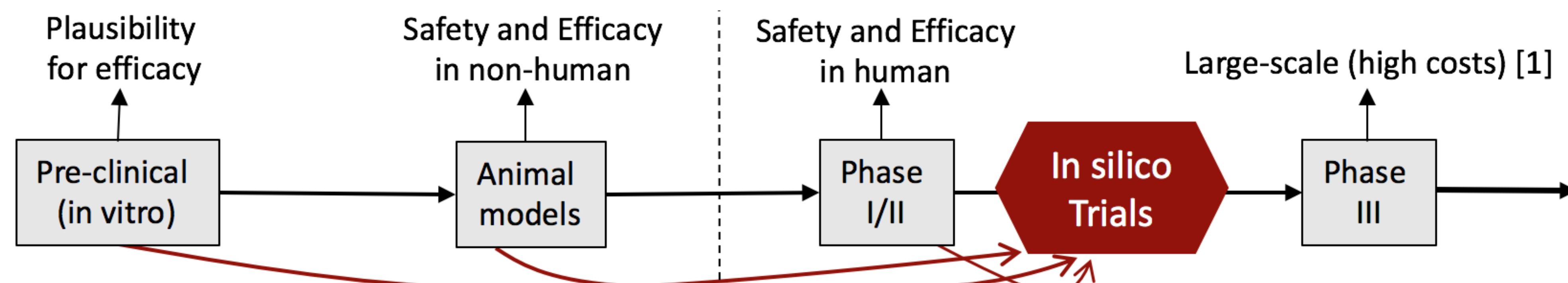
¹ Inria, Project Team SISTM, Bordeaux, France

² Inserm U1219 (BPH), Bordeaux, France

³ Vaccine Research Institute, Créteil, Paris, France

Introduction

- An in silico clinical trial is an individualised computer simulation used in the development of a medicinal product or intervention.
- Expected benefits : provide a mechanistic understanding, optimise the strategies of delivery and improve de clinical trials designs.



- Therapeutic relief is crucial for HIV infected patients under highly active antiretrovirals (ARVs) therapies (HAARTs). Multiple ongoing studies test mono/bi-therapies or short cycle therapies for HAARTs. In this work, we aim at validating these strategies in silico.

Dynamical LIM

Two-step Linear increment models (LIM):

$$\left(\frac{V_{t+1} - V_t}{T_{t+1} - T_t}\right)_i = \beta_{0i} + \beta_{CD4} CD4_t^i + \beta_{VL} VL_t^i + \sum_{k=1}^{n_{HAART}} \alpha_{HAART_k} HAART_k^i(t)$$

$$\alpha_{HAART_k} = \beta_0 + \sum_{j=1}^{n_{ARV}} \beta_{ARV_j} I_{ARV_j \in HAART_k}$$

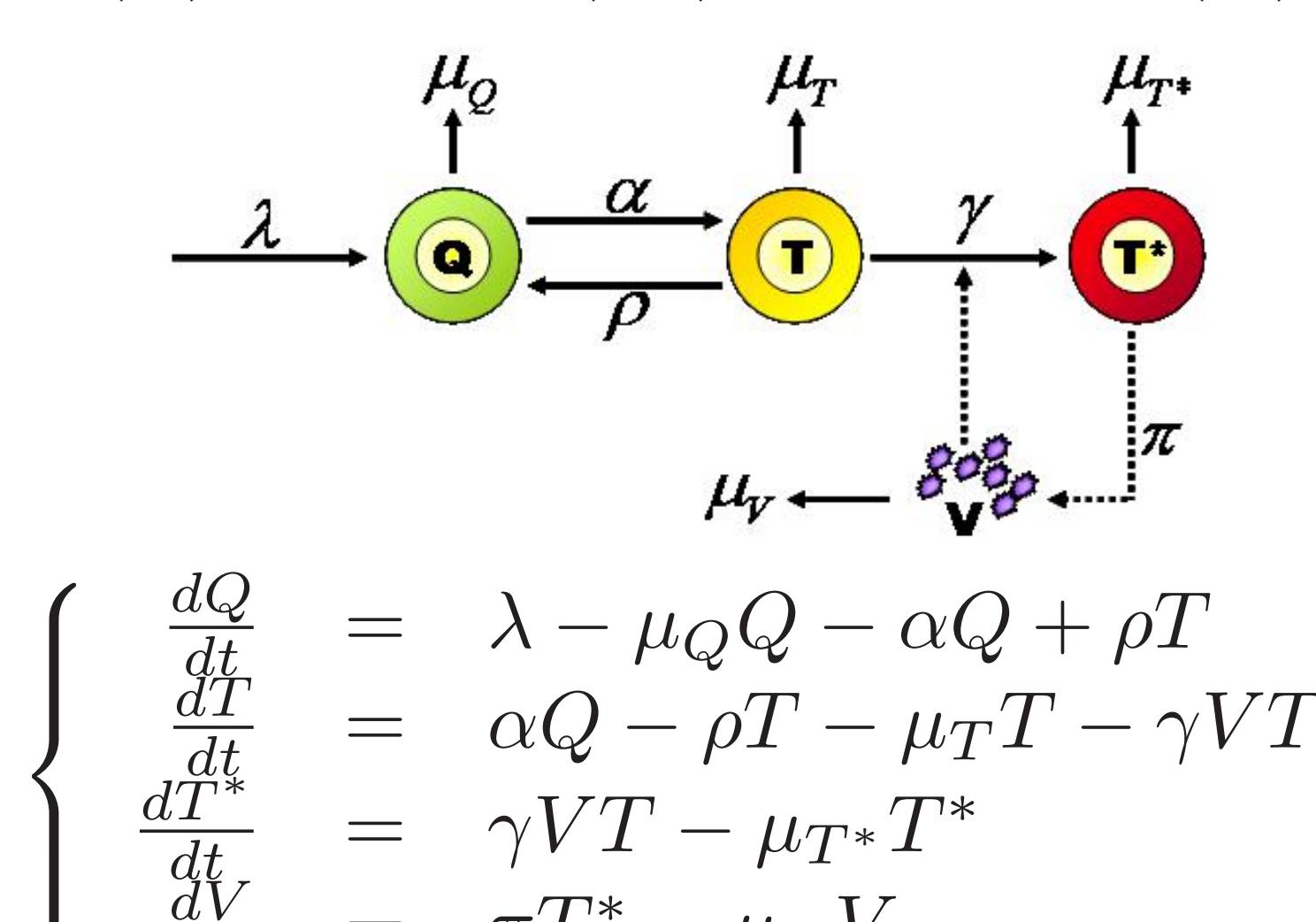
One-step LIM [2]:

$$\left(\frac{V_{t+1} - V_t}{T_{t+1} - T_t}\right)_i = \beta_{0i} + \beta_{CD4} CD4_t^i + \beta_{VL} VL_t^i + \sum_{j=1}^{n_{ARV}} \beta_{ARV_j} ARV_j^i(t)$$

Estimation Method: R library lme4 [3]

Mechanistic NLME-ODE

Mathematical Model: Ordinary differential equation (ODE) modeling CD4 quiescent (Q), target (T), infected (T^*) and viruses (V).



$$\begin{cases} \frac{dQ}{dt} = \lambda - \mu_Q Q - \alpha Q + \rho T \\ \frac{dT}{dt} = \alpha Q - \rho T - \mu_T T - \gamma V T \\ \frac{dT^*}{dt} = \gamma V T - \mu_{T^*} T^* \\ \frac{dV}{dt} = \pi T^* - \mu_V V \end{cases}$$

Statistical Model: Transition rates modelled with non linear mixed effect models (NLME).

$$\lambda_i = \lambda_0 + u_i^\lambda \quad u^\lambda \sim \mathcal{N}(0, \sigma_\lambda^2)$$

$$\alpha_i = \alpha_0 + u_i^\alpha \quad u^\alpha \sim \mathcal{N}(0, \sigma_\alpha^2)$$

$$\gamma_i(t) = \gamma_0 + \sum_{j=1}^{n_{ARV}} \beta_{ARV_j} ARV_j^i(t)$$

Observation Model: Viral load and CD4.

$$VL_{ij} = \log_{10}(V_i(j)) + \epsilon_{ij1}$$

$$CD4_{ij} = (Q_i(j) + T_i(j) + T_i^*(j))^{0.25} + \epsilon_{ij2}$$

$$\epsilon_{ij1} \sim \mathcal{N}(0, \sigma_1^2) \text{ and } \epsilon_{ij2} \sim \mathcal{N}(0, \sigma_2^2)$$

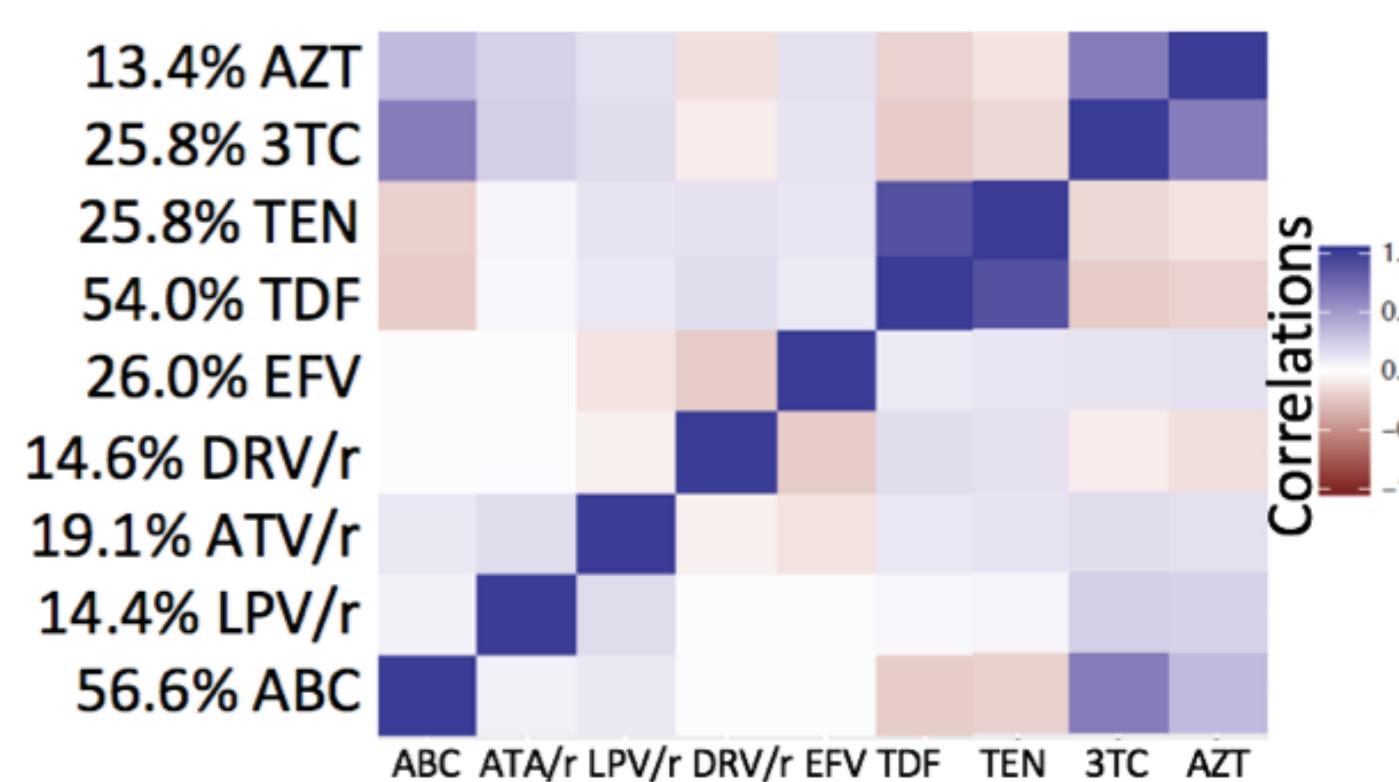
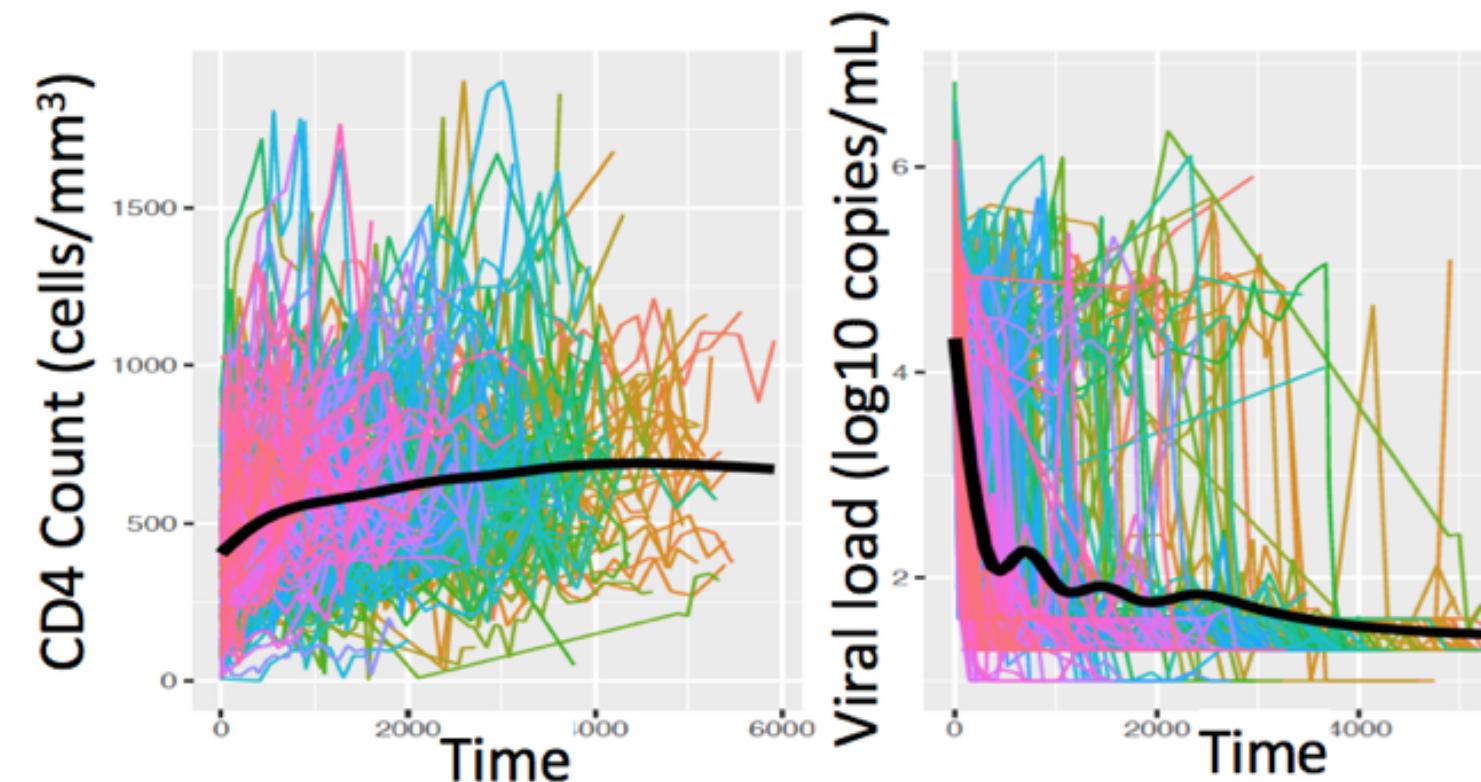
Estimation Method: NIMROD, penalised likelihood maximisation for NLME-ODE [4,5]

References

- [1] Arrowsmith et al. Nat. Rev. 2013
- [2] Prague et al. Biometrics 2016
- [3] Bates et al. J. Stat. Soft. 2015
- [4] Prague et al. Computer Meth. Prog. Biomed. 2013
- [5] Prague et al. Biometrics 2012
- [6] Thiébaut et al. J. AIDS 2000
- [7] Jilek et al. Nat. Med. 2012
- [8] Arribas et al. Lancet 2015
- [9] Perez-Molina et al. Lancet 2015
- [10] Casado et al. J. antimicrob. Chemo. 2015
- [11] DeTruchis et al., IAS, 2016
- [12] Breather trial group, Lancet, 2016

The Aquitaine ANRS CO3 Cohort [6]

Treatment-naive patients included after 1/1/2000 with at least two follow-up and baseline viral load > 10,000 copies/mm³ under investigated ARVs. Total N=248 out of 2550 patients in the cohort.



ARVs Effects

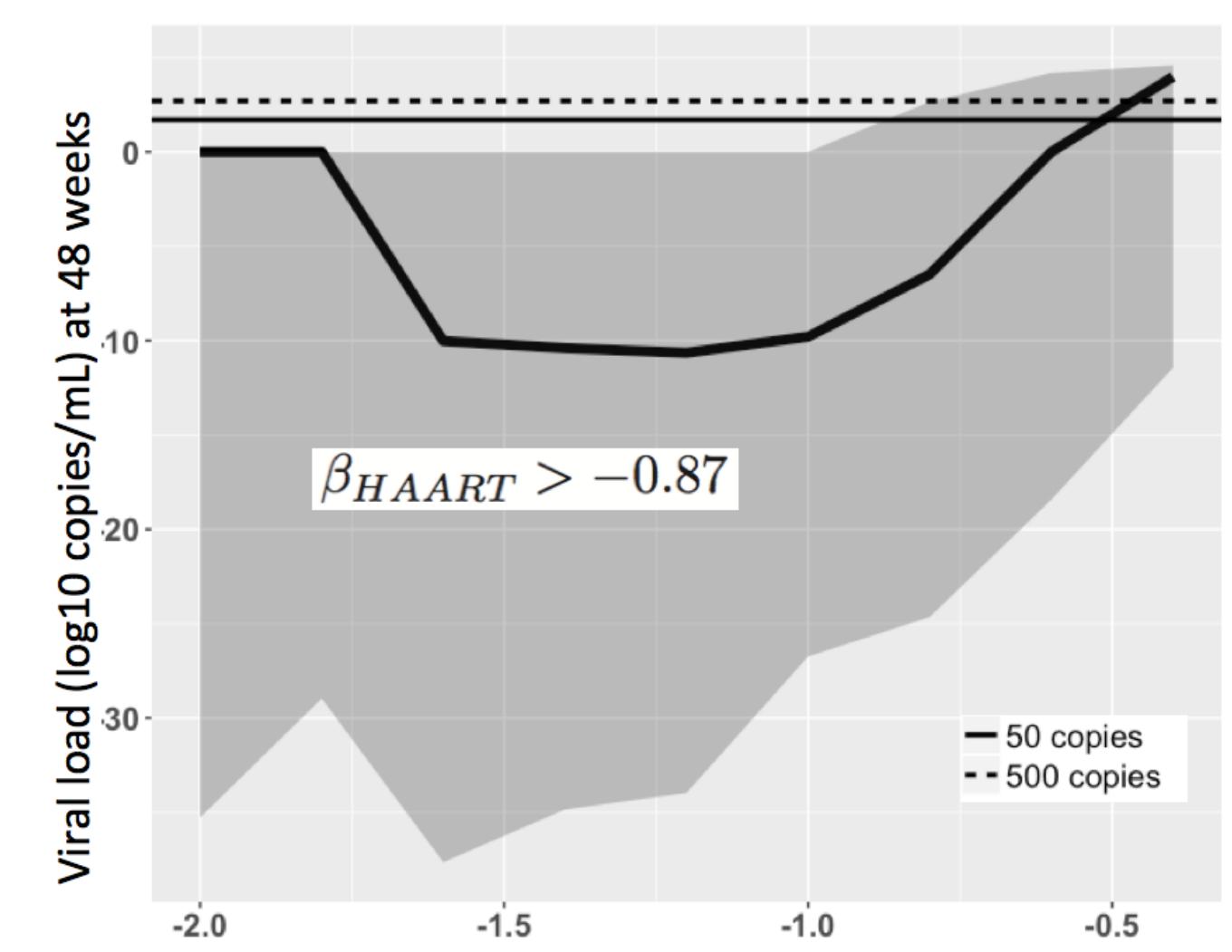
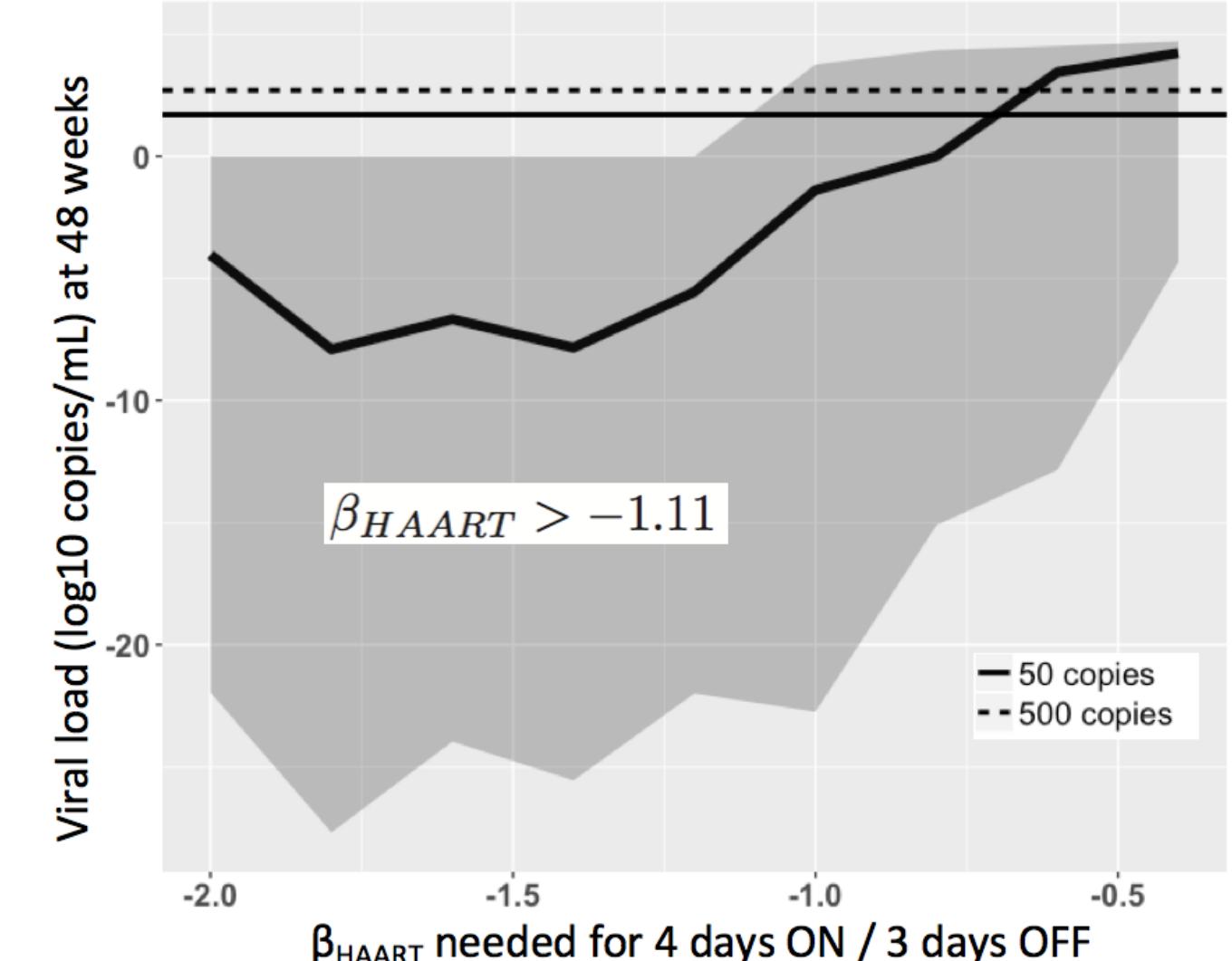
Reasonable concordance between in-vitro/in-vivo indicators of efficacy.

β_{ARV_j}	Two-step LIM	One-step LIM	NLME ODE
AZT	-1.3 [-4.0; 1.6]	-1.3 [-2.5; -0.2]	-0.33 [-0.36; -0.30]
3TC	-3.8 [-7.4; -0.1]	-2.8 [-5.0; -0.7]	-0.36 [-0.40; -0.32]
FTC	-3.7 [-7.4; 0.1]	-3.2 [-5.3; -1.0]	-0.40 [-0.45; -0.34]
ABC	-1.5 [-3.9; 1.1]	-1.6 [-2.7; -0.4]	-0.29 [-0.32; -0.26]
TEN	-1.1 [-3.6; 1.5]	-1.5 [-2.7; -0.4]	-0.30 [-0.35; -0.24]
EFV	-3.8 [-5.9; -1.4]	-2.4 [-3.6; -1.2]	-0.34 [-0.36; -0.32]
LPV/r	-3.5 [-5.6; -1.2]	-1.9 [-3.1; -0.7]	-0.28 [-0.33; -0.23]
ATA	-3.0 [-5.8; -0.1]	-2.3 [-3.4; -1.1]	-0.35 [-0.36; -0.34]
DRV/r	-3.4 [-6.0; -0.5]	-2.5 [-3.6; -1.3]	-0.34 [-0.36; -0.32]
Reg.	-2.1 (p=0.003)	-5.3 (p<0.001)	-13.6 (p=0.005)
	Model fitted $\beta \times$ IIP, p-values are for R^2 adequation		
p-value	0.097	0.097	0.463
	Spearman Corr. Instantaneous Inhibitory Potential (IIP) [7]		

In silico Short-cycle therapies

Predictive ability of NLME-ODE [1] are used to predict the probability to have viral control at 48 weeks under various On/off strategies.

$$\gamma_i(t) = \gamma_0 + \sum_{j=1}^{n_{ARV}} \beta_{ARV_j} ARV_j(t) I_{\{t=\text{dayON}\}}$$

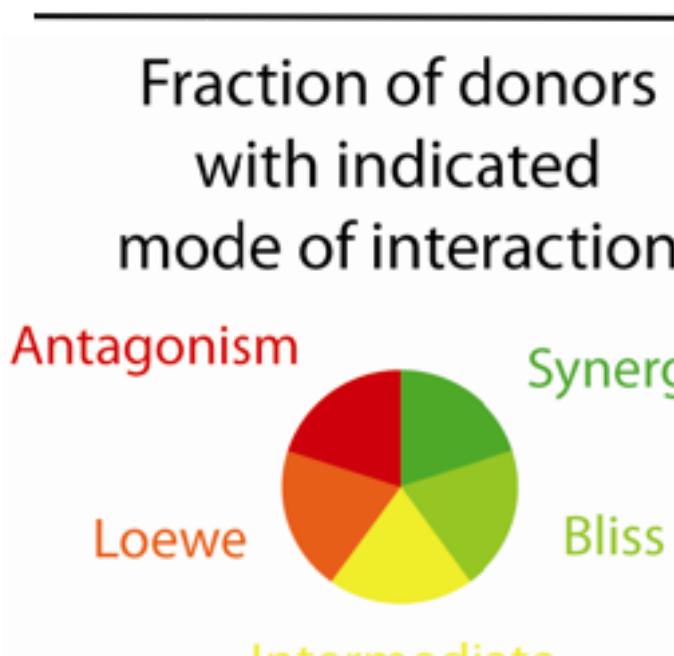


This is consistent with on-going studies. Strategies such as in 4D ANRS 162 [11] shows 96% fo viral control at 48 weeks with PI or NNRTI + 2NRTI and BREATHER trial [12] shows 94% of viral control at 48 weeks with EFV + 2NRTI.

In silico ARVs relief

Reduction of the number of ARV: The OLE trial [8], the SALT study [9] and the MADRID cohort [10] show that regarding viral control at 48 weeks, DRV/r+3TC (98%) lead to more successes than LPV/r+3TC (91%), which is more powerful than ATV+3TC (84%). We investigate in silico the probability of viral control at 48 weeks.

In vitro [7]



In vivo (1-step LIM)

ATV/r+3TC 92.9% [89.2;96.7]
DRV/r+3TC 93.8% [92.0;98.9]
LPV/r+3TC 89.5% [84.6;92.9]

Conclusion

- Proof-of-concept, need to add virus mutations & pharmacological modeling
- Optimal design for patient/regimen-specific strategies using Bayesian control [5]