

# Status Update

## Hierarchical Inference: PET and sMRI

We infer a coupled model of FKPP and atrophy:

$$\begin{aligned} \frac{dc_i}{dt} &= -\rho \sum_{j=1}^N L_{ij} c_j + \alpha c_i (1 - c_i) \\ \frac{dq_i}{dt} &= G_c c_i (1 - q_i) \end{aligned}$$

## Inference Results

We use hierarchical priors on all model parameters,  $\rho, \alpha, G_c$ . We have the following model structure:

$$\begin{aligned} \sigma_t &\sim \Gamma^{-1}(2, 3) \\ \sigma_a &\sim \Gamma^{-1}(2, 3) \end{aligned}$$

$$\begin{aligned} \rho_\mu &\sim \mathcal{N}^+(0, 1) \\ \rho_\sigma &\sim \mathcal{N}^+(0, 1) \end{aligned}$$

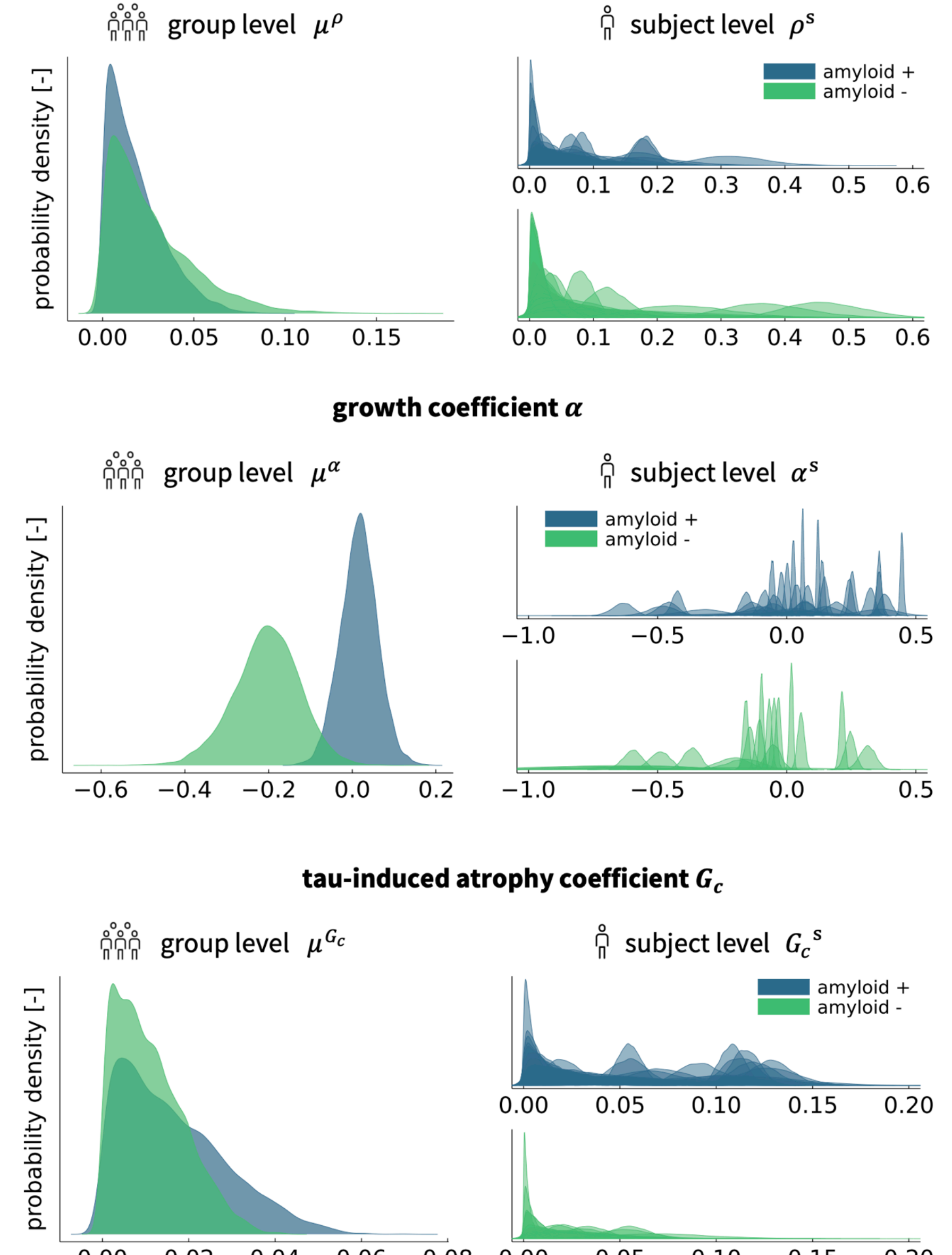
$$\begin{aligned} \alpha_\mu &\sim \mathcal{N}(0, 1) \\ \alpha_\sigma &\sim \mathcal{N}^+(0, 1) \end{aligned}$$

$$\begin{aligned} \beta_\mu &\sim \mathcal{N}^+(0, 1) \\ \beta_\sigma &\sim \mathcal{N}^+(0, 1) \end{aligned}$$

$$\begin{aligned} \rho_i &\sim \mathcal{N}^+(\rho_\mu, \rho_\sigma) \\ \alpha_i &\sim \mathcal{N}(\alpha_\mu, \alpha_\sigma) \\ \beta_i &\sim \mathcal{N}^+(\beta_\mu, \beta_\sigma) \end{aligned}$$

$$\begin{aligned} y_i^{tra} &\sim \mathcal{N}(f(\mathbf{u}, t, \{\rho_i, \alpha_i, \beta_i\}), \sigma_t) \\ y_i^{atr} &\sim \mathcal{N}(f(\mathbf{u}, t, \{\rho_i, \alpha_i, \beta_i\}), \sigma_a) \end{aligned}$$

for  $i \in 1 \dots N$  subjects. Notice that we assume the same noise distribution across all subjects. Initial tests with independent noise for each subject showed poor convergence. Identical noise for each subjects does not account for inter-subject movement in scanners or differences in scanner hardware and protocols. However, the hierarchical distributions for transport and growth are consistent with those reported in previous studies. There are clear differences in the hierarchical distributions between the AB+ groups and the AB- groups, with the latter having a lower density around smaller values and a wider tail. This is reflected in the subject-specific distributions, which show a significantly greater portion of posterior distributions away from 0 for AB+ compared to AB-.



## Inferring Seeding Locations

Problems:

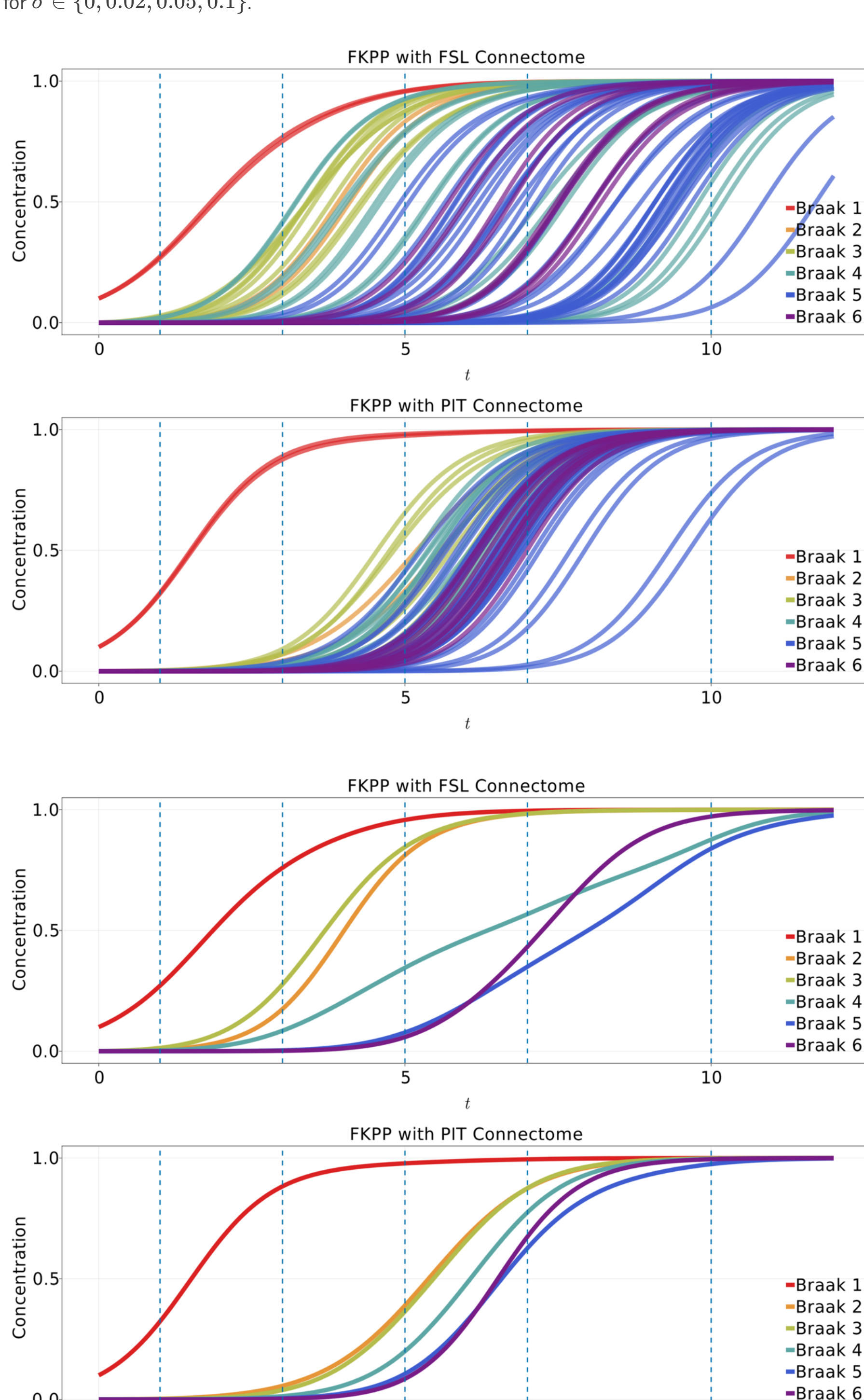
- Given some data from  $t_n = t_{0+n}$ , can we infer initial conditions at  $t = t_0$ ?
- Does parameter identifiability vary given connectome topology?

I first explore identification of 10% seeding in bilateral EC. Synthetic data is generated using FKPP simulations on the FSL and PIT connectomes, with parameters  $\rho = 0.5$  and  $\alpha = 1.5$ . I test 5 time intervals for  $n \in \{1, 3, 5, 7, 10\}$ , shown by the dashed lines. For each  $n$ , FKPP solutions at each node are saved at  $t_n, t_{n+1}$  and  $t_{n+2}$ , giving  $83 \times 3$  data points per test case.

Additionally, for each value of  $n$ , we test identifiability at 4 noise levels, given by the generative process:

$$y = f(\mathbf{u}, t, \mathbf{p}) + \mathcal{N}(0, \sigma)$$

for  $\sigma \in \{0, 0.02, 0.05, 0.1\}$ .



## Inference Model

I use a horseshoe prior to enforce sparsity in solutions to the inference problem. The full generative process is then defined as:

$$\sigma \sim \Gamma^{-1}(2, 3)$$

$$\tau \sim \mathcal{C}^+(0, 0.1)$$

$$\lambda_i \sim \mathcal{C}^+(0, 1)$$

$$\omega_i \sim \mathcal{N}(0, 1, [0, 1])$$

$$\rho \sim \mathcal{N}^+(0, 1)$$

$$\alpha \sim \mathcal{N}^+(0, 1)$$

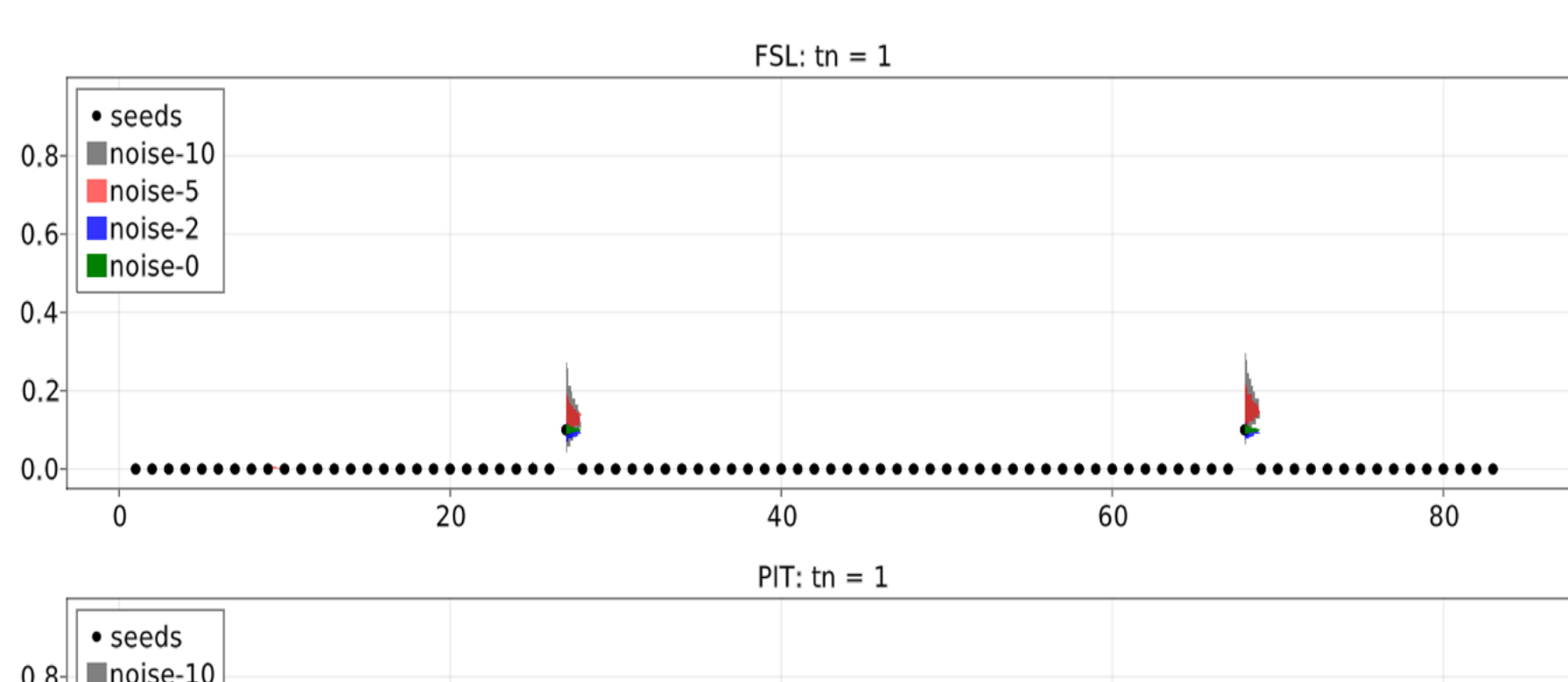
$$u_i = \omega_i * (\tau * \lambda_i)$$

$$y \sim \mathcal{N}(f(\mathbf{u}, t, \theta)|_{t=t_n}, \sigma)$$

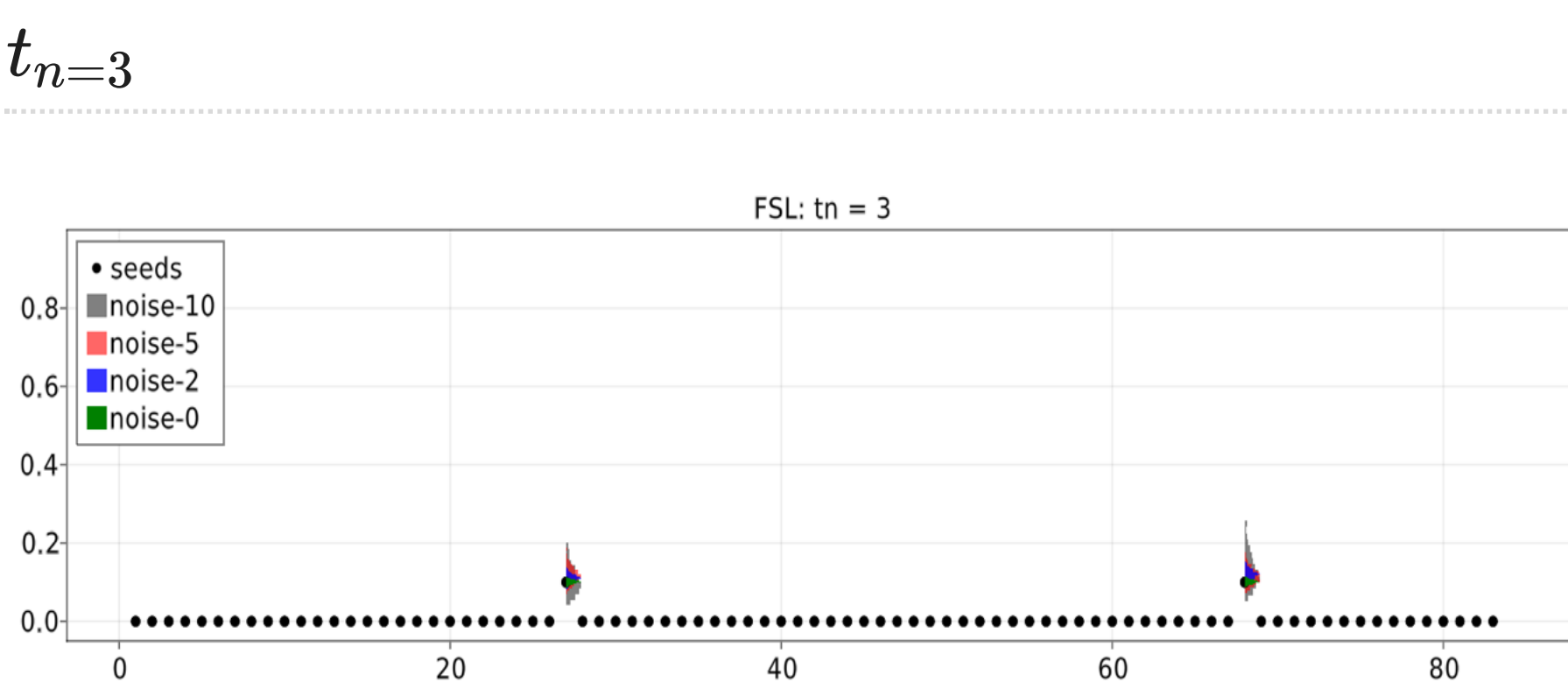
## Inference Results

For  $n = 1$  and  $n = 3$ , the locations of the initial conditions are identified for all noise levels using the FSL and PIT connectomes. However, in both cases, posteriors are broader for the PIT connectome than the FSL connectome at higher noise levels (0.05 and 0.1).

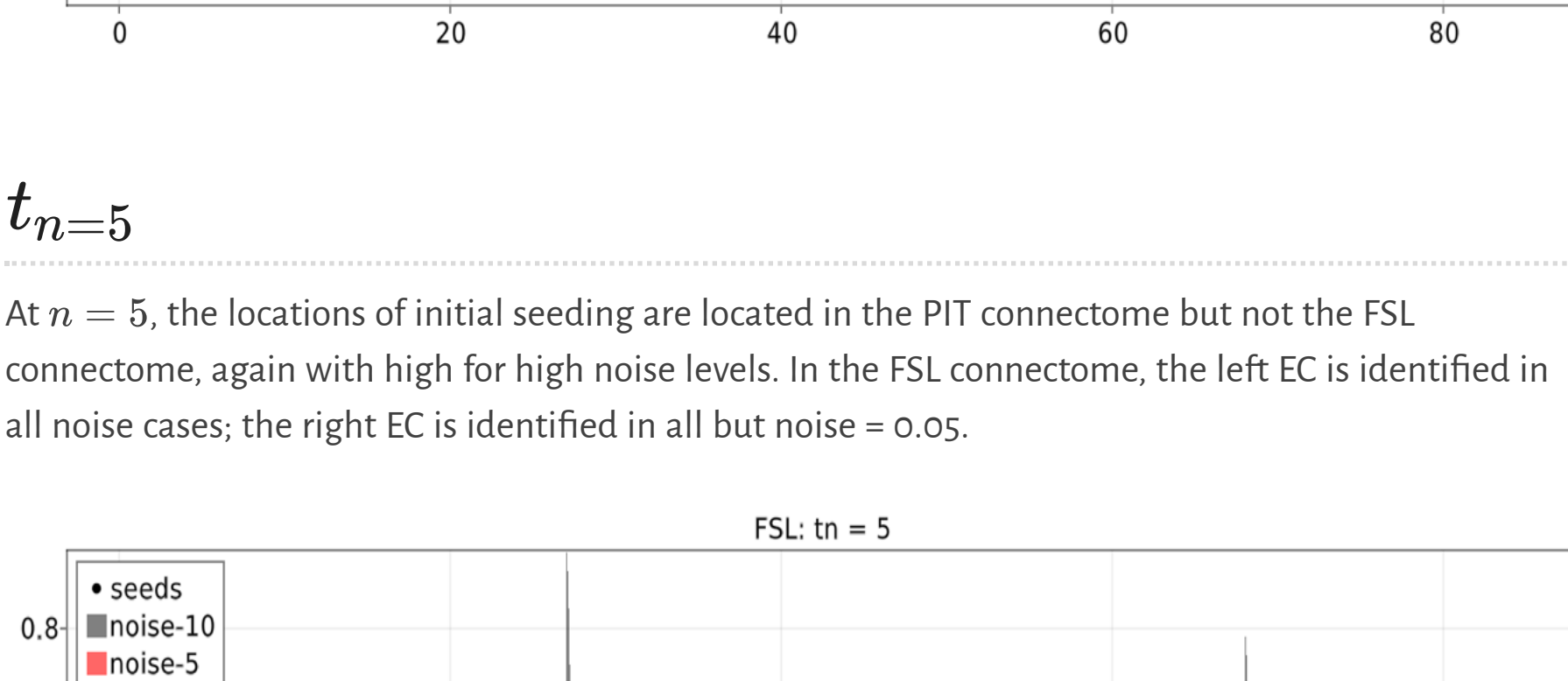
$t_{n=1}$



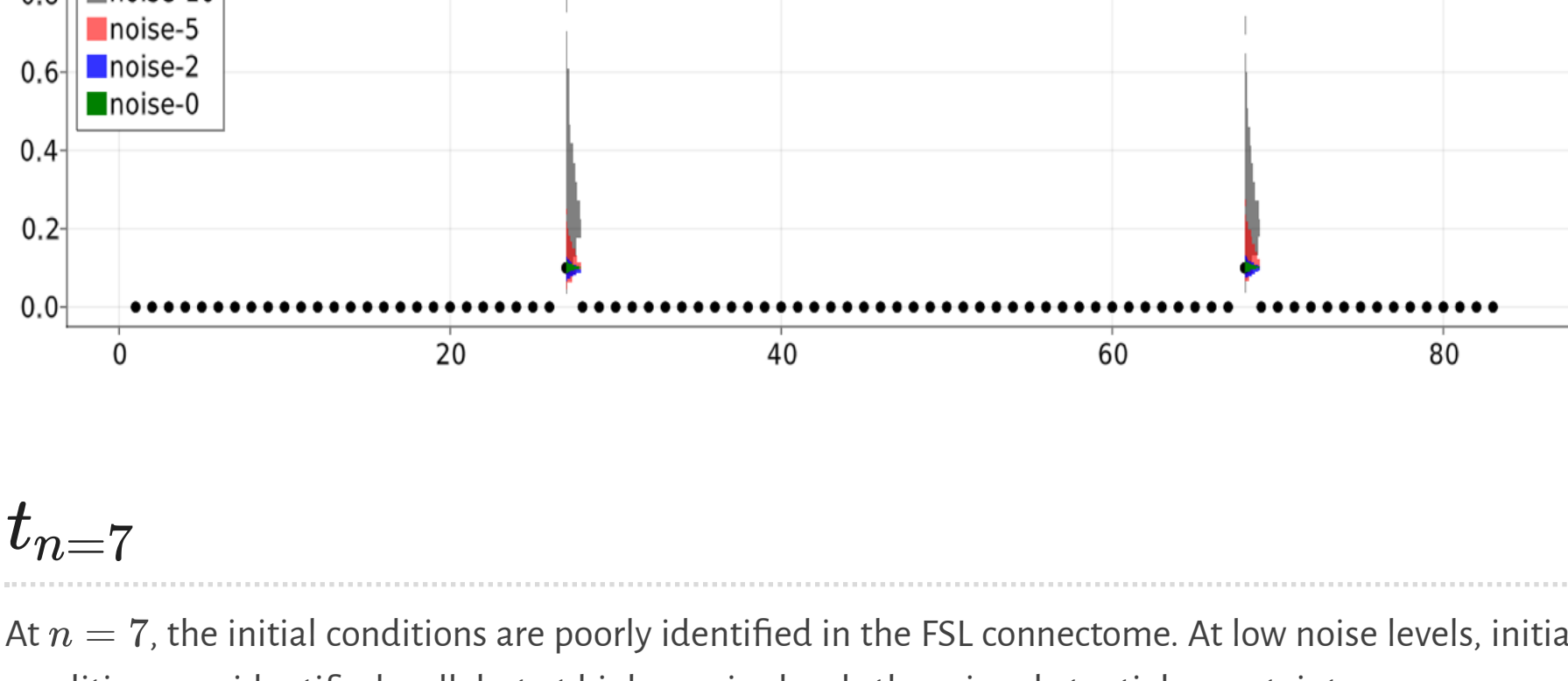
$t_{n=3}$



$t_{n=5}$



$t_{n=7}$



$t_{n=10}$

