

Aladynoulli Model Improvements

From gradient repair to time-varying genetic effects

1. Original model: incomplete gradient flow to genetic effects (γ)
2. Reparameterization fix: direct NLL gradients \rightarrow no κ shrinkage needed
3. Slope extension: time-varying genetic effects (γ_{slope})
4. Holdout evaluation: AUC gains across 28 diseases

The Problem: Incomplete Gradient Flow

Original Model ("nolr")

λ, ϕ are direct nn.Parameters

γ, ψ appear ONLY in GP prior

$\partial \text{NLL} / \partial \gamma = 0$ (no direct gradient!)

γ learns only from weak GP signal

Required κ shrinkage to compensate

fix



Reparameterized Model

$\lambda = \text{mean}_{\lambda}(\gamma) + \delta$

$\phi = \text{mean}_{\phi}(\psi) + \varepsilon$

$\partial \text{NLL} / \partial \gamma \neq 0$ (direct gradient!)

γ, ψ get strong NLL signal

$\kappa = 1$ (no shrinkage needed!)

Key Insight

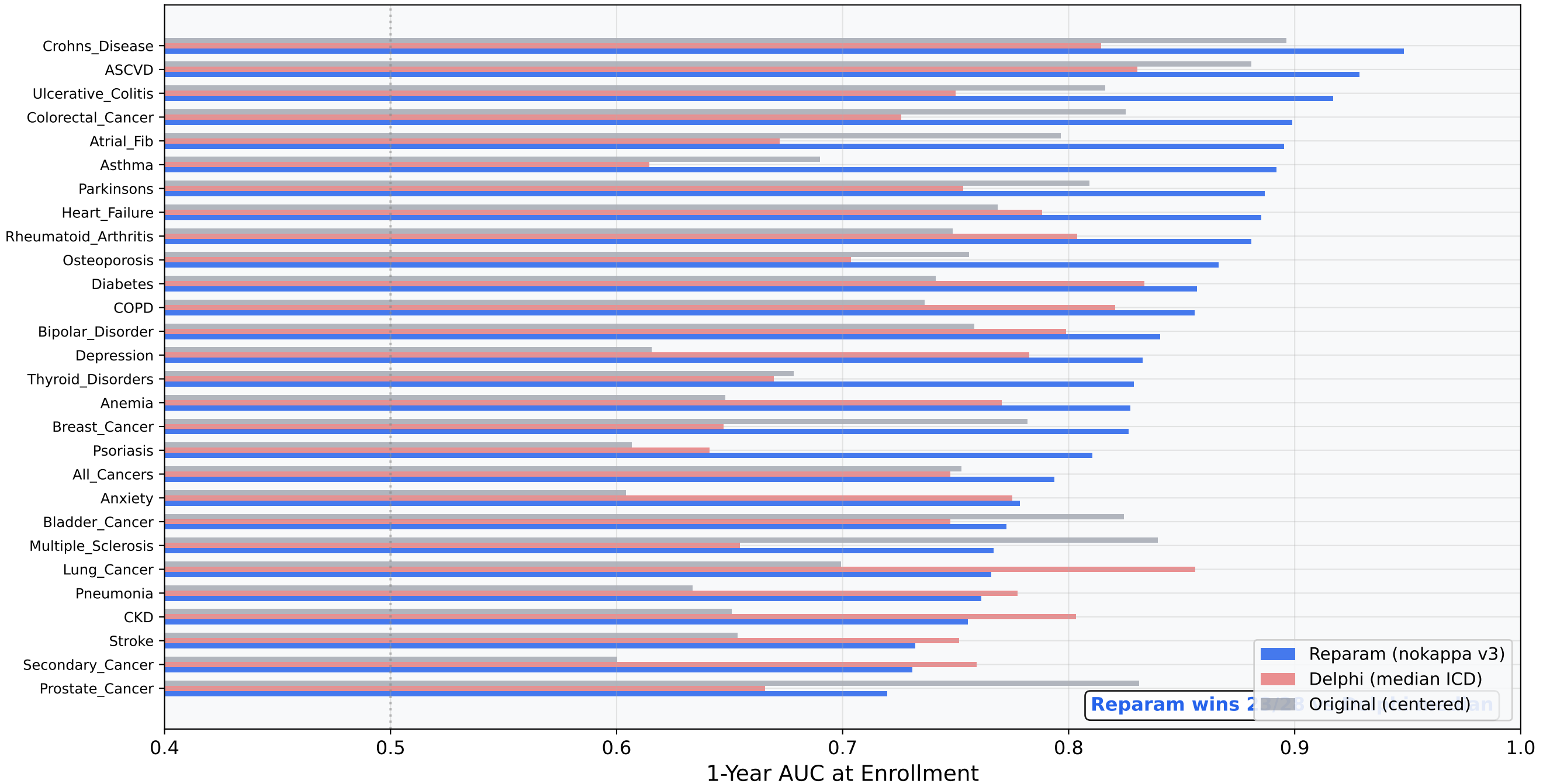
The need for κ shrinkage was a symptom, not the disease.

The real problem was that γ had no direct NLL gradient in the original architecture.

With reparameterization, γ receives direct gradients $\rightarrow \kappa = 1$ works best.

Reparameterized Model vs Baselines

1-Year Static AUC at Enrollment (400k patients)



Extension: Time-Varying Genetic Effects

Reparam (Level Only)

$$\lambda = \sigma_{\text{ref}} + \text{scale} \cdot (G @ \gamma) + \delta$$

γ captures static genetic effects – same at all ages

Cannot model PRS effects that wane or strengthen

Slope Model

$$\lambda = \sigma_{\text{ref}} + \text{scale} \cdot (G @ \gamma_{\text{level}}) + t \cdot \text{scale} \cdot (G @ \gamma_{\text{slope}}) + \delta$$

γ_{level} : baseline genetic effect

γ_{slope} : **time-varying change**

Captures waning/strengthening

Two-Phase Training Strategy

Phase 1 (200 epochs)

δ FROZEN (patient residual)

γ_{slope} forced to learn population-level time effects from NLL directly

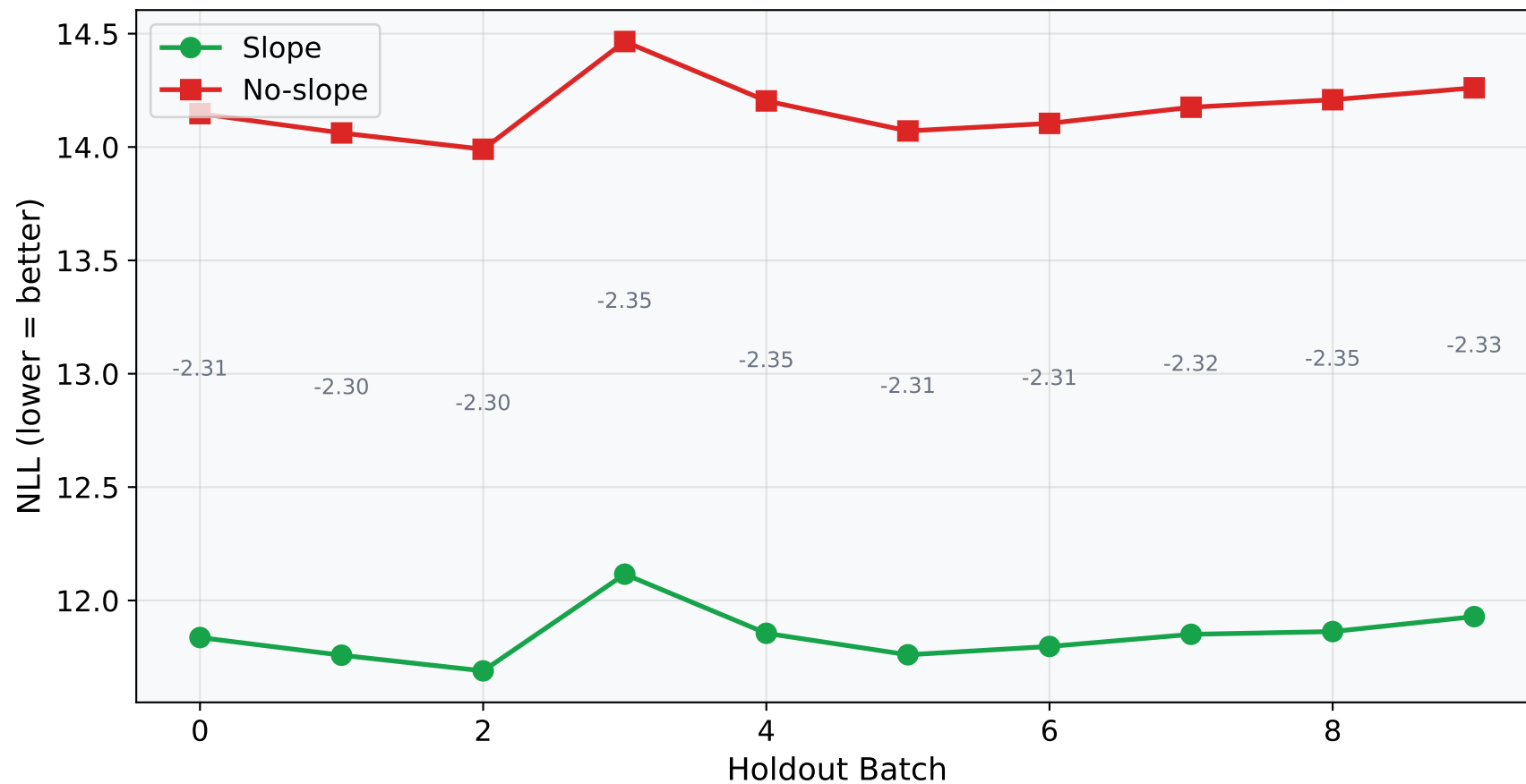
then

Phase 2 (100 epochs)

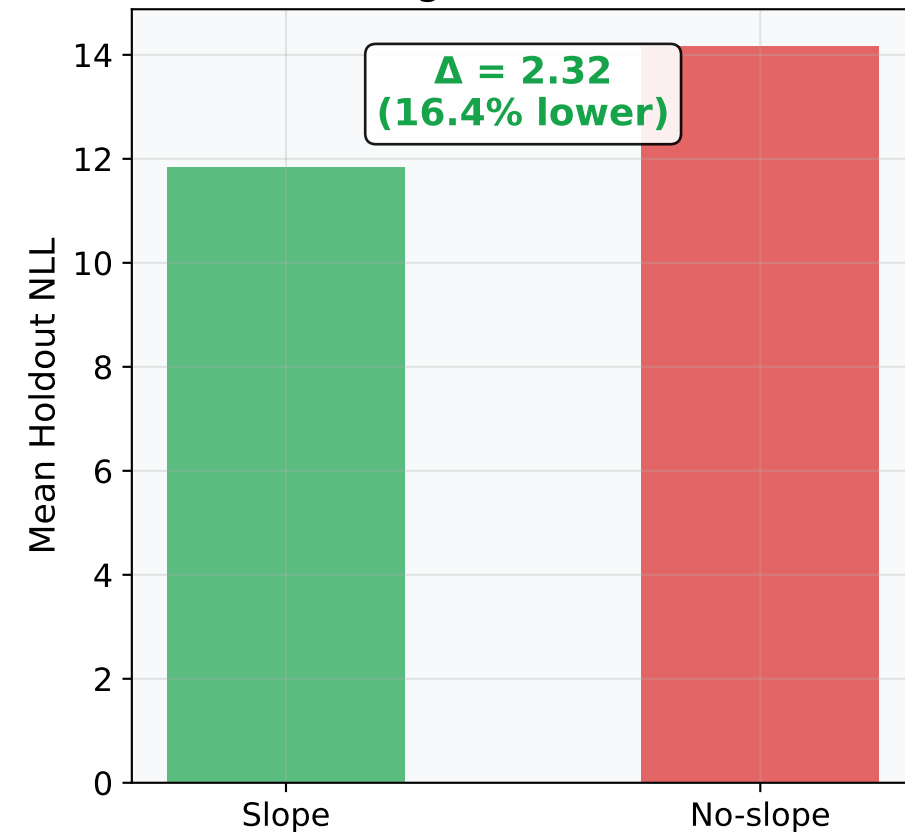
ALL parameters unfrozen
Fine-tune together
 δ absorbs patient-specific residual after slope is set

Holdout NLL: Slope vs No-Slope (100k patients)

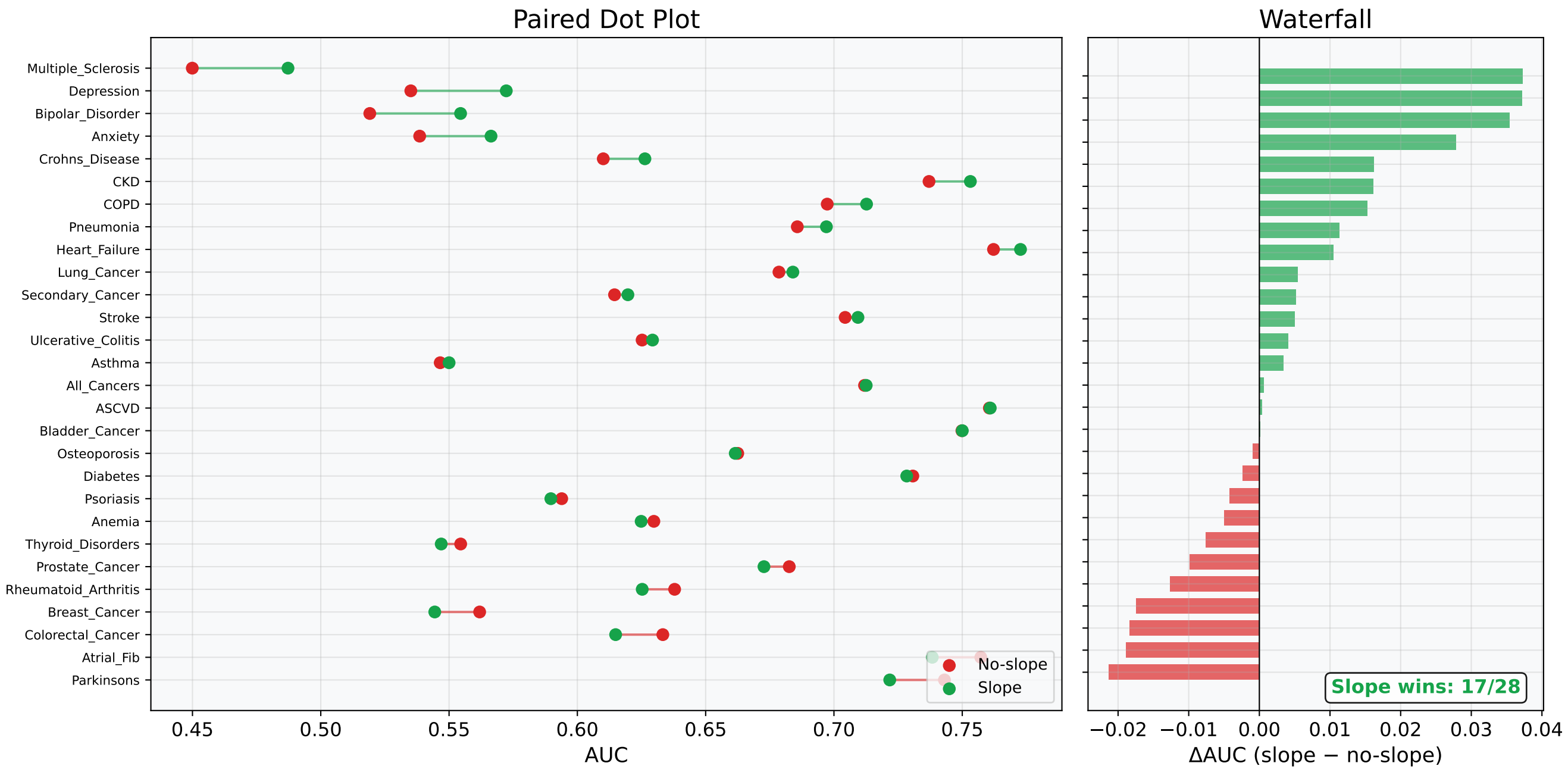
Per-Batch Holdout NLL



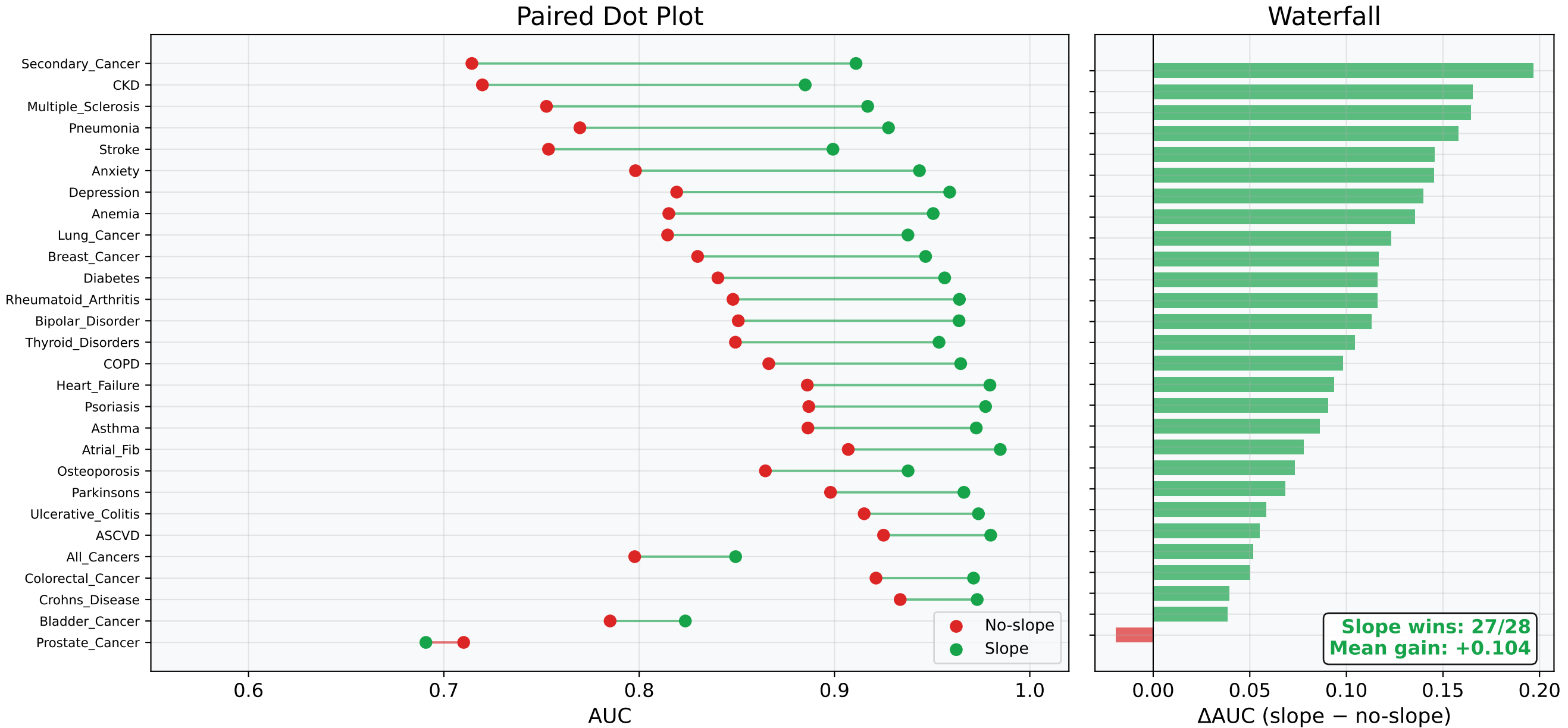
Average (10 batches)



Holdout AUC: Static 10-Year (Slope vs No-Slope)



Holdout AUC: Static 1-Year at Enrollment (Slope vs No-Slope)



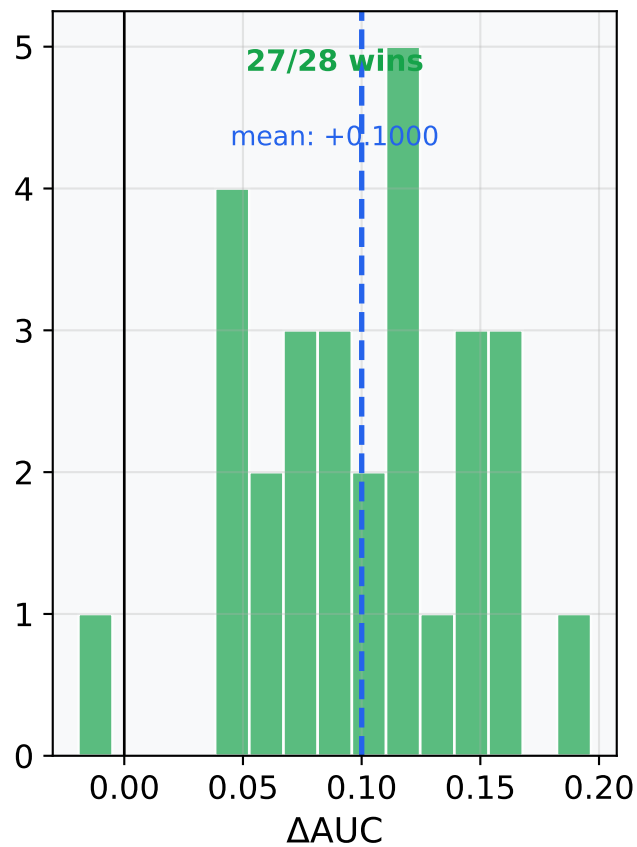
Biggest 1-Year AUC Improvements with Slope Model

Disease	Slope AUC	No-Slope AUC	Gain	% Improvement
Secondary Cancer	0.911	0.714	+0.197	+27.5%
CKD	0.885	0.720	+0.165	+23.0%
Multiple Sclerosis	0.917	0.753	+0.164	+21.9%
Pneumonia	0.928	0.770	+0.158	+20.5%
Stroke	0.899	0.754	+0.146	+19.3%
Anxiety	0.943	0.798	+0.145	+18.2%
Depression	0.959	0.819	+0.140	+17.1%
Anemia	0.951	0.815	+0.135	+16.6%
Lung Cancer	0.938	0.815	+0.123	+15.1%
Breast Cancer	0.947	0.830	+0.117	+14.1%
Diabetes	0.956	0.840	+0.116	+13.8%
Rheumatoid Arthritis	0.964	0.848	+0.116	+13.7%
Bipolar Disorder	0.964	0.851	+0.113	+13.3%
Thyroid Disorders	0.954	0.849	+0.104	+12.3%
COPD	0.965	0.866	+0.098	+11.3%

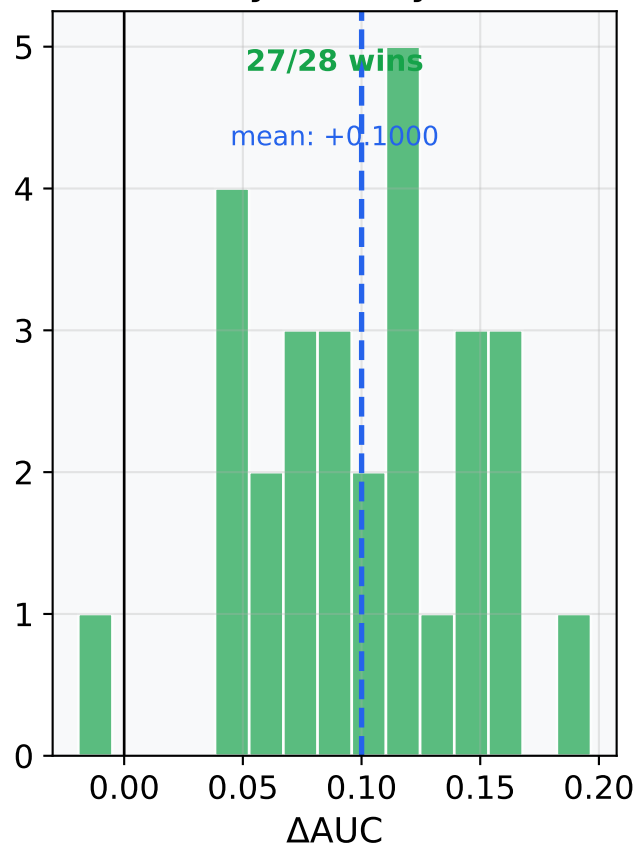
Across all 28 diseases: slope wins 27/28 | Mean AUC gain = +0.100 | Mean improvement = +12.3%

Slope Model Advantage Across All Evaluation Horizons

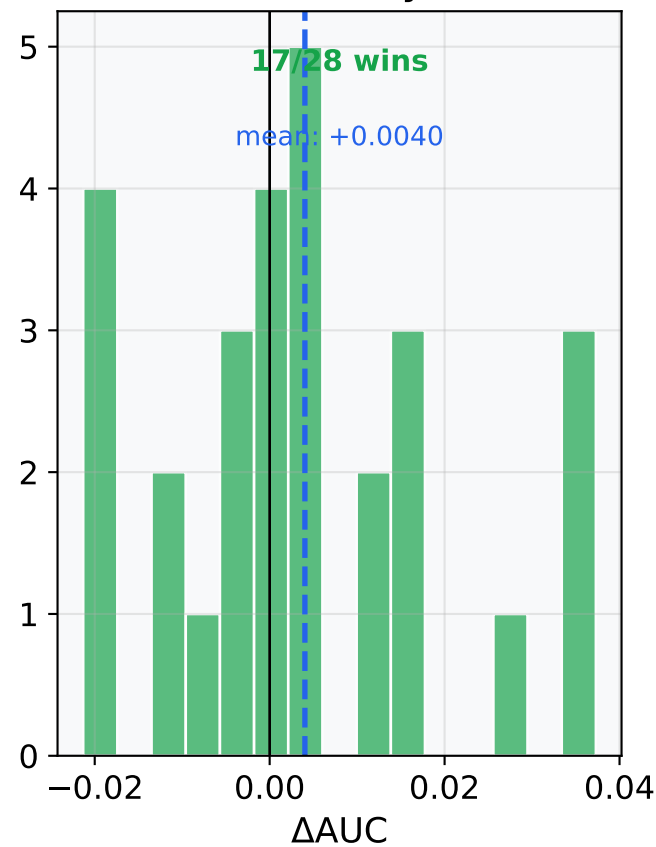
**Static 1yr
(enrollment)**



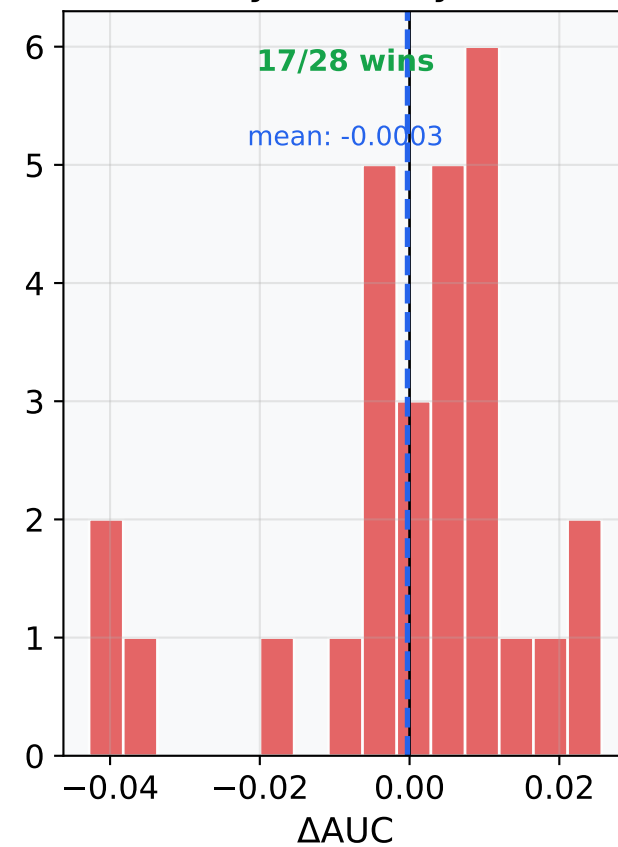
Dynamic 1yr



Static 10yr



Dynamic 10yr



Summary & Next Steps

Key Findings

1. Reparameterization fixed the gradient flow problem — κ shrinkage was a band-aid
2. Reparam (nokappa v3) beats Delphi ICD-level baselines on most diseases
3. Time-varying γ_{slope} captures waning/strengthening PRS effects with age
4. Holdout NLL: slope model $\sim 16\%$ lower (better fit on unseen patients)
5. 1-year AUC: slope wins 27/28 diseases, mean improvement $+10\%$
6. 10-year AUC: slope wins 18/28 diseases with smaller but consistent gains

Holdout NLL

Mean $\Delta = -2.32$ (slope lower)

1-Year AUC

Mean gain = $+0.100$ (27/28 wins)

In Progress

- Ablation study: is two-phase training necessary? (single-phase comparison running)
- Disease-specific γ_{slope} interpretation and biological validation