A Fisher matrix code for population analysis of gravitational-wave events

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Teongrav meeting

Rome, September 16

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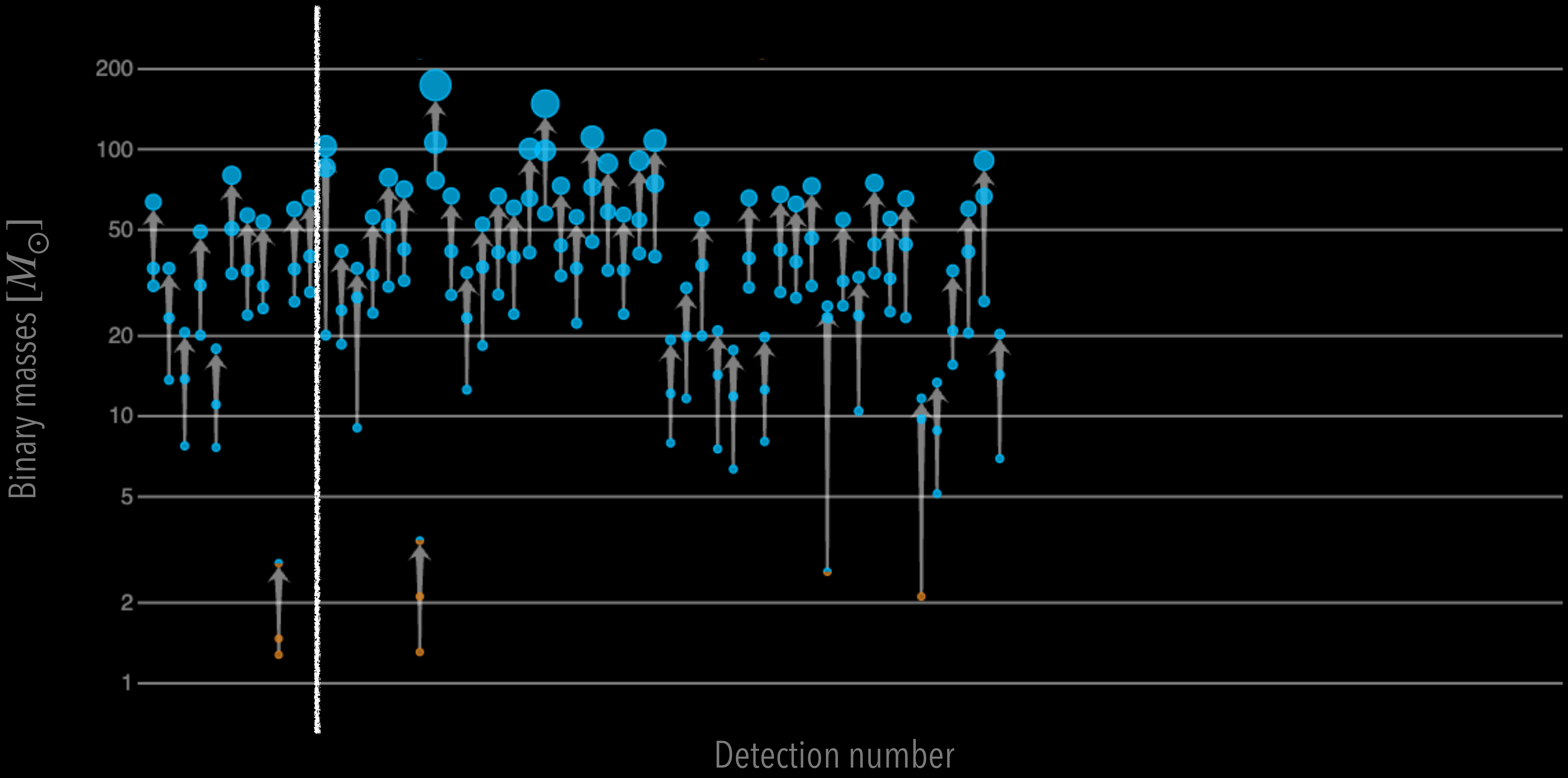
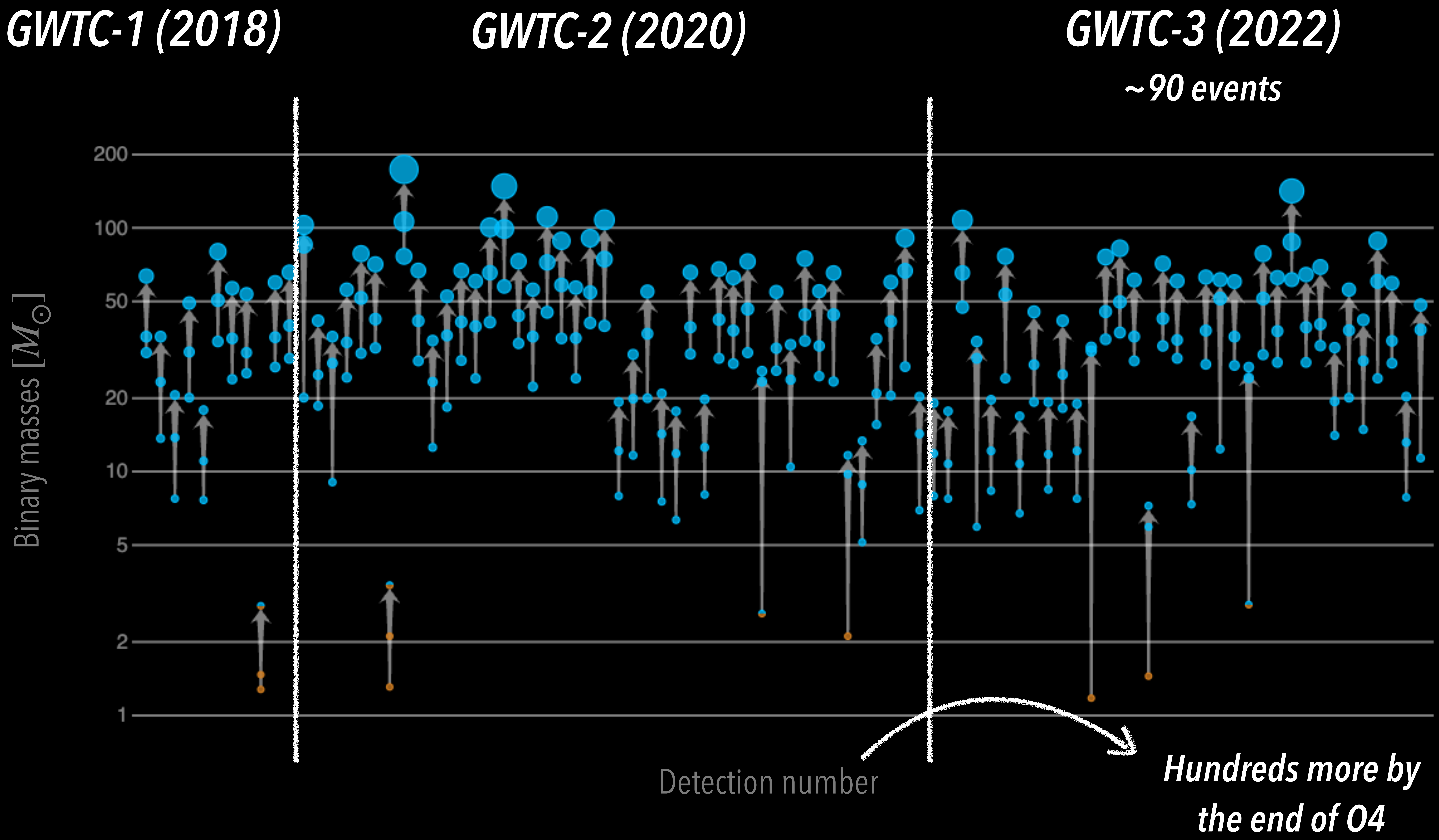
GWTC-1 (2018)

GWTC-1 (2018)

GWTC-2 (2020)




GWTC-1 (2018)
GWTC-2 (2020)
GWTC-3 (2022)
~90 events
200
100
50
20
10
5
2
1
Binary masses [$M_\odot$]
Detection number



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~90 events
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Binary masses [$M_\odot$]
Detection number
Hundreds more by the end of O4


GWTC-1 (2018)
GWTC-2 (2020)
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~90 events
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100
50
20
10
5
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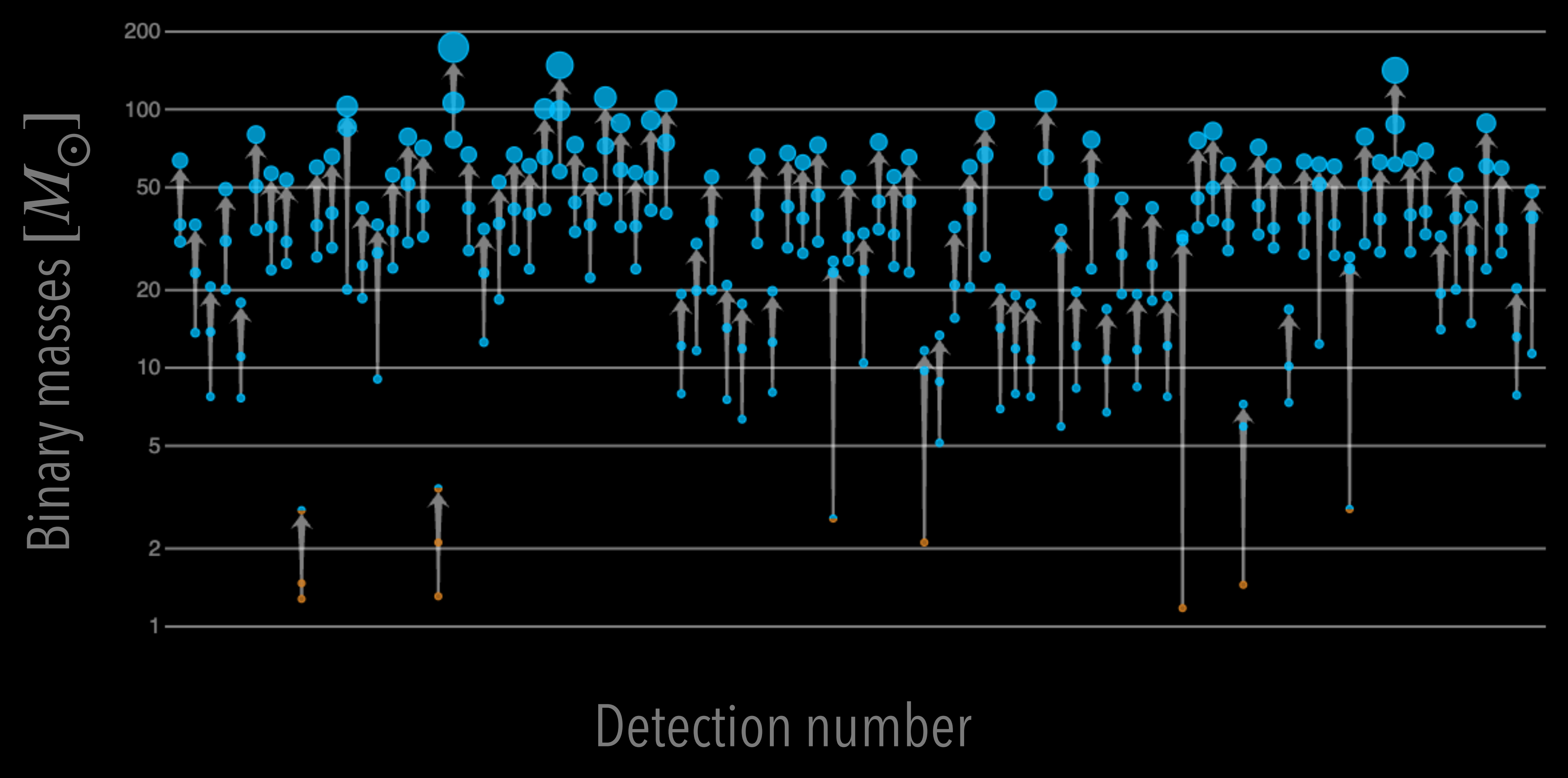
Binary masses $[M_\odot]$
Detection number
Millions more in ~20 years
with 3G detectors

Hierarchical Bayesian analysis for population studies

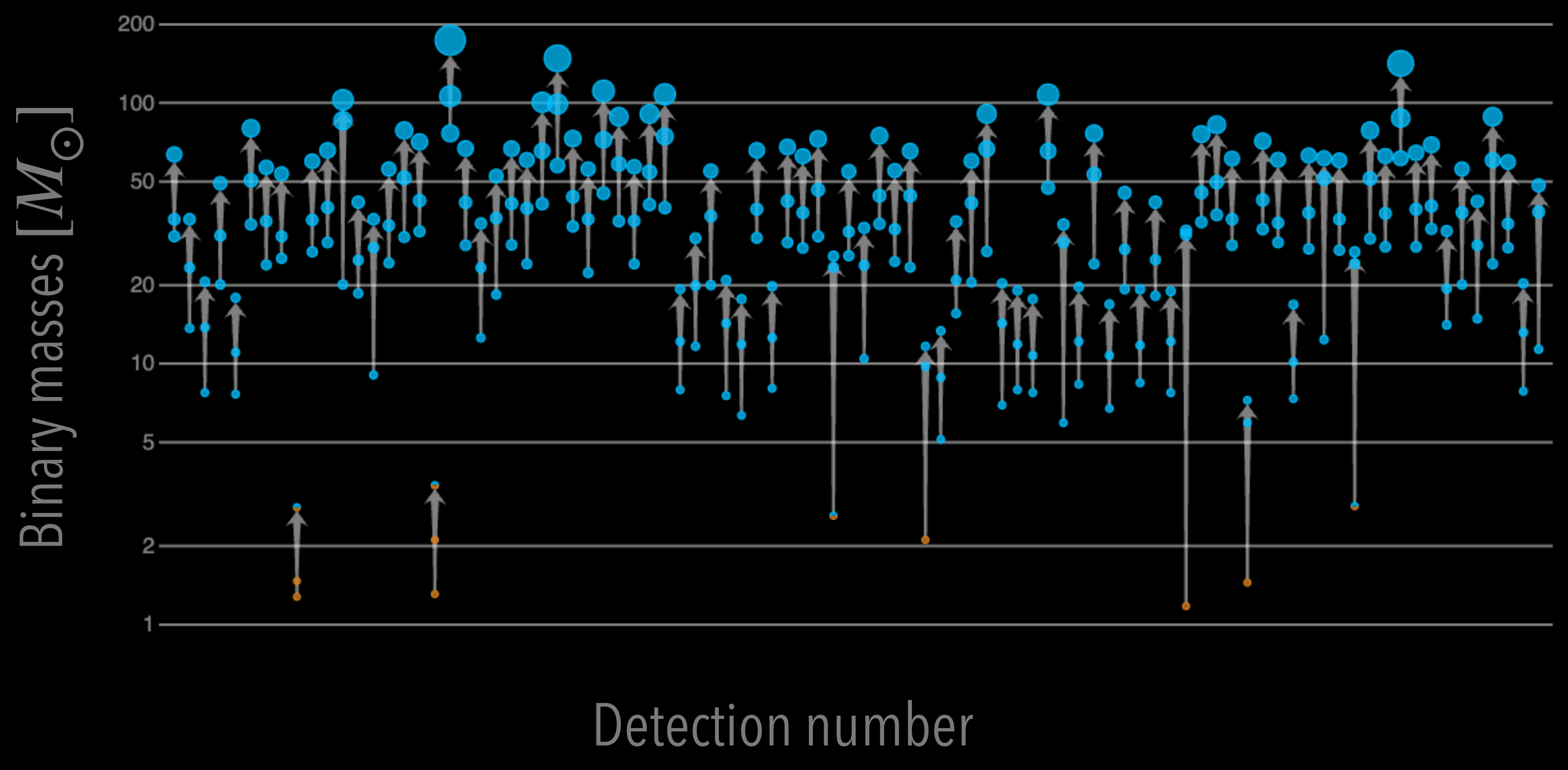


- **Lowest level**:

  What are the properties of **individual** GW sources?

[Thrane & Talbolt, 2018]

Hierarchical Bayesian analysis for population studies



- **Lowest level**:
  What are the properties of **individual** GW sources?

- **Next level**:
  What are the properties of the **underlying population** of GW sources?

[Thrane & Talbolt, 2018]

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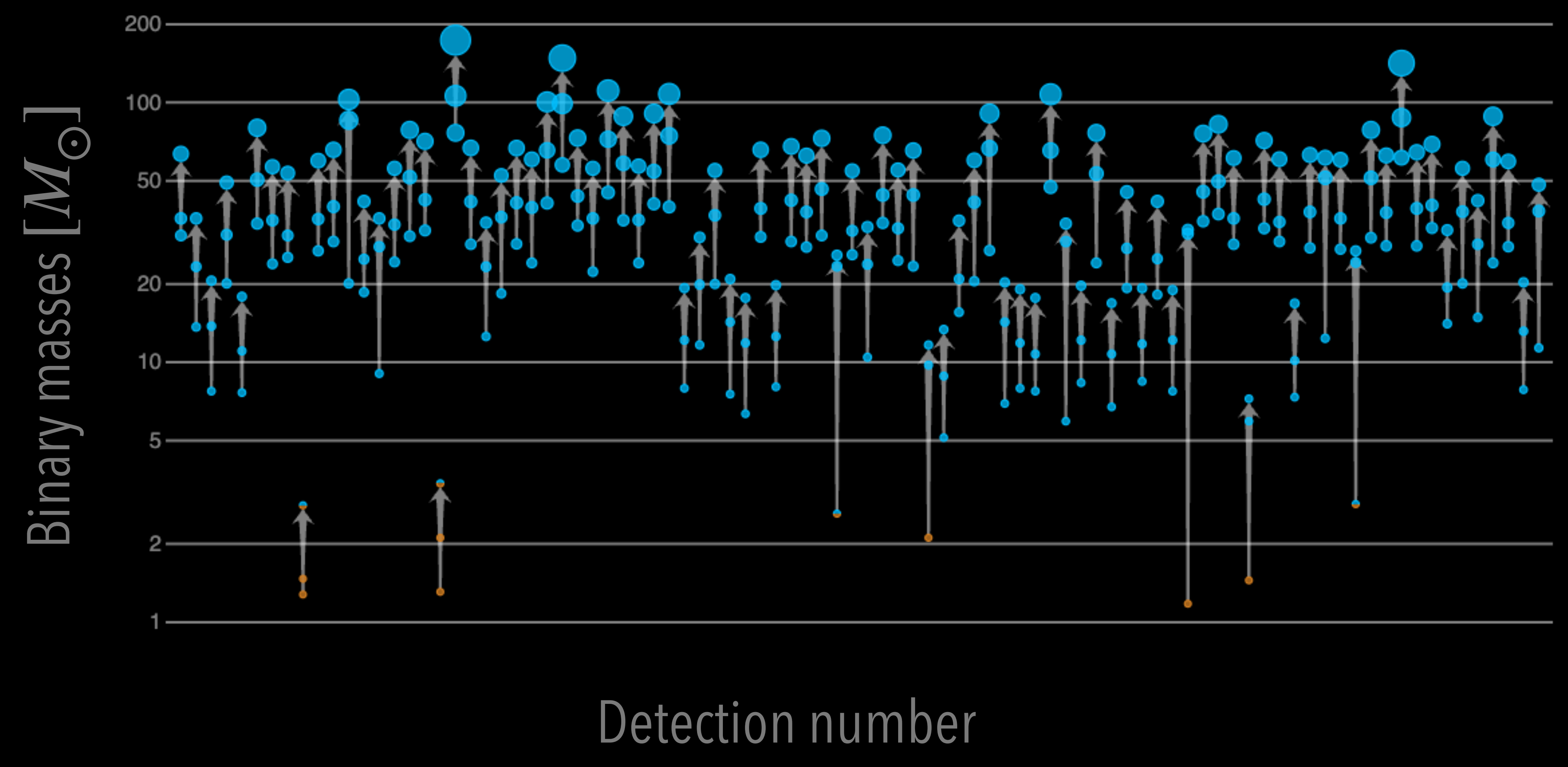


- Lowest level:

  What are the properties of individual GW sources?

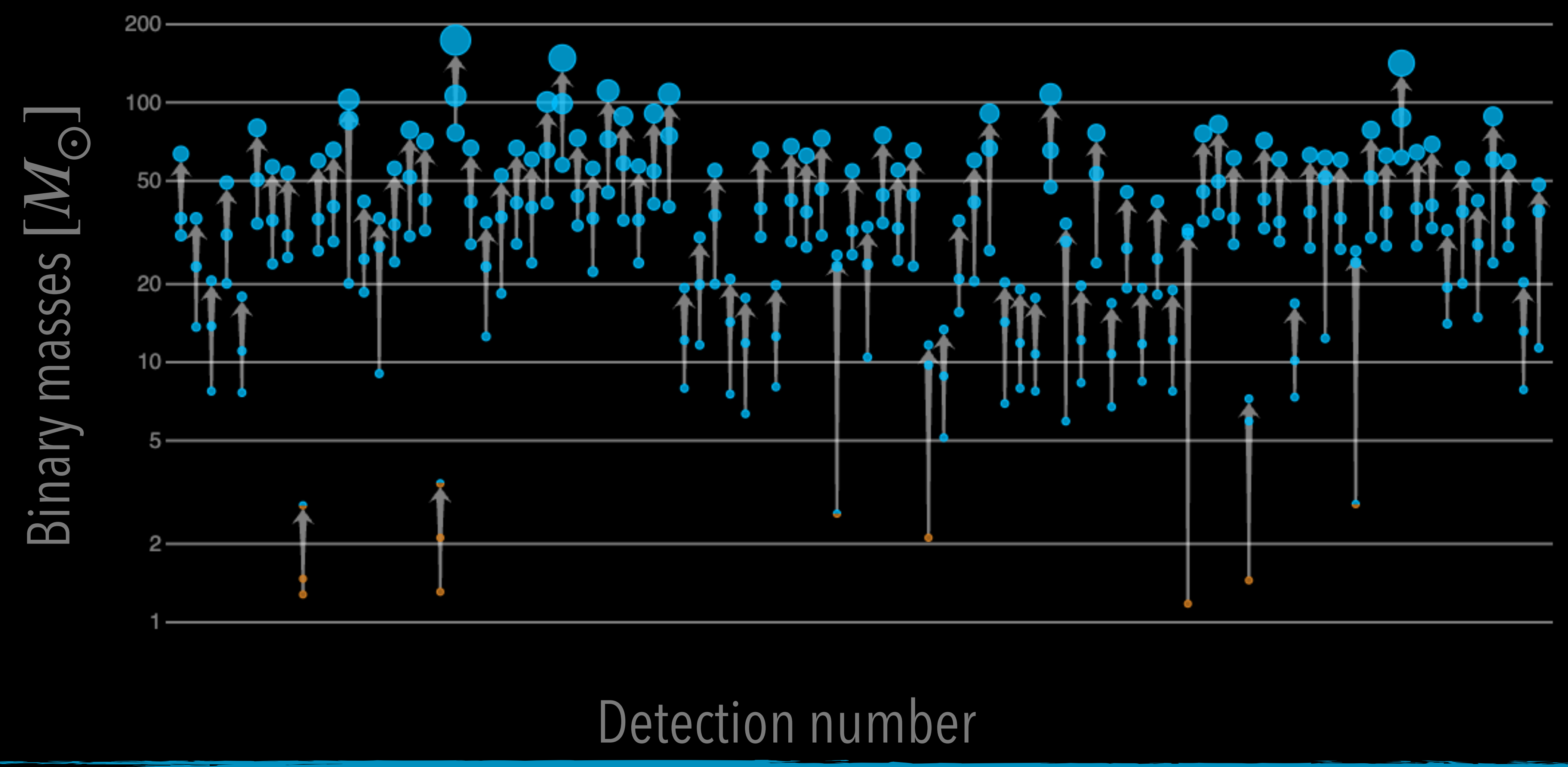
- Next level:

  What are the properties of the underlying population of GW sources?

- Ultimate goal: Figure out the formation pathways of compact binary systems
  - how many formation channels?
  - properties of each individual channel (common envelope, kicks…)
  - merger rate for each channel
  - many more open questions

[Thrane & Talbolt, 2018]

Hierarchical Bayesian analysis for population studies



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Hierarchical Bayesian inference

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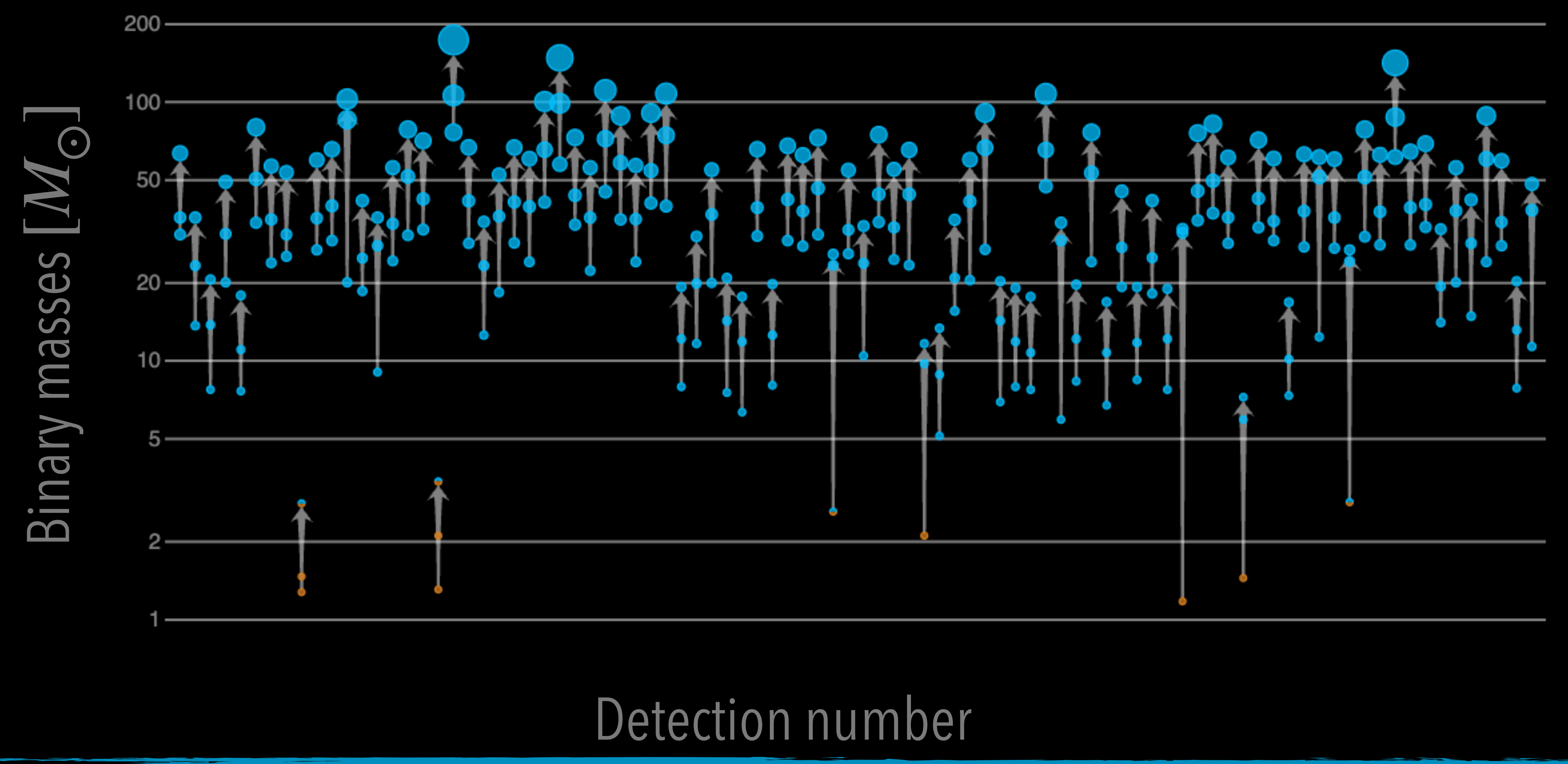
Hierarchical Bayesian analysis for population studies



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$$p(\vec{\theta}\,|\,d) \propto \mathscr{L}(d\,|\,\vec{\theta})\pi(\vec{\theta})$$

$\vec{\theta}$ = individual source parameters

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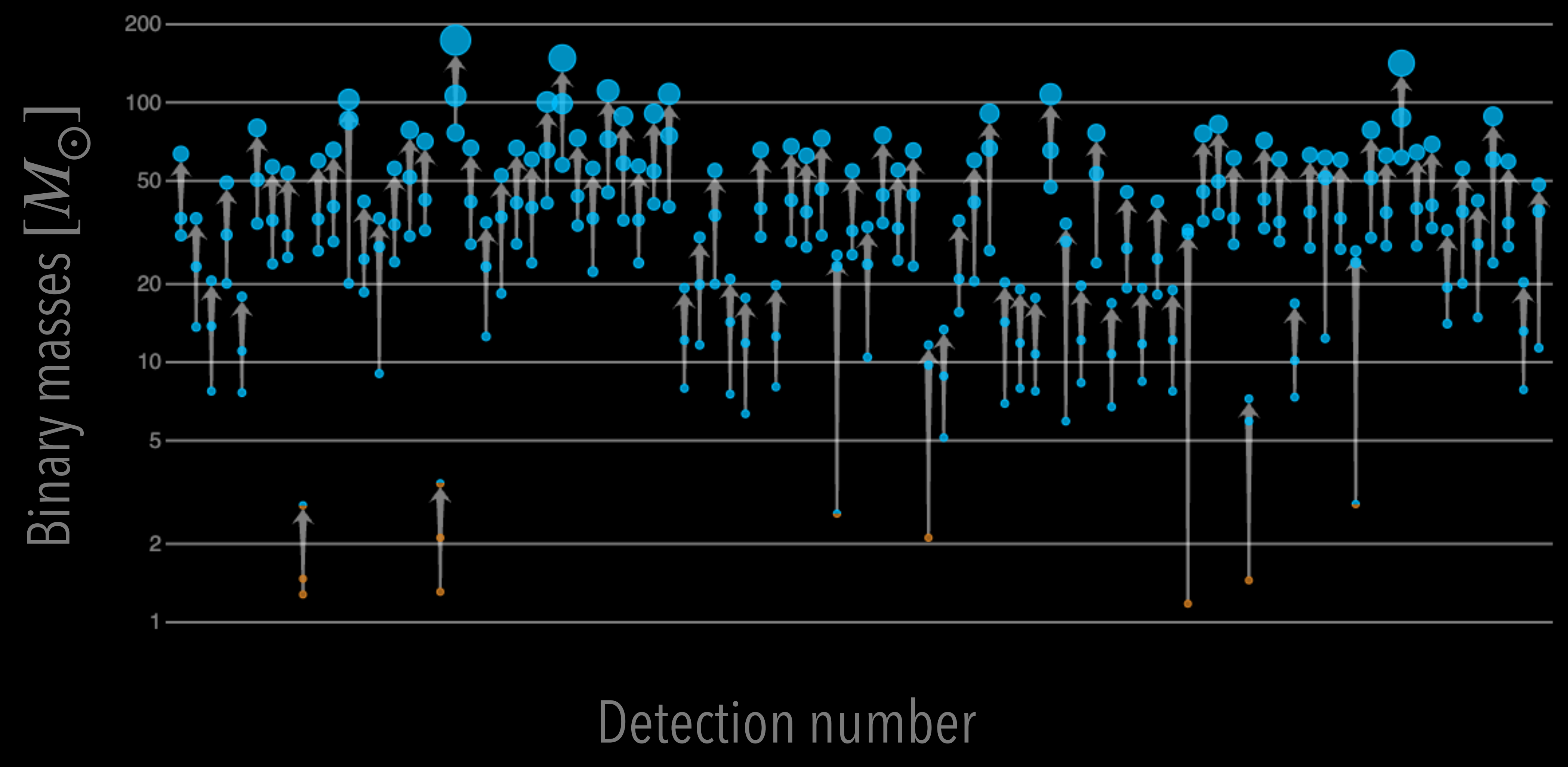
  What are the properties of the **underlying population** of GW sources?

← **Hierarchical Bayesian inference**

[Thrane & Talbolt, 2018]

Hierarchical Bayesian analysis for population studies



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Single-event likelihood

Population model

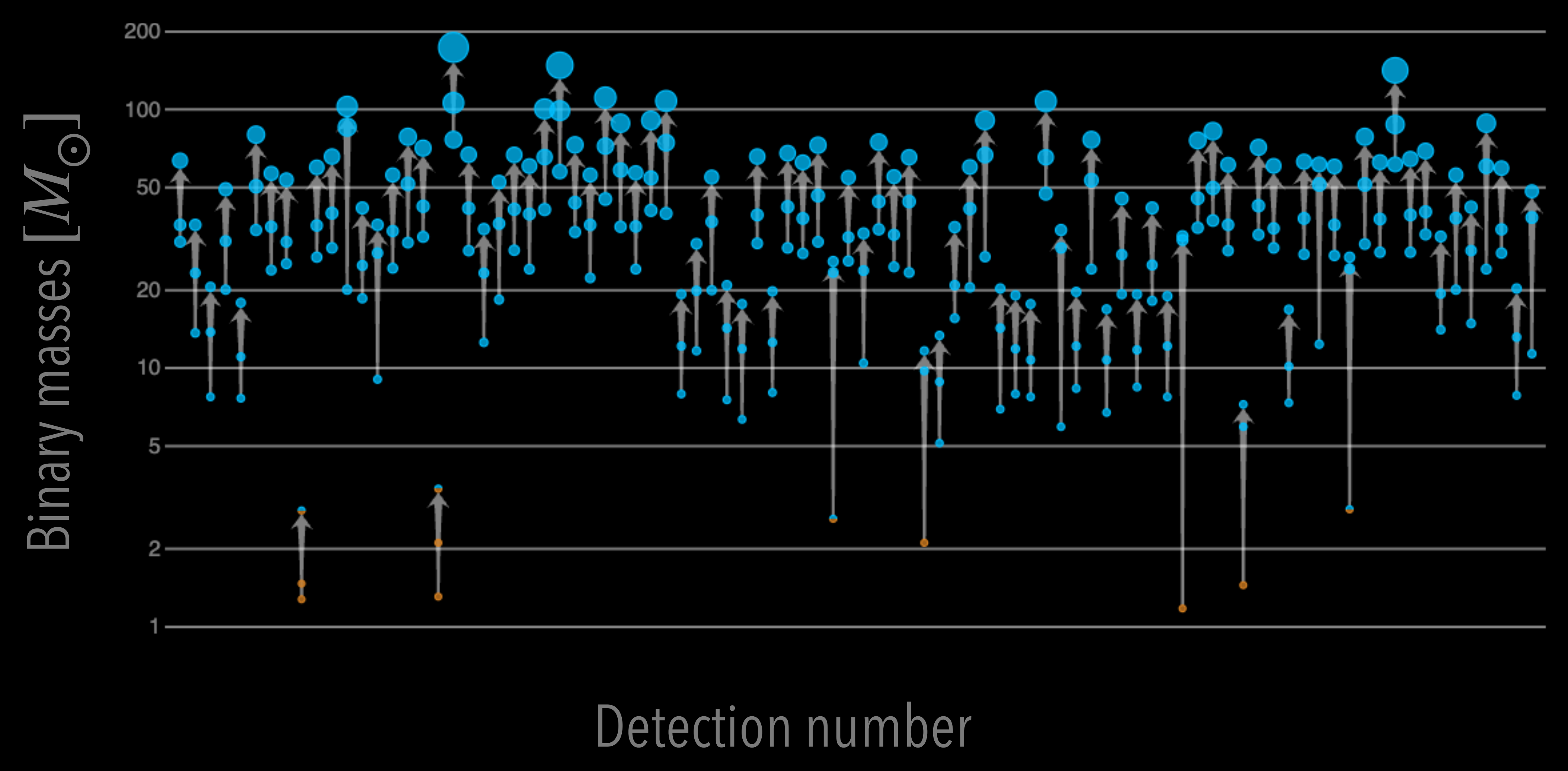
$$p\left(\{d_i\}\,|\,\vec{\lambda}\right) = \frac{\int \mathscr{L}\left(d\,|\,\vec{\theta}\right)\, p\left(\vec{\theta}\,|\,\vec{\lambda}\right)\, d\vec{\theta}}{P_{\text{det}}\left(\vec{\lambda}\right)}$$

Population Likelihood

Not all sources are equally easy to detect

[Thrane & Talbolt, 2018]

Hierarchical Bayesian analysis for population studies



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Population Likelihood

Selection effects

$$P_{\rm det}(\vec{\lambda}) = \int P_{\rm det}(\vec{\theta})p(\theta\,|\,\lambda)d\vec{\theta}$$

Detection probability:

$$P_{\rm det}(\vec{\theta}) = \int_{d>d_{th}} \mathscr{L}(d\,|\,\vec{\theta}){\rm d}d$$

Individual-event parameter estimation

- Bayesian inference codes (BILBY, lalsimulation, PyCBC, RIFT, DINGO…)

[Ashton et al, 2018]
[Henshaw et al, 2022]
[Dax et al, 2021]

- Fisher codes (GWfast, GWbench, GWfish)

[Iacovelli et al, 2022]
[Borhanian, 2021]
[Branchesi et al, 2023]

Population level parameter estimation

- Bayesian inference codes (GWpopulation, BILBY, deep learning codes, non-parametric models…)
- No fisher codes to make forecasts about the population properties that will be observed with 3G detectors

↓

We are developing a user-friendly python code to estimate the parameters that characterize a population of GW events including selection effects

Population Fisher Matrix

$$(\Gamma_\lambda)_{ij} \equiv N_{\rm det}\left[(\Gamma_{\rm I})_{ij} + (\Gamma_{\rm II})_{ij} + (\Gamma_{\rm III})_{ij} + (\Gamma_{\rm IV})_{ij} + (\Gamma_{\rm V})_{ij}\right]$$

$$(\Gamma_{\rm I})_{ij} = -\int \frac{\partial^2 \ln\left(p(\vec{\theta}\,|\,\vec{\lambda})/P_{\rm det}(\vec{\lambda})\right)}{\partial\lambda^i\partial\lambda^j}\frac{P_{\rm det}(\vec{\theta})}{P_{\rm det}(\vec{\lambda})}p(\vec{\theta}\,|\,\vec{\lambda})\mathrm{d}\vec{\theta}$$

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[Gair et al., 2023]

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1. Population model: $p(\vec\theta\,|\,\vec\lambda)$

[Gair et al., 2023]

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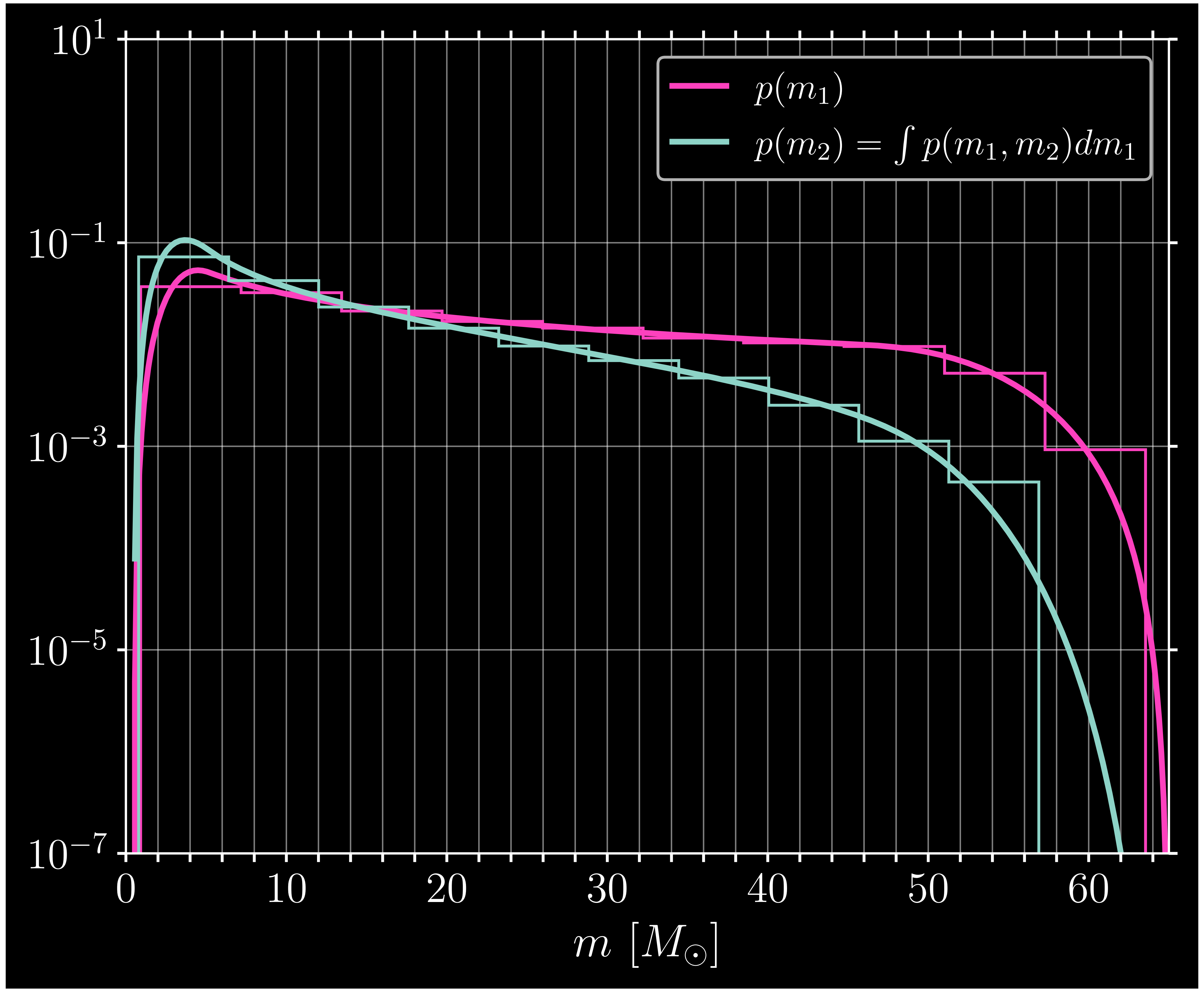
1. Masses: Power law?



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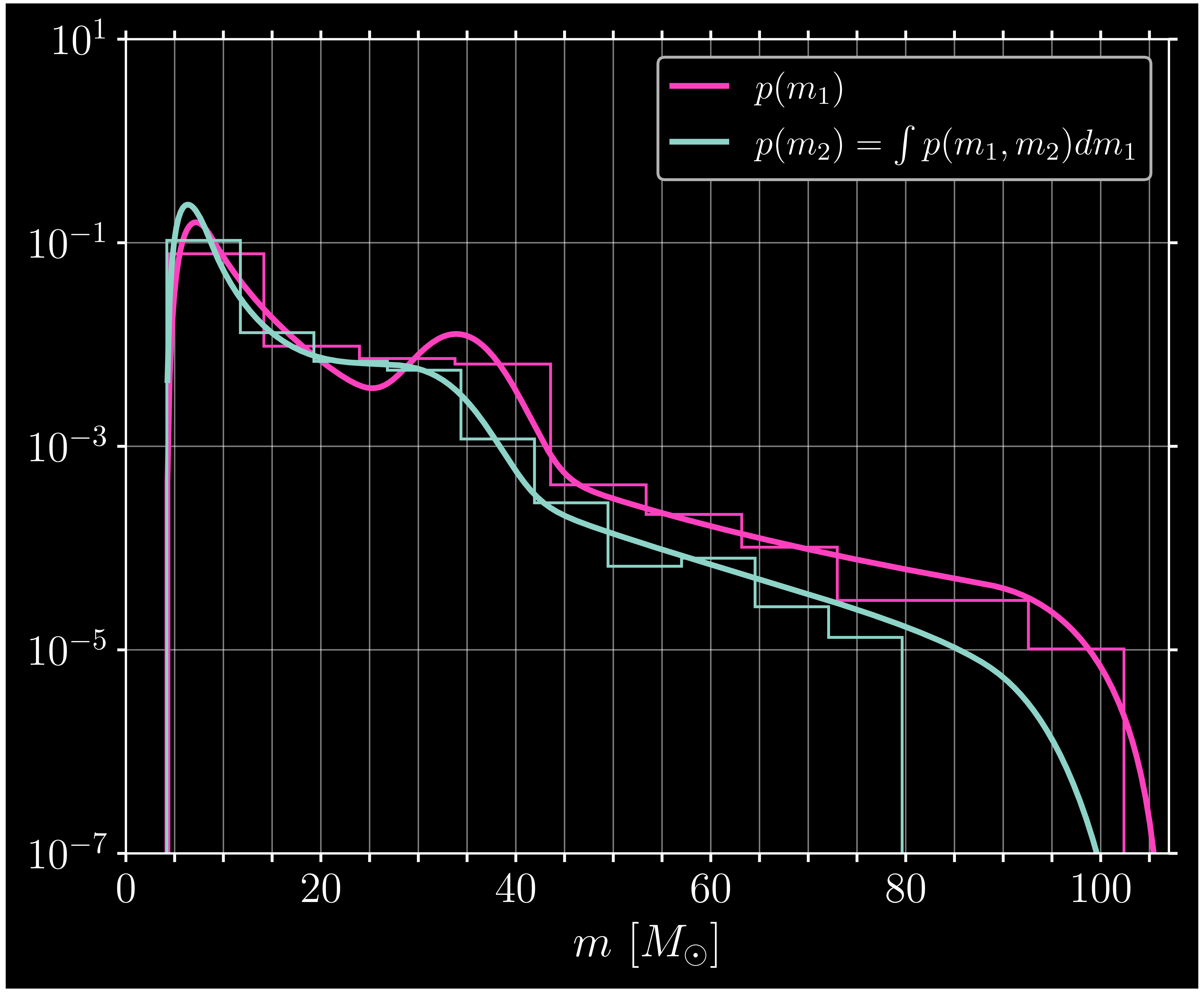
1. Masses: power law + peak?



[Gair et al., 2023]

Population Fisher Matrix

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$$(\Gamma_{\text{I}})_{ij} = -\int \frac{\partial^2 \ln\left(p(\vec{\theta} \mid \vec{\lambda})/P_{\text{det}}(\vec{\lambda})\right)}{\partial\lambda^i \partial\lambda^j} \frac{P_{\text{det}}(\vec{\theta})}{P_{\text{det}}(\vec{\lambda})} p(\vec{\theta} \mid \vec{\lambda}) \mathrm{d}\vec{\theta}$$

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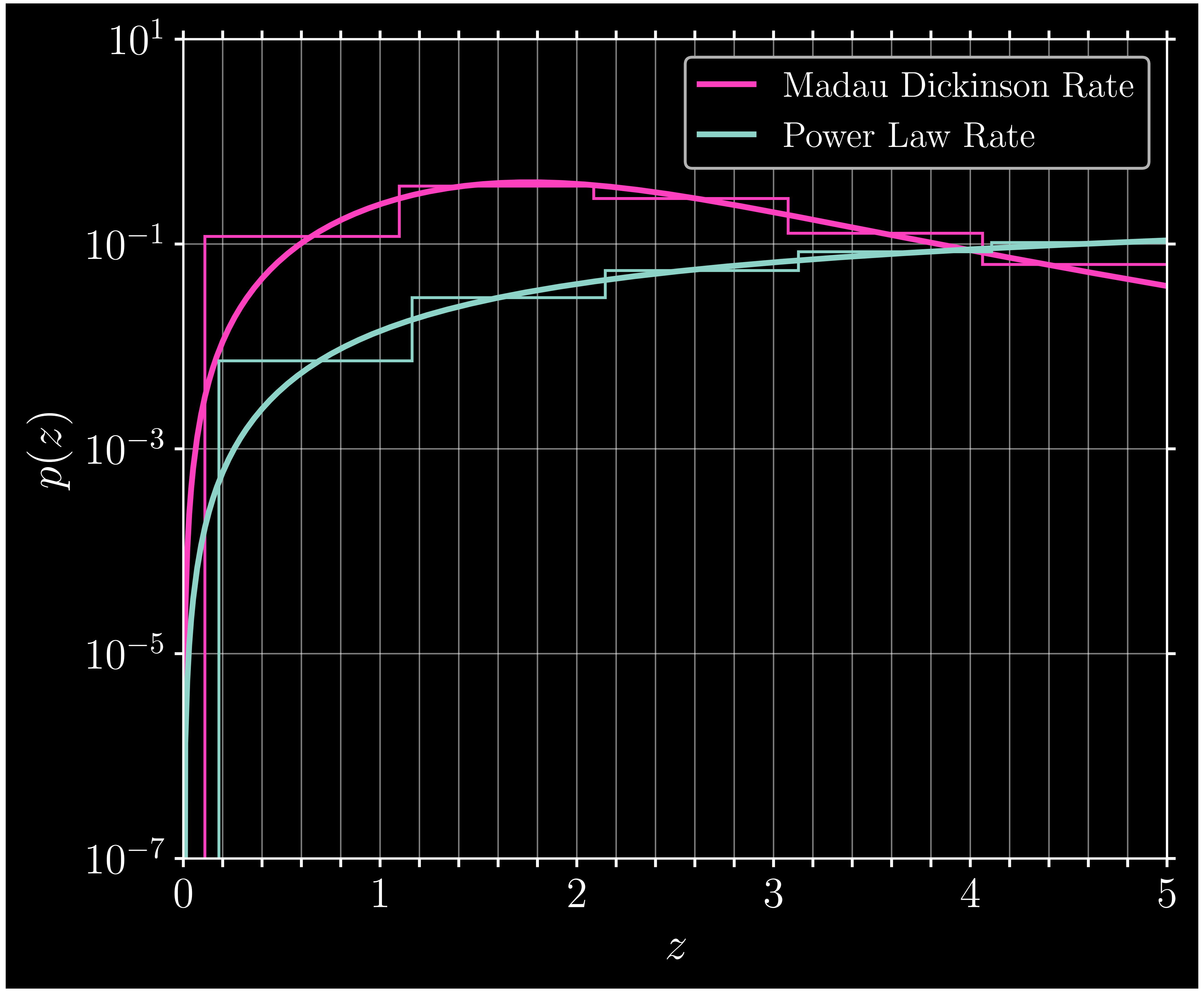
1\. Redshift: PL/Madau Dickinson?



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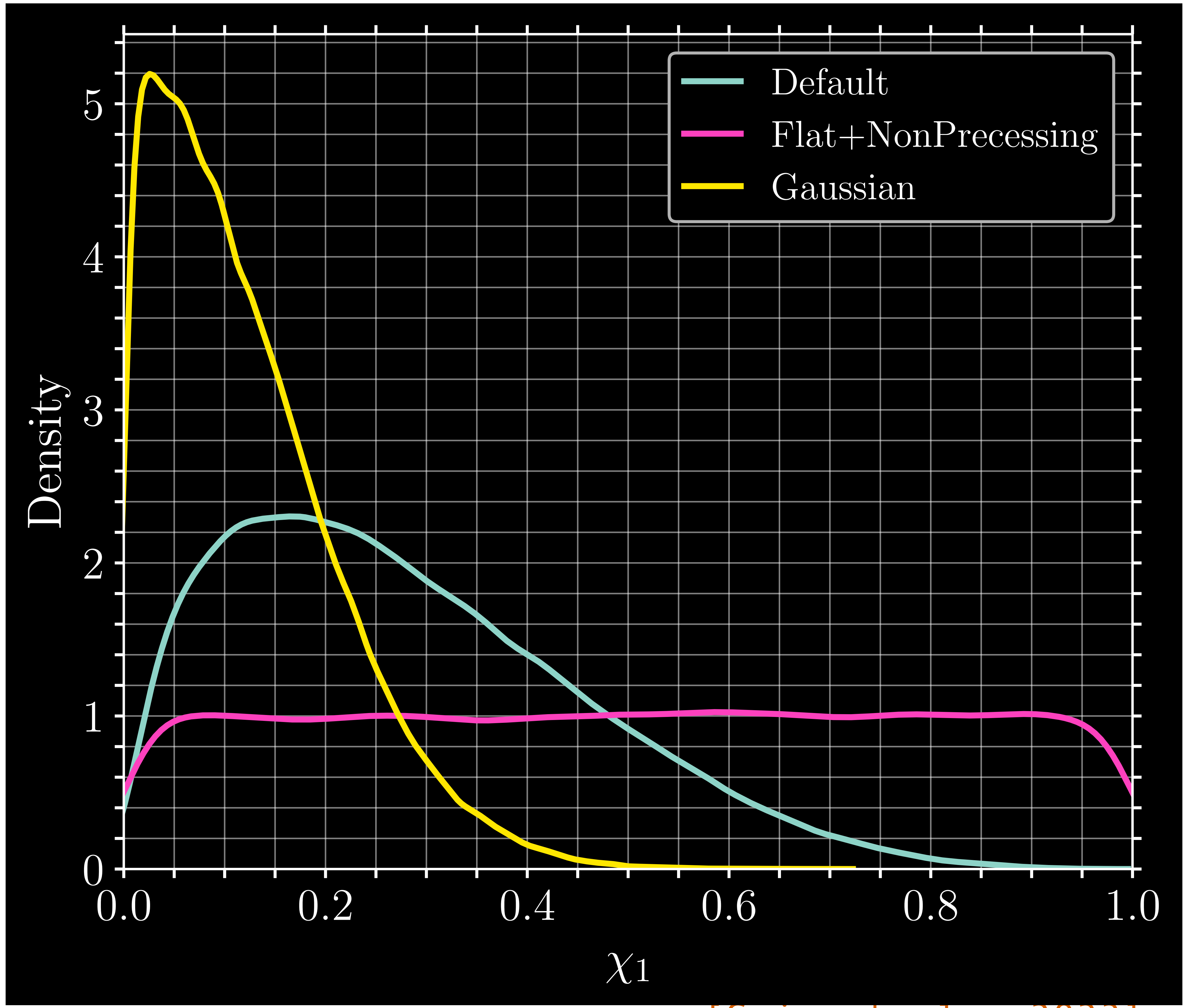
1.

Spins:
Default/Flat,Gaussian?



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Whatever functional form you like!
(as long as it is differentiable)

[Gair et al., 2023]

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1. Population model: $p(\vec\theta \mid \vec\lambda)$

with its first and second derivatives

$$P_i = \frac{\partial \ln p(\vec\theta \mid \vec\lambda)}{\partial\theta^i}$$

$$H_{ij} = -\frac{\partial^2 \ln p(\vec\theta \mid \vec\lambda)}{\partial\theta^i\partial\theta^j}$$

[Gair et al., 2023]

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$$(\Gamma_{\rm III})_{ij} = -\frac{1}{2}\int \frac{\partial^2}{\partial\lambda^i\partial\lambda^j}\left[\left(\Gamma + H\right)^{-1}_{kl}\right]\Gamma_{kl}\,\frac{p(\vec{\theta}\,|\,\vec{\lambda})}{P_{\rm det}(\vec{\lambda})}\,\mathrm{d}\vec{\theta}$$

$$(\Gamma_{\rm IV})_{ij} = -\int \frac{\partial^2}{\partial\lambda^i\partial\lambda^j}\left[P_k\left(\Gamma + H\right)^{-1}_{kl}\right]D_l\,\frac{p(\vec{\theta}\,|\,\vec{\lambda})}{P_{\rm det}(\vec{\lambda})}\,\mathrm{d}\vec{\theta}$$

$$(\Gamma_{\rm V})_{ij} = -\frac{1}{2}\int \frac{\partial^2}{\partial\lambda^i\partial\lambda^j}\left[P_k\left(\Gamma + H\right)^{-1}_{kl}P_l\right]\frac{P_{\rm det}(\vec{\theta})}{P_{\rm det}(\vec{\lambda})}\,p(\vec{\theta}\,|\,\vec{\lambda})$$

1. Population model: $p(\vec{\theta}\,|\,\vec{\lambda})$

2. Selection effects:

$$P_{\rm det}(\vec{\lambda}) = \int P_{\rm det}(\vec{\theta})p(\theta|\lambda)d\vec{\theta}$$

[Gair et al., 2023]

Population Fisher Matrix

$$(\Gamma_\lambda)_{ij} \equiv N_{\text{det}} \left[(\Gamma_{\text{I}})_{ij} + (\Gamma_{\text{II}})_{ij} + (\Gamma_{\text{III}})_{ij} + (\Gamma_{\text{IV}})_{ij} + (\Gamma_{\text{V}})_{ij}\right]$$

$$(\Gamma_{\text{I}})_{ij} = -\int \frac{\partial^2 \ln\left(p(\vec{\theta}\,|\,\vec{\lambda})\, P_{\text{det}}(\vec{\lambda})\right)}{\partial\lambda^i\partial\lambda^j} \frac{P_{\text{det}}(\vec{\theta})}{P_{\text{det}}(\vec{\lambda})} p(\vec{\theta}\,|\,\vec{\lambda})$$

$$(\Gamma_{\text{II}})_{ij} = \frac{1}{2}\int \frac{\partial^2 \ln\det\left(\Gamma + H\right)}{\partial\lambda^i\partial\lambda^j} \frac{P_{\text{det}}(\vec{\theta})}{P_{\text{det}}(\vec{\lambda})} p(\vec{\theta}\,|\,\vec{\lambda})$$

$$(\Gamma_{\text{III}})_{ij} = -\frac{1}{2}\int \frac{\partial^2}{\partial\lambda^i\partial\lambda^j}\left[(\Gamma + H)^{-1}_{kl}\right]\Gamma_{kl} \frac{p(\vec{\theta}\,|\,\vec{\lambda})}{P_{\text{det}}(\vec{\lambda})} \mathrm{d}\vec{\theta}$$

$$(\Gamma_{\text{IV}})_{ij} = -\int \frac{\partial^2}{\partial\lambda^i\partial\lambda^j}\left[P_k(\Gamma + H)^{-1}_{kl}\right] D_l \frac{p(\vec{\theta}\,|\,\vec{\lambda})}{P_{\text{det}}(\vec{\lambda})} \mathrm{d}\vec{\theta}$$

$$(\Gamma_{\text{V}})_{ij} = -\frac{1}{2}\int \frac{\partial^2}{\partial\lambda^i\partial\lambda^j}\left[P_k(\Gamma + H)^{-1}_{kl} P_l\right] \frac{P_{\text{det}}(\vec{\theta})}{P_{\text{det}}(\vec{\lambda})} p(\vec{\theta}\,|\,\vec{\lambda})$$

1. Population model: $p(\vec{\theta}\,|\,\vec{\lambda})$

2. Selection effects:

$$P_{\text{det}}(\vec{\lambda}) = \int P_{\text{det}}(\vec{\theta}) p(\theta\,|\,\lambda) d\vec{\theta}$$

3. Detection probability:

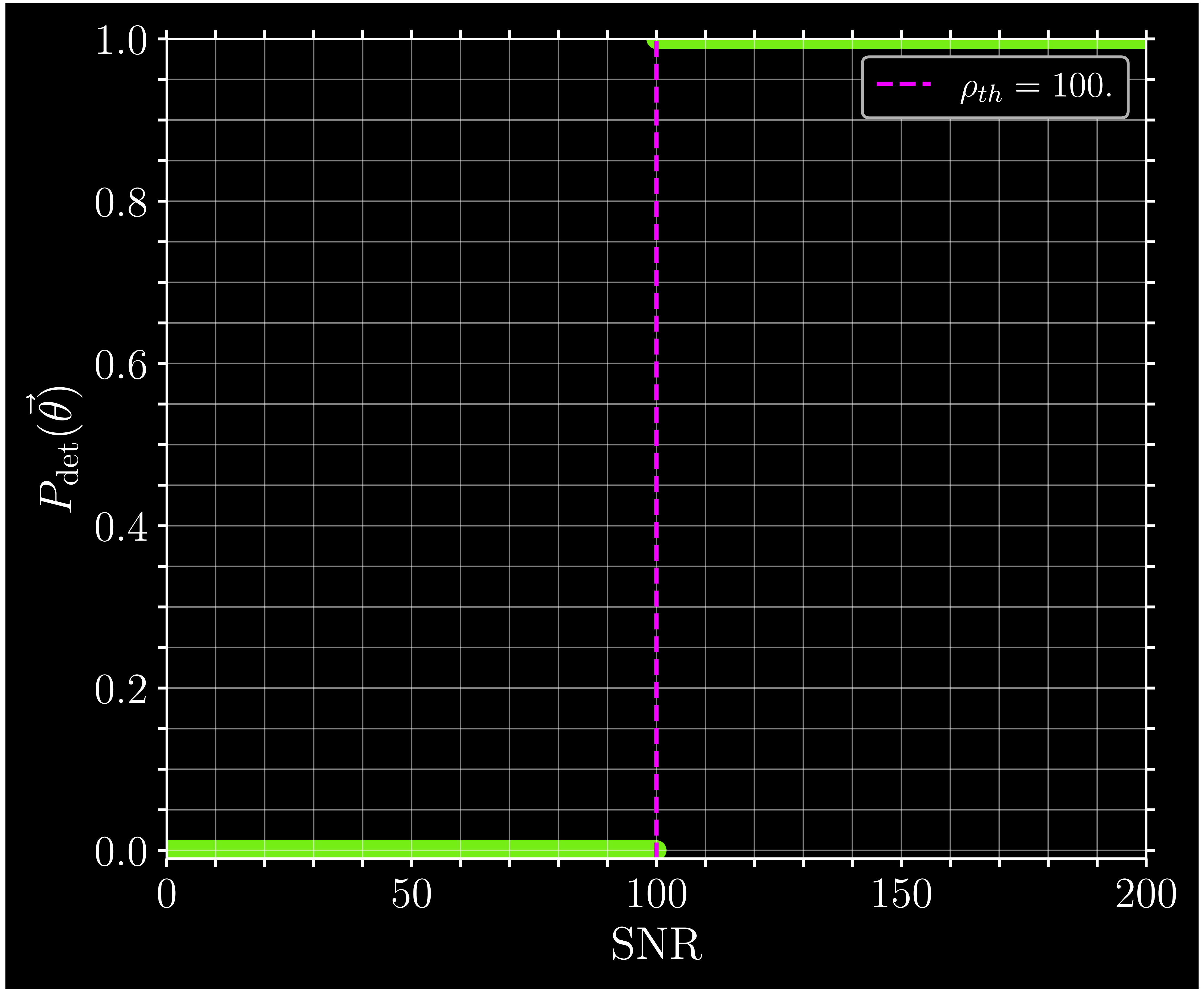
$$P_{\text{det}}(\vec{\theta}) = \int_{d>d_{th}} p(d\,|\,\vec{\theta})\mathrm{d}\vec{\theta}$$

[Gair et al., 2023]

Population Fisher Matrix

$$(\Gamma_\lambda)_{ij} \equiv N_{\mathrm{det}} \left[(\Gamma_{\mathrm{I}})_{ij} + (\Gamma_{\mathrm{II}})_{ij} + (\Gamma_{\mathrm{III}})_{ij} + (\Gamma_{\mathrm{IV}})_{ij} + (\Gamma_{\mathrm{V}})_{ij}\right]$$

$P_{\mathrm{det}}(\vec{\theta})$ = Heaviside function



1. Population model: $p(\vec{\theta} \mid \vec{\lambda})$

2. Selection effects:

$$P_{\mathrm{det}}(\vec{\lambda}) = \int P_{\mathrm{det}}(\vec{\theta}) p(\theta \mid \lambda) d\vec{\theta}$$

3. Detection probability:

$$P_{\mathrm{det}}(\vec{\theta}) = \int_{d>d_{th}} p(d \mid \vec{\theta}) \mathrm{d}\vec{\theta}$$

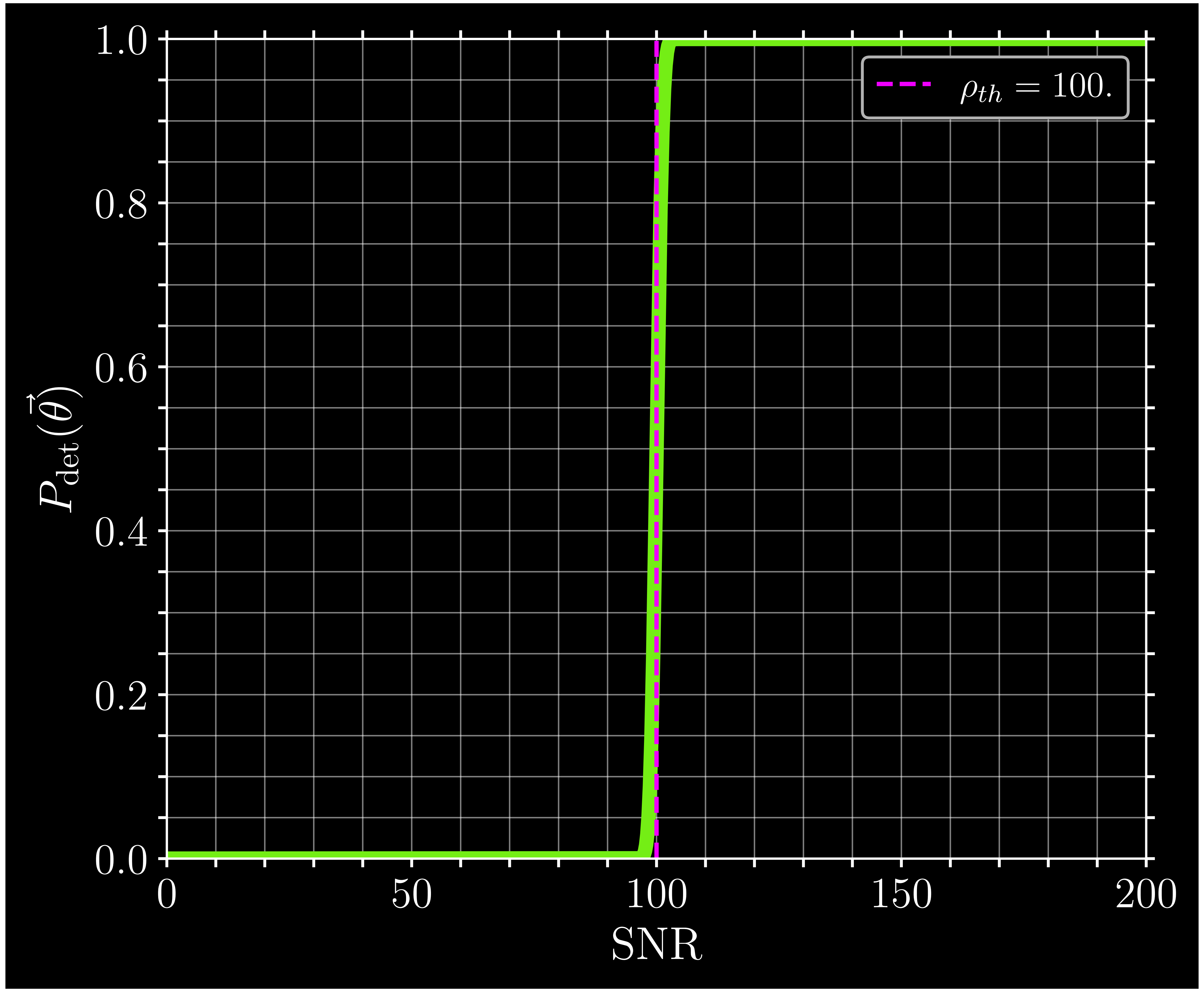
[Gair et al., 2023]

Population Fisher Matrix

$$(\Gamma_\lambda)_{ij} \equiv N_{\text{det}} \left[(\Gamma_{\text{I}})_{ij} + (\Gamma_{\text{II}})_{ij} + (\Gamma_{\text{III}})_{ij} + (\Gamma_{\text{IV}})_{ij} + (\Gamma_{\text{V}})_{ij}\right]$$

We opted for a more regular error function, i.e

$$P_{\text{det}}(\vec{\theta}) = \frac{1}{2}\text{erfc}\frac{(\rho - \rho_{\text{th}})}{\sqrt{2}\sigma}$$



1. Population model: $p(\vec{\theta} \mid \vec{\lambda})$

2. Selection effects:

$$P_{\text{det}}(\vec{\lambda}) = \int P_{\text{det}}(\vec{\theta}) p(\theta \mid \lambda) d\vec{\theta}$$

3. Detection probability:

$$P_{\text{det}}(\vec{\theta}) = \int_{d>d_{th}} p(d \mid \vec{\theta}) \mathrm{d}\vec{\theta}$$

[Gair et al., 2023]

Population Fisher Matrix

$$(\Gamma_\lambda)_{ij} \equiv N_{\rm det} \left[(\Gamma_{\rm I})_{ij} + (\Gamma_{\rm II})_{ij} + (\Gamma_{\rm III})_{ij} + (\Gamma_{\rm IV})_{ij} + (\Gamma_{\rm V})_{ij}\right]$$

$$(\Gamma_{\rm I})_{ij} = -\int \frac{\partial^2 \ln\left(p(\vec\theta\,|\,\vec\lambda)\; P_{\rm det}(\vec\lambda)\right)}{\partial\lambda^i\partial\lambda^j} \frac{P_{\rm det}(\vec\theta)}{P_{\rm det}(\vec\lambda)} p(\vec\theta\,|\,\vec\lambda)$$

$$(\Gamma_{\rm II})_{ij} = \frac{1}{2}\int \frac{\partial^2 \ln\det\left(\Gamma + H\right)}{\partial\lambda^i\partial\lambda^j} \frac{P_{\rm det}(\vec\theta)}{P_{\rm det}(\vec\lambda)} p(\vec\theta\,|\,\vec\lambda)$$

$$(\Gamma_{\rm III})_{ij} = -\frac{1}{2}\int \frac{\partial^2}{\partial\lambda^i\partial\lambda^j}\left[(\Gamma + H)^{-1}_{kl}\right]\Gamma_{kl} \frac{p(\vec\theta\,|\,\vec\lambda)}{P_{\rm det}(\vec\lambda)} {\rm d}\vec\theta$$

$$(\Gamma_{\rm IV})_{ij} = -\int \frac{\partial^2}{\partial\lambda^i\partial\lambda^j}\left[P_k(\Gamma + H)^{-1}_{kl}\right] D_l \frac{p(\vec\theta\,|\,\vec\lambda)}{P_{\rm det}(\vec\lambda)} {\rm d}\vec\theta$$

$$(\Gamma_{\rm V})_{ij} = -\frac{1}{2}\int \frac{\partial^2}{\partial\lambda^i\partial\lambda^j}\left[P_k(\Gamma + H)^{-1}_{kl} P_l\right] \frac{P_{\rm det}(\vec\theta)}{P_{\rm det}(\vec\lambda)} p(\vec\theta\,|\,\vec\lambda)$$

1. Population model: $p(\vec\theta\,|\,\vec\lambda)$

2. Selection effects:

$$P_{\rm det}(\vec\lambda) = \int P_{\rm det}(\vec\theta) p(\theta\,|\,\lambda) d\vec\theta$$

3. Detection probability:

$$P_{\rm det}(\vec\theta) = \int_{d>d_{th}} p(d\,|\,\vec\theta){\rm d}\vec\theta$$

with its first derivative

$$D_l = \frac{\partial P_{\rm det}(\vec\theta)}{\partial\theta^i}$$

[Gair et al., 2023]

Population Fisher Matrix

$$(\Gamma_\lambda)_{ij} \equiv N_{\rm det}\left[(\Gamma_{\rm I})_{ij} + (\Gamma_{\rm II})_{ij} + (\Gamma_{\rm III})_{ij} + (\Gamma_{\rm IV})_{ij} + (\Gamma_{\rm V})_{ij}\right]$$

$$(\Gamma_{\rm I})_{ij} = -\int \frac{\partial^2 \ln\left(p(\vec\theta\,|\,\vec\lambda)\, P_{\rm det}(\vec\lambda)\right)}{\partial\lambda^i\partial\lambda^j}\,\frac{P_{\rm det}(\vec\theta)}{P_{\rm det}(\vec\lambda)}\,p(\vec\theta\,|\,\vec\lambda)$$

$$(\Gamma_{\rm II})_{ij} = \frac{1}{2}\int \frac{\partial^2 \ln\det\left(\Gamma+H\right)}{\partial\lambda^i\partial\lambda^j}\,\frac{P_{\rm det}(\vec\theta)}{P_{\rm det}(\vec\lambda)}\,p(\vec\theta\,|\,\vec\lambda)\,{\rm d}\vec\theta$$

$$(\Gamma_{\rm III})_{ij} = -\frac{1}{2}\int \frac{\partial^2}{\partial\lambda^i\partial\lambda^j}\left[(\Gamma+H)^{-1}_{kl}\right]\Gamma_{kl}\,\frac{p(\vec\theta\,|\,\vec\lambda)}{P_{\rm det}(\vec\lambda)}\,{\rm d}\vec\theta$$

$$(\Gamma_{\rm IV})_{ij} = -\int \frac{\partial^2}{\partial\lambda^i\partial\lambda^j}\left[P_k(\Gamma+H)^{-1}_{kl}\right]D_l\,\frac{p(\vec\theta\,|\,\vec\lambda)}{P_{\rm det}(\vec\lambda)}\,{\rm d}\vec\theta$$

$$(\Gamma_{\rm V})_{ij} = -\frac{1}{2}\int \frac{\partial^2}{\partial\lambda^i\partial\lambda^j}\left[P_k(\Gamma+H)^{-1}_{kl}P_l\right]\frac{P_{\rm det}(\vec\theta)}{P_{\rm det}(\vec\lambda)}\,p(\vec\theta\,|\,\vec\lambda)\,{\rm d}\vec\theta$$

1. Population model: $p(\vec\theta\,|\,\vec\lambda)$

2. Selection effects:

$$P_{\rm det}(\vec\lambda) = \int P_{\rm det}(\vec\theta)p(\theta|\lambda)d\vec\theta$$

3. Detection probability:

$$P_{\rm det}(\vec\theta) = \int_{d>d_{th}} p(d\,|\,\vec\theta)\,{\rm d}\vec\theta$$

4. Γ = Single event Fisher matrix with GWfast

[Iacovelli et al, 2022]

[Gair et al., 2023]

Population Fisher Matrix

$$(\Gamma_\lambda)_{ij} \equiv N_{\rm det}\left[(\Gamma_{\rm I})_{ij} + (\Gamma_{\rm II})_{ij} + (\Gamma_{\rm III})_{ij} + (\Gamma_{\rm IV})_{ij} + (\Gamma_{\rm V})_{ij}\right]$$

$$(\Gamma_{\rm I})_{ij} = -\int \frac{\partial^2 \ln\left(p(\vec\theta\,|\,\vec\lambda)\;P_{\rm det}(\vec\lambda)\right)}{\partial\lambda^i\partial\lambda^j}\,\frac{P_{\rm det}(\vec\theta)}{P_{\rm det}(\vec\lambda)}\,p(\vec\theta\,|\,\vec\lambda)$$

$$(\Gamma_{\rm II})_{ij} = \int B(\vec\theta)\frac{P_{\rm det}(\vec\theta)}{P_{\rm det}(\vec\lambda)}p(\vec\theta\,|\,\vec\lambda)\mathrm{d}\vec\theta$$

$$(\Gamma_{\rm III})_{ij} = \int C(\vec\theta)\frac{p(\vec\theta\,|\,\vec\lambda)}{P_{\rm det}(\vec\lambda)}\mathrm{d}\vec\theta$$

$$(\Gamma_{\rm IV})_{ij} = \int D(\vec\theta)\frac{p(\vec\theta\,|\,\vec\lambda)}{P_{\rm det}(\vec\lambda)}\mathrm{d}\vec\theta$$

$$(\Gamma_{\rm V})_{ij} = \int E(\vec\theta)\frac{P_{\rm det}(\vec\theta)}{P_{\rm det}(\vec\lambda)}p(\vec\theta\,|\,\vec\lambda)\mathrm{d}\vec\theta$$

1. Population model: $p(\vec\theta\,|\,\vec\lambda)$

2. Selection effects:

$$P_{\rm det}(\vec\lambda) = \int P_{\rm det}(\vec\theta)p(\theta|\lambda)d\vec\theta$$

3. Detection probability:

$$P_{\rm det}(\vec\theta) = \int_{d>d_{th}} p(d\,|\,\vec\theta)\mathrm{d}\vec\theta$$

4. Γ = Single event Fisher matrix with GWfast

Errors on the single-event parameters $\vec\theta$ enter in the last four terms!

[Iacovelli et al, 2022]

[Gair et al., 2023]

Population Fisher Matrix

$$(\Gamma_\lambda)_{ij} \equiv N_{\rm det}\left[(\Gamma_{\rm I})_{ij} + (\Gamma_{\rm II})_{ij} + (\Gamma_{\rm III})_{ij} + (\Gamma_{\rm IV})_{ij} + (\Gamma_{\rm V})_{ij}\right]$$

$$(\Gamma_{\rm I})_{ij} = -\int \frac{\partial^2 \ln\left(p(\vec{\theta}\,|\,\vec{\lambda})\,P_{\rm det}(\vec{\lambda})\right)}{\partial\lambda^i\partial\lambda^j}\,\frac{P_{\rm det}(\vec{\theta})}{P_{\rm det}(\vec{\lambda})}\,p(\vec{\theta}\,|\,\vec{\lambda})$$

$$(\Gamma_{\rm II})_{ij} = \int B(\vec{\theta})\,\frac{P_{\rm det}(\vec{\theta})}{P_{\rm det}(\vec{\lambda})}\,p(\vec{\theta}\,|\,\vec{\lambda})\,{\rm d}\vec{\theta}$$

$$(\Gamma_{\rm III})_{ij} = \int C(\vec{\theta})\,\frac{p(\vec{\theta}\,|\,\vec{\lambda})}{P_{\rm det}(\vec{\lambda})}\,{\rm d}\vec{\theta}$$

$$(\Gamma_{\rm IV})_{ij} = \int D(\vec{\theta})\,\frac{p(\vec{\theta}\,|\,\vec{\lambda})}{P_{\rm det}(\vec{\lambda})}\,{\rm d}\vec{\theta}$$

$$(\Gamma_{\rm V})_{ij} = \int E(\vec{\theta})\,\frac{P_{\rm det}(\vec{\theta})}{P_{\rm det}(\vec{\lambda})}\,p(\vec{\theta}\,|\,\vec{\lambda})\,{\rm d}\vec{\theta}$$

1. Population model: $p(\vec{\theta}\,|\,\vec{\lambda})$

2. Selection effects:

$$P_{\rm det}(\vec{\lambda}) = \int P_{\rm det}(\vec{\theta})\,p(\theta|\lambda)\,d\vec{\theta}$$

3. Detection probability:

$$P_{\rm det}(\vec{\theta}) = \int_{d>d_{th}} p(d\,|\,\vec{\theta})\,{\rm d}\vec{\theta}$$

4. $\Gamma =$ Single event Fisher matrix with GWfast

If the single-event errors are small, $\Gamma_{\rm I}$ is the dominant term

[Iacovelli et al, 2022]

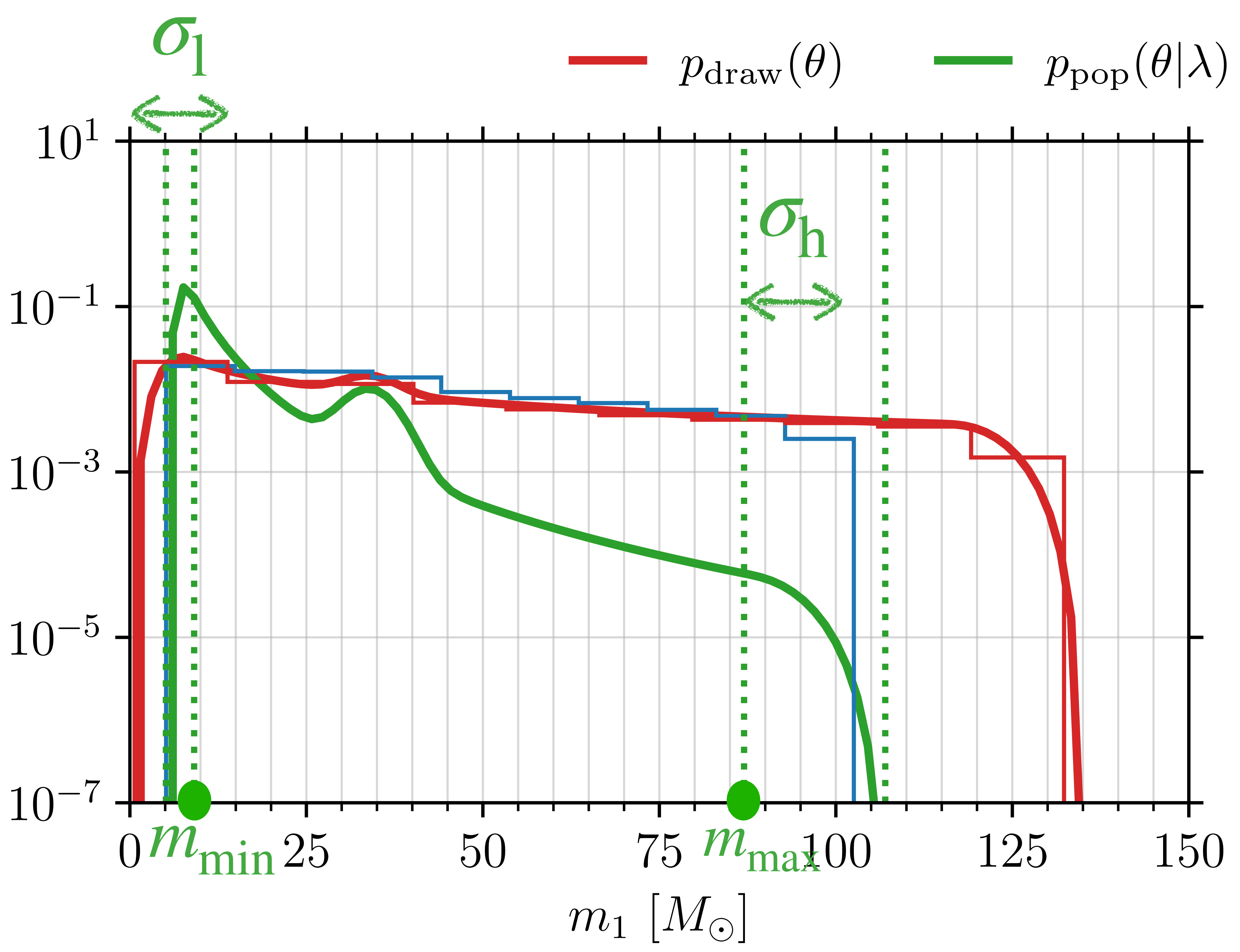
[Gair et al., 2023]

Monte Carlo integration

We approximate the equation for $\Gamma_{I}, \Gamma_{II}, \Gamma_{III}, \Gamma_{IV}, \Gamma_{V}$ with Monte Carlo integrals

$$I(\lambda) = \int X(\theta, \lambda) p_{\mathrm{draw}}(\theta) d\theta \simeq \frac{1}{N_{\mathrm{draw}}} \sum_{i}^{N_{\mathrm{draw}}} X(\theta_i, \lambda)$$

Mass distribution $p_{\mathrm{pop}}(\theta | \lambda)$=Power Law Plus Peak



Fiducial values for $p_{\mathrm{draw}}(\theta)$

$\alpha_m = \beta_q = 0.7$

$\sigma_l = 8.7 M_\odot \quad \sigma_h = 20 M_\odot$

$m_{\mathrm{min}} = 9.1 M_\odot \quad m_{\mathrm{max}} = 115 M_\odot$

Fiducial values for $p_{\mathrm{pop}}(\theta | \lambda)$

$\alpha_m = 3.4 \quad \beta_q = 1.1$

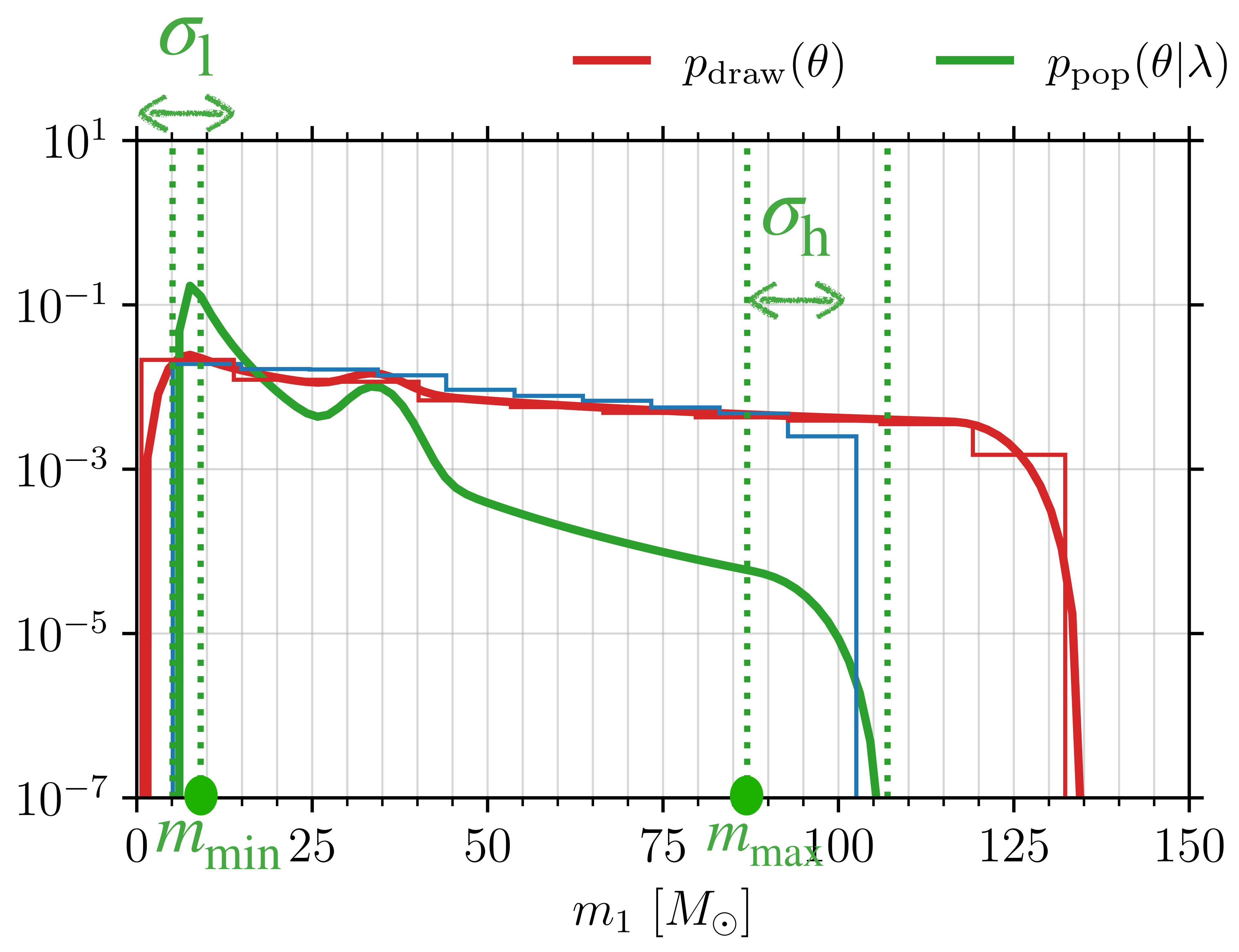
$\sigma_l = 5 M_\odot \quad \sigma_h = 20 M_\odot$

$m_{\mathrm{min}} = 9.1 M_\odot \quad m_{\mathrm{max}} = 87 M_\odot$

3G forecasts

- **Mass distribution =Power Law Plus Peak**
- Redshift distribution = Madau Dickinson
- Spin= Default distribution

- Detectors: ET,ET+2CE
- SNR threshold=12

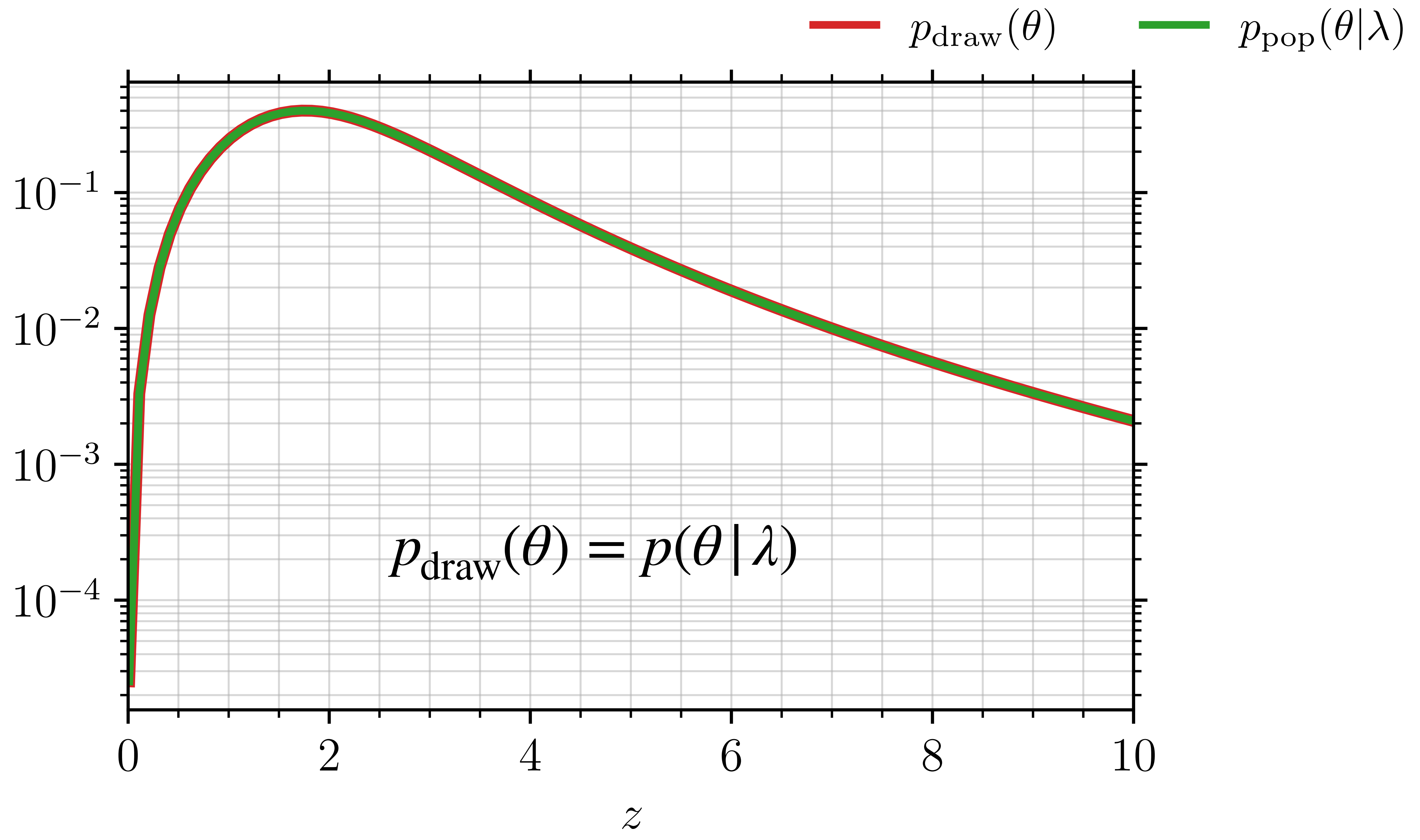


Parameter	Description	Fiducial Value
	Mass model: Power Law Plus Peak	
α_m	Spectral index for the power-law of the primary mass distribution.	3.4
β_q	Spectral index for the power-law of the mass ratio distribution.	1.1
$m_{\rm min}$	Minimum mass of the power-law component of the primary mass distribution.	9.1 $M_\odot$
$m_{\rm max}$	Maximum mass of the power-law component of the primary mass distribution.	87 $M_\odot$
$\lambda_{\rm p}$	Fraction of binary BHs in the Gaussian component.	0.039
μ_m	Mean of the Gaussian component in the primary mass distribution.	34
σ_m	Width of the Gaussian component in the primary mass distribution.	3.6
σ_l	Width of mass smoothing at the lower end of the mass distribution.	4.0
σ_h	Width of mass smoothing at the upper end of the mass distribution.	0.5

3G forecasts

- Mass distribution =Power Law Plus Peak
- **Redshift distribution = Madau Dickinson**
- Spin= Default distribution

- Detectors: ET+2CE
- SNR threshold=12

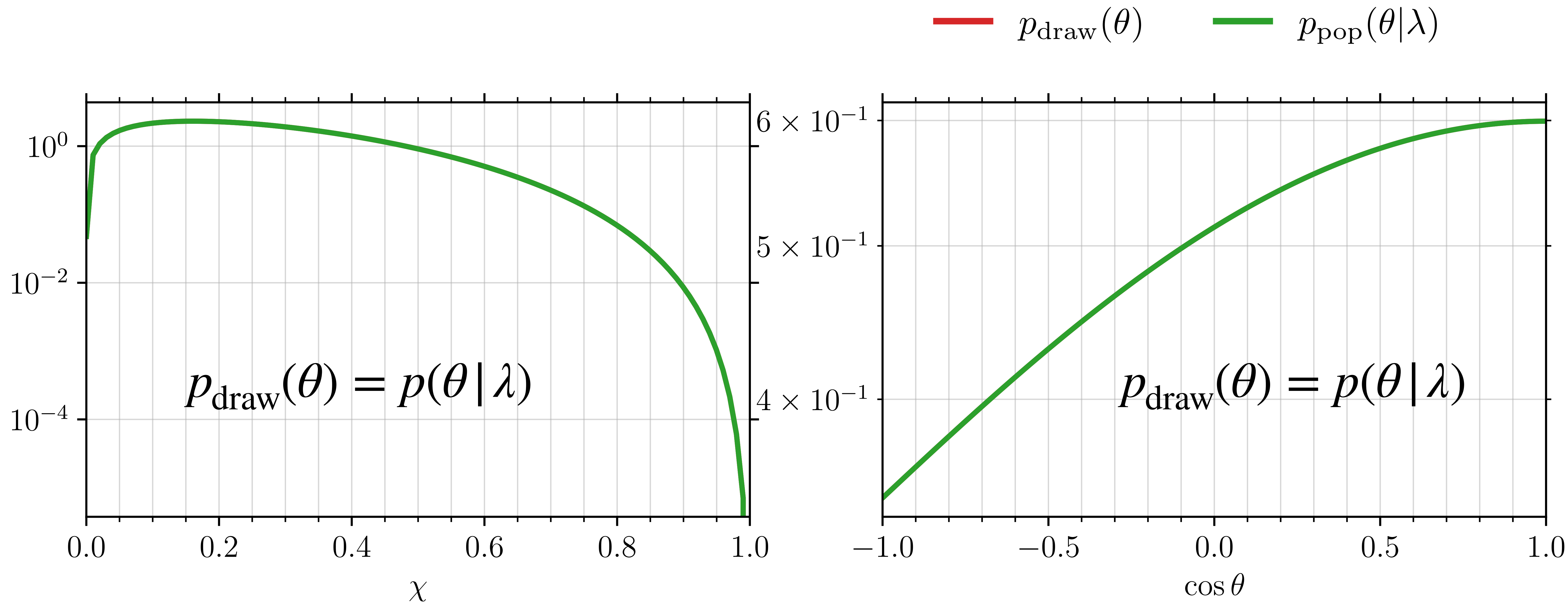


Parameter	Description	Fiducial Value
	Rate model: Madau Dickinson	
α_z	Power-law index governing the rise of the star formation rate at low redshift.	2.7
β_z	Power-law index governing the decline of the star formation rate at high redshift.	3.0
z_p	Redshift at which the star formation rate peaks.	2.0

3G forecasts

- Mass distribution =Power Law Plus Peak
- Redshift distribution = Madau Dickinson
- **Spin= Default distribution**

- Detectors: ET, ET+2CE
- SNR threshold=12



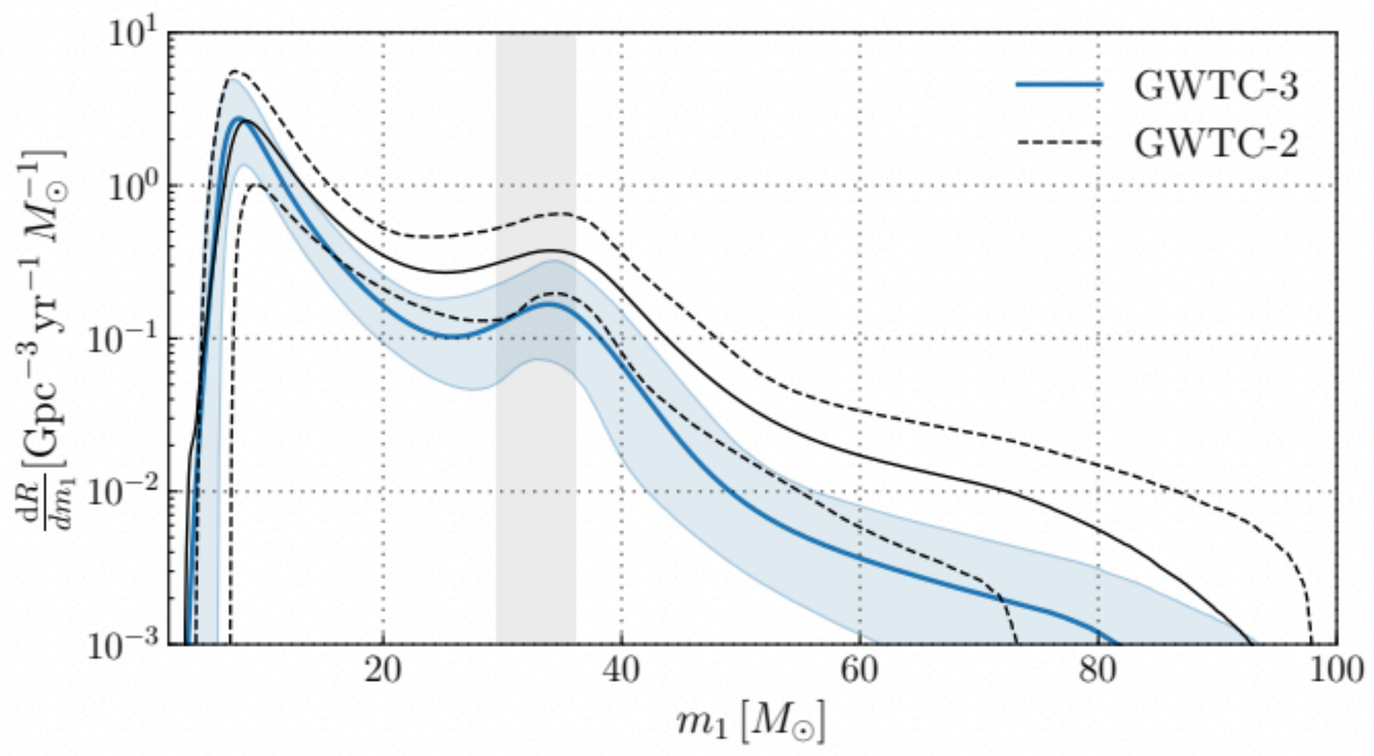
Parameter	Description	Fiducial Value
	Spin model: DEFAULT	
α_χ	Shape parameter of the Beta distribution of the spin magnitudes.	1.6
β_χ	Shape parameter of the Beta distribution of the spin magnitudes.	4.12
ζ	Mixing fraction of mergers from the truncated Gaussian component for spin orientations.	0.66
σ_t	Width of the truncated Gaussian component for spin orientations, determining the typical spin misalignment.	1.5

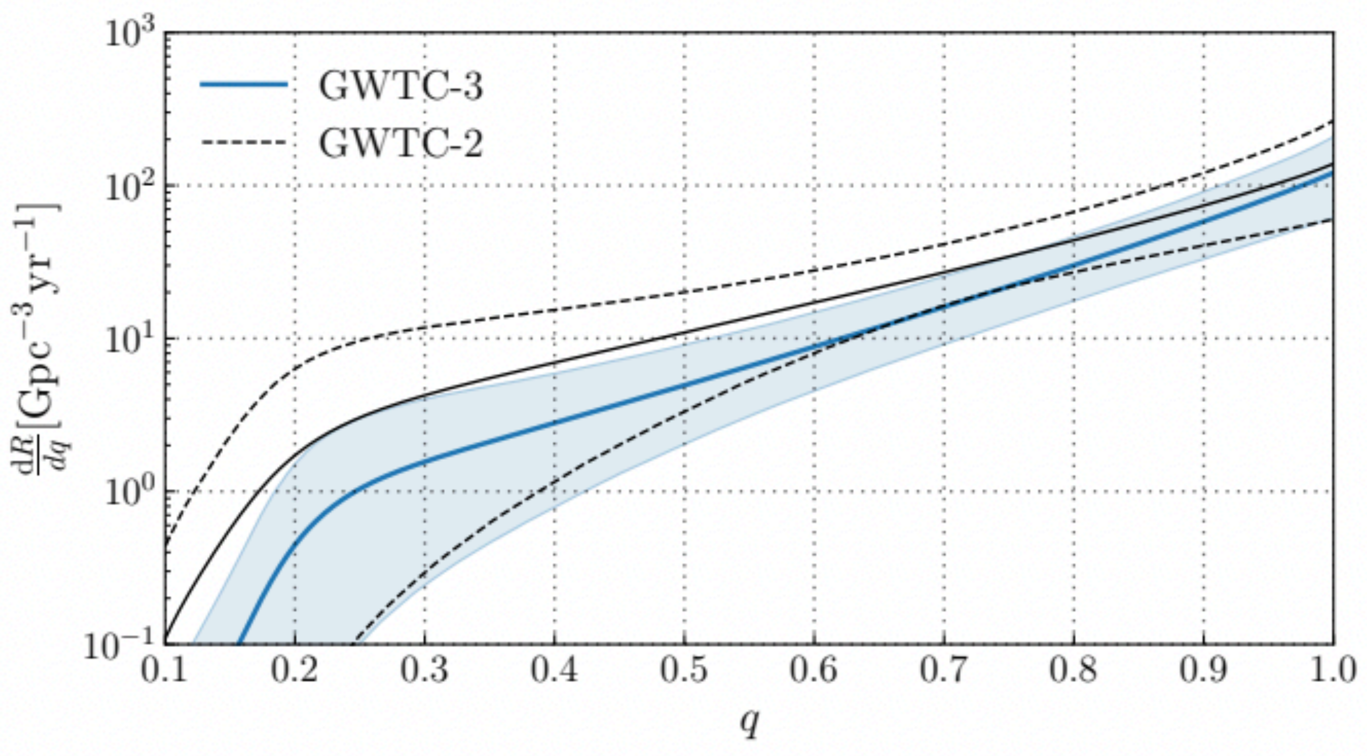
Spin tilts

$$p(\cos\theta_i|\zeta,\sigma_t) = \frac{1}{2}(1-\zeta) + \zeta\, \mathcal{N}_{[-1,1]}(\cos\theta_i; 1, \sigma_t).$$

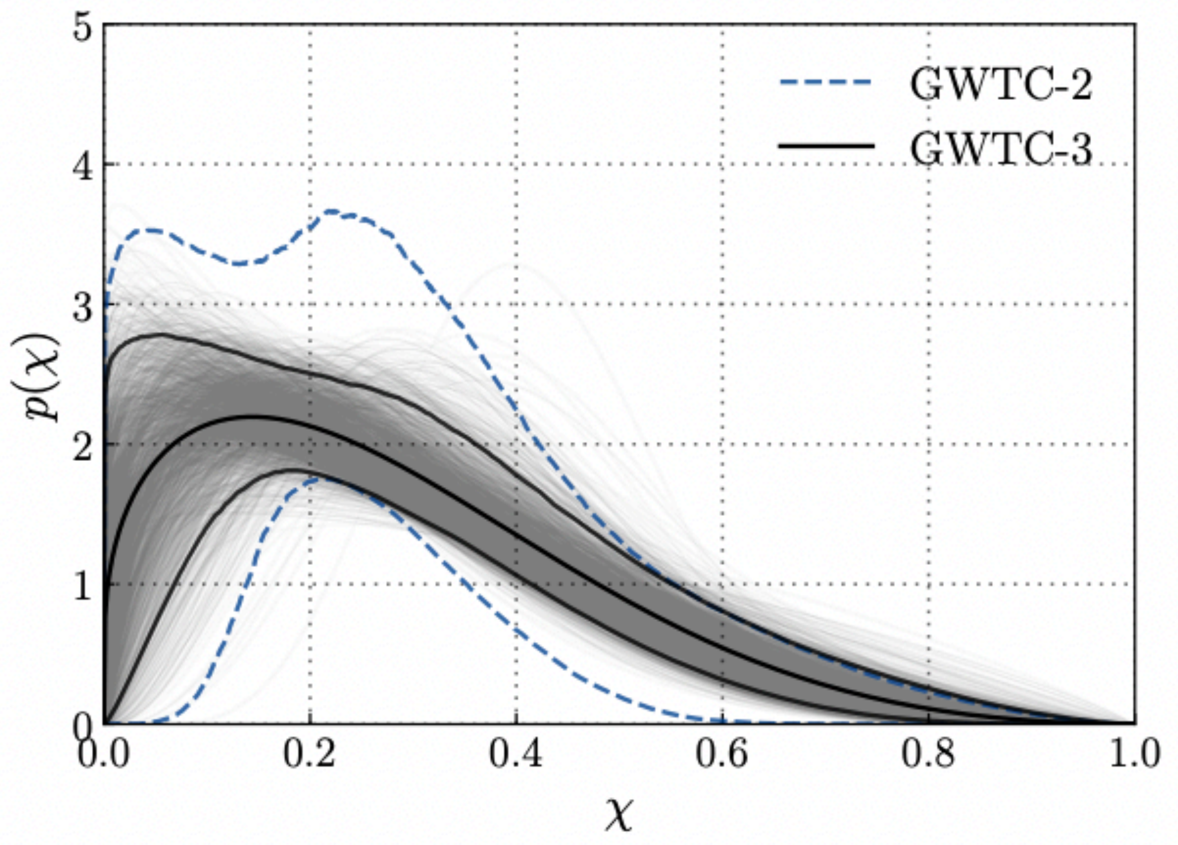
Astrophysical implications

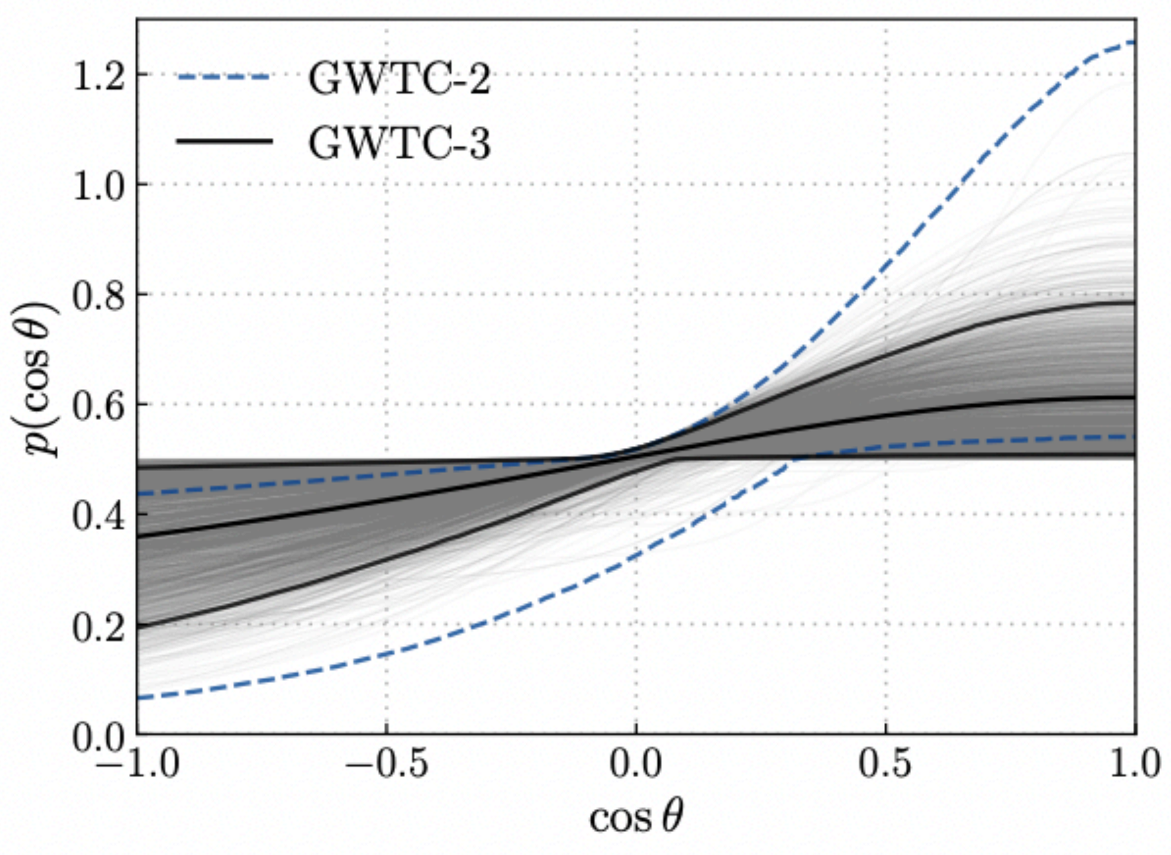
What's the formation, evolution, and distribution of BBHs in the universe?





- Lower mass end at ~ $10M_\odot$ → Field binaries
- $m_{max} \simeq 90M_\odot$ → Hierarchical mergers in dense environments
- Peak at $\sim 34M_\odot$ → Support for PISN mass gap between $\sim[40,60]M_\odot$



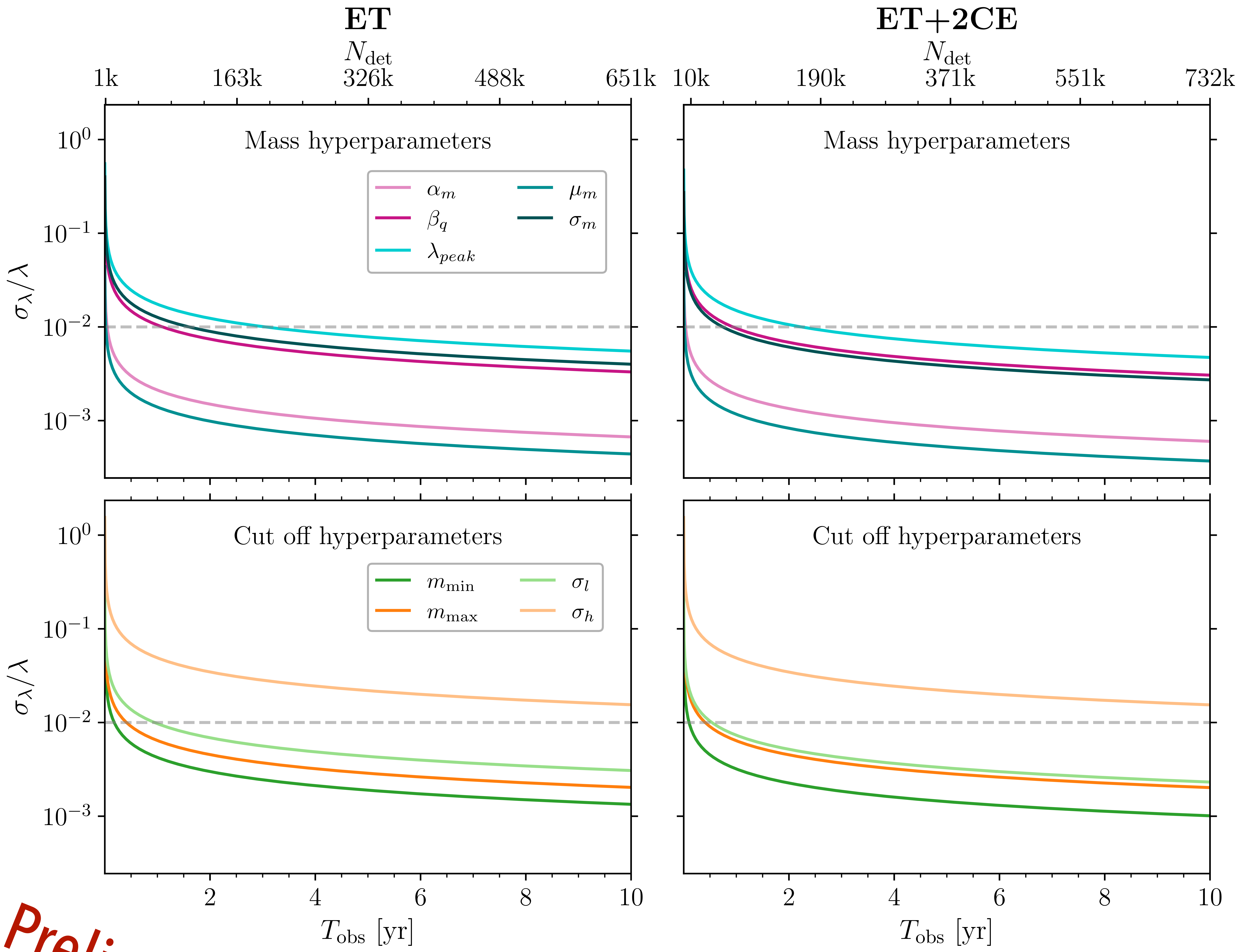


- Low (but non-zero) spin magnitudes
- Mixture of aligned and misaligned spins
- Weak precession

Mix of BBH formation channels (dynamical and isolated)

[LVK, 2022]

Forecasts for the mass and cut off hyperparameters with 3G detectors



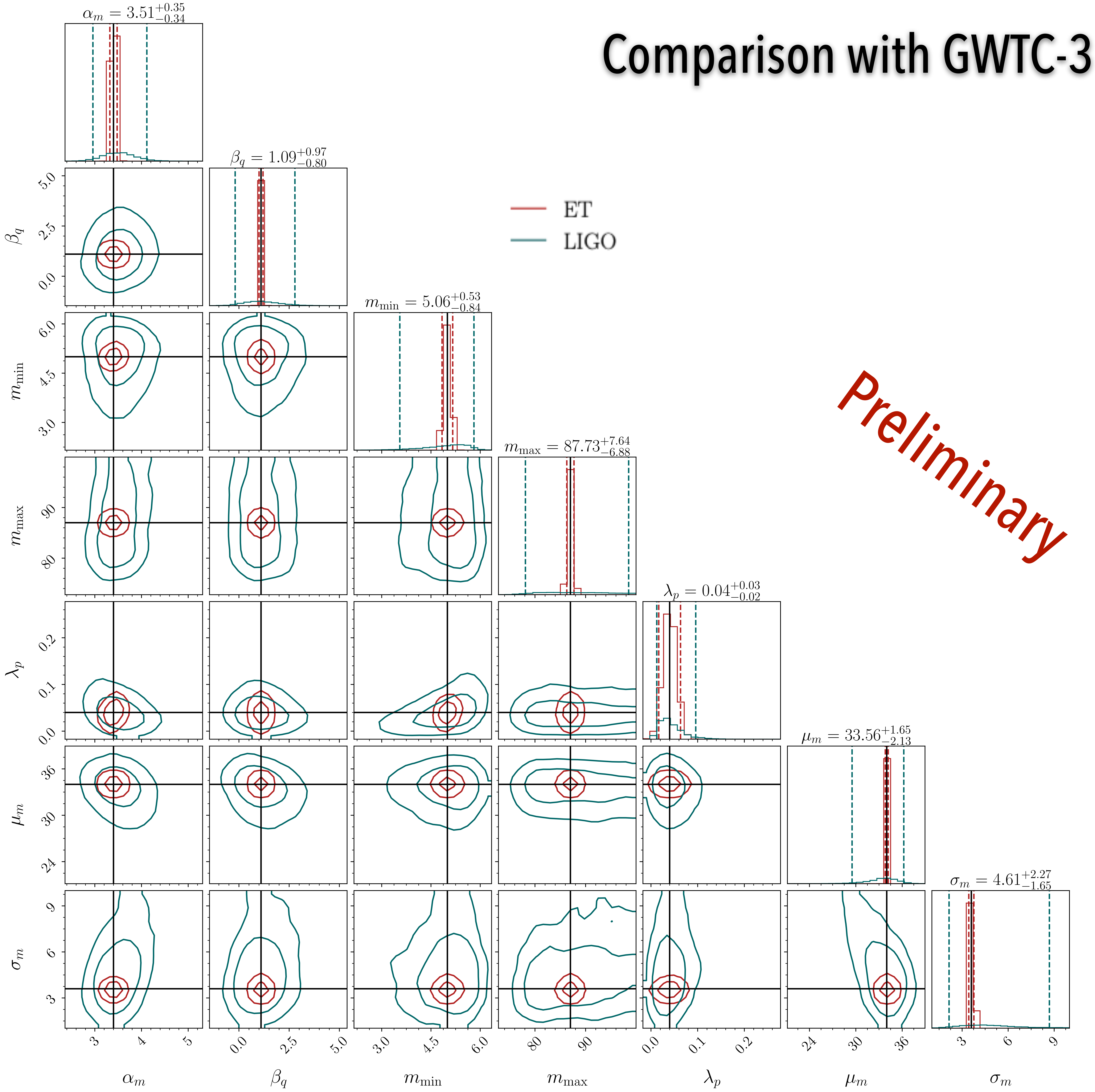
Preliminary

- No big difference between ET and ET+2CE (the scale of the problem is the number of detections!)
- α_m and μ_m are the best measured parameters
- σ_h is the worst measured

Relative errors after 10 years of observation

σ_λ/λ	**ET**	**ET+2CE**
α_m	$6.7 \cdot 10^{-4}$	$6.0 \cdot 10^{-4}$
β_q	$3.3 \cdot 10^{-3}$	$3.1 \cdot 10^{-3}$
$m_{\rm min}$	$1.3 \cdot 10^{-3}$	$1.0 \cdot 10^{-3}$
$m_{\rm max}$	$2.0 \cdot 10^{-3}$	$2.0 \cdot 10^{-3}$
$\lambda_{\rm peak}$	$5.5 \cdot 10^{-3}$	$4.7 \cdot 10^{-3}$
σ_l	$3.1 \cdot 10^{-3}$	$2.3 \cdot 10^{-3}$
σ_h	$1.5 \cdot 10^{-2}$	$1.5 \cdot 10^{-2}$
μ_m	$4.4 \cdot 10^{-4}$	$3.7 \cdot 10^{-4}$
σ_m	$4.0 \cdot 10^{-3}$	$2.7 \cdot 10^{-3}$

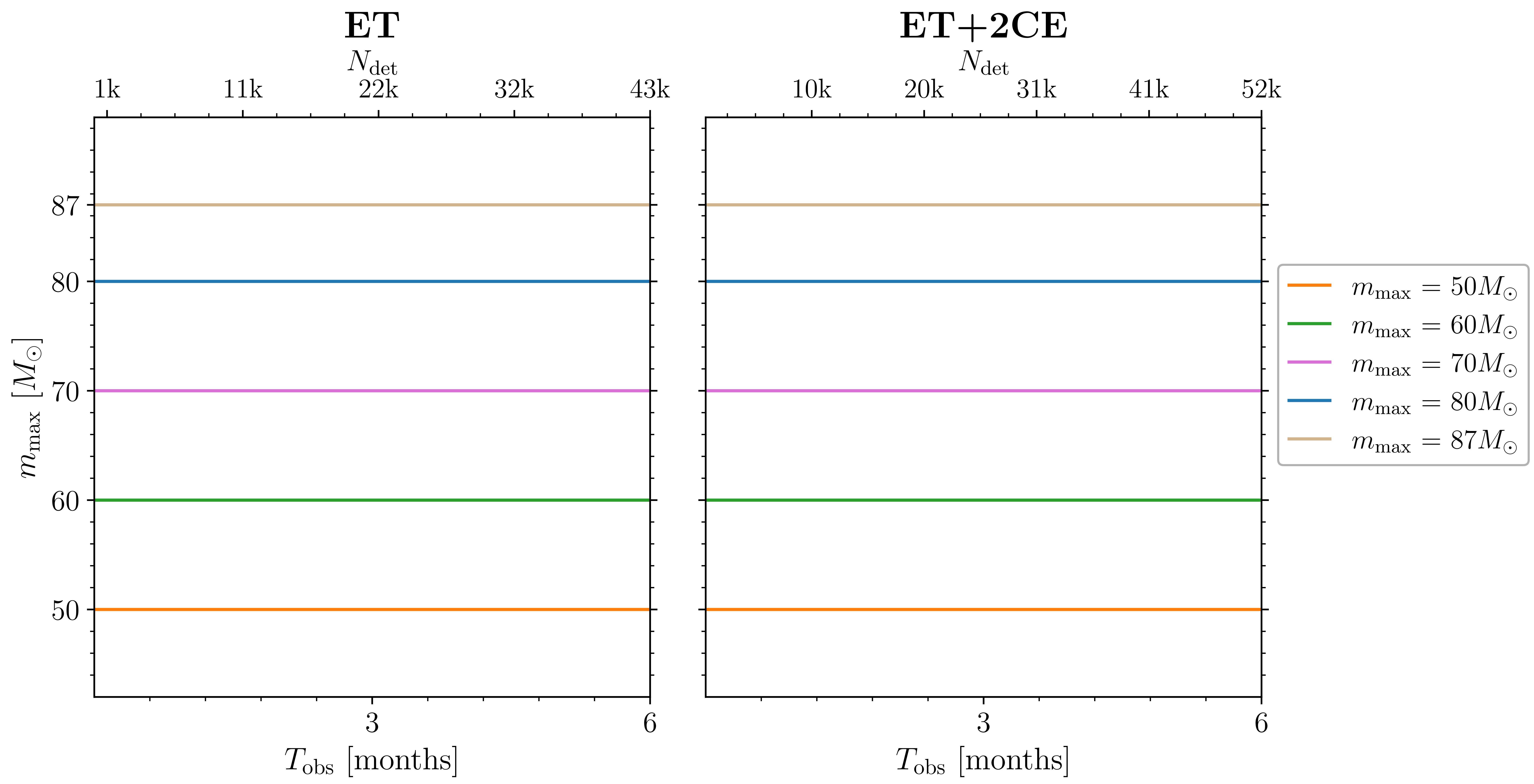
Comparison with GWTC-3 results



Relative errors after 10 years of observation

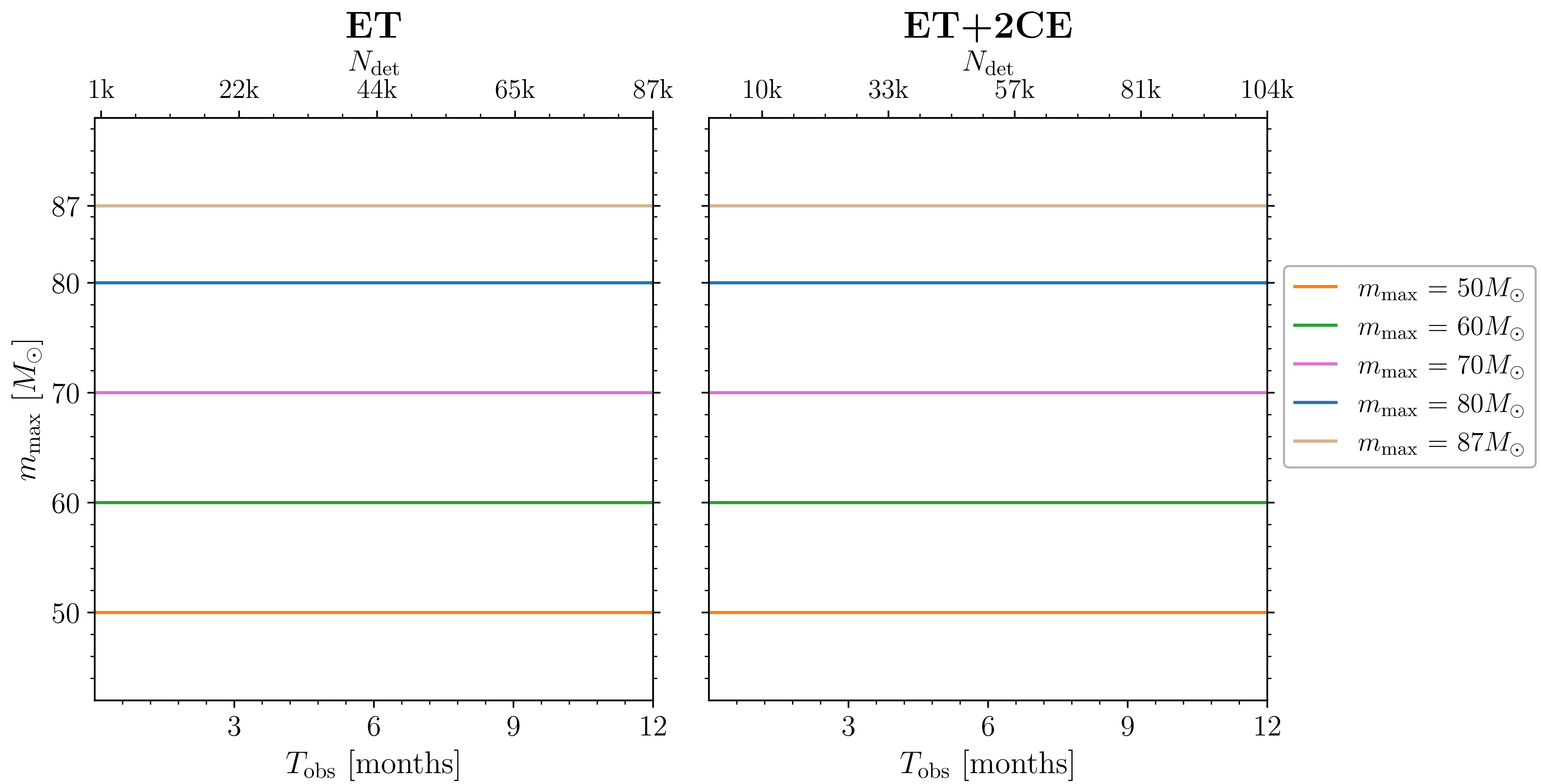
σ_λ/λ	**ET**	**ET+2CE**
α_m	$6.7 \cdot 10^{-4}$	$6.0 \cdot 10^{-4}$
β_q	$3.3 \cdot 10^{-3}$	$3.1 \cdot 10^{-3}$
$m_{\rm min}$	$1.3 \cdot 10^{-3}$	$1.0 \cdot 10^{-3}$
$m_{\rm max}$	$2.0 \cdot 10^{-3}$	$2.0 \cdot 10^{-3}$
$\lambda_{\rm peak}$	$5.5 \cdot 10^{-3}$	$4.7 \cdot 10^{-3}$
σ_l	$3.1 \cdot 10^{-3}$	$2.3 \cdot 10^{-3}$
σ_h	$1.5 \cdot 10^{-2}$	$1.5 \cdot 10^{-2}$
μ_m	$4.4 \cdot 10^{-4}$	$3.7 \cdot 10^{-4}$
σ_m	$4.0 \cdot 10^{-3}$	$2.7 \cdot 10^{-3}$

Variation of $m_{\max}$ vs $T_{\rm obs} =$ 6 months



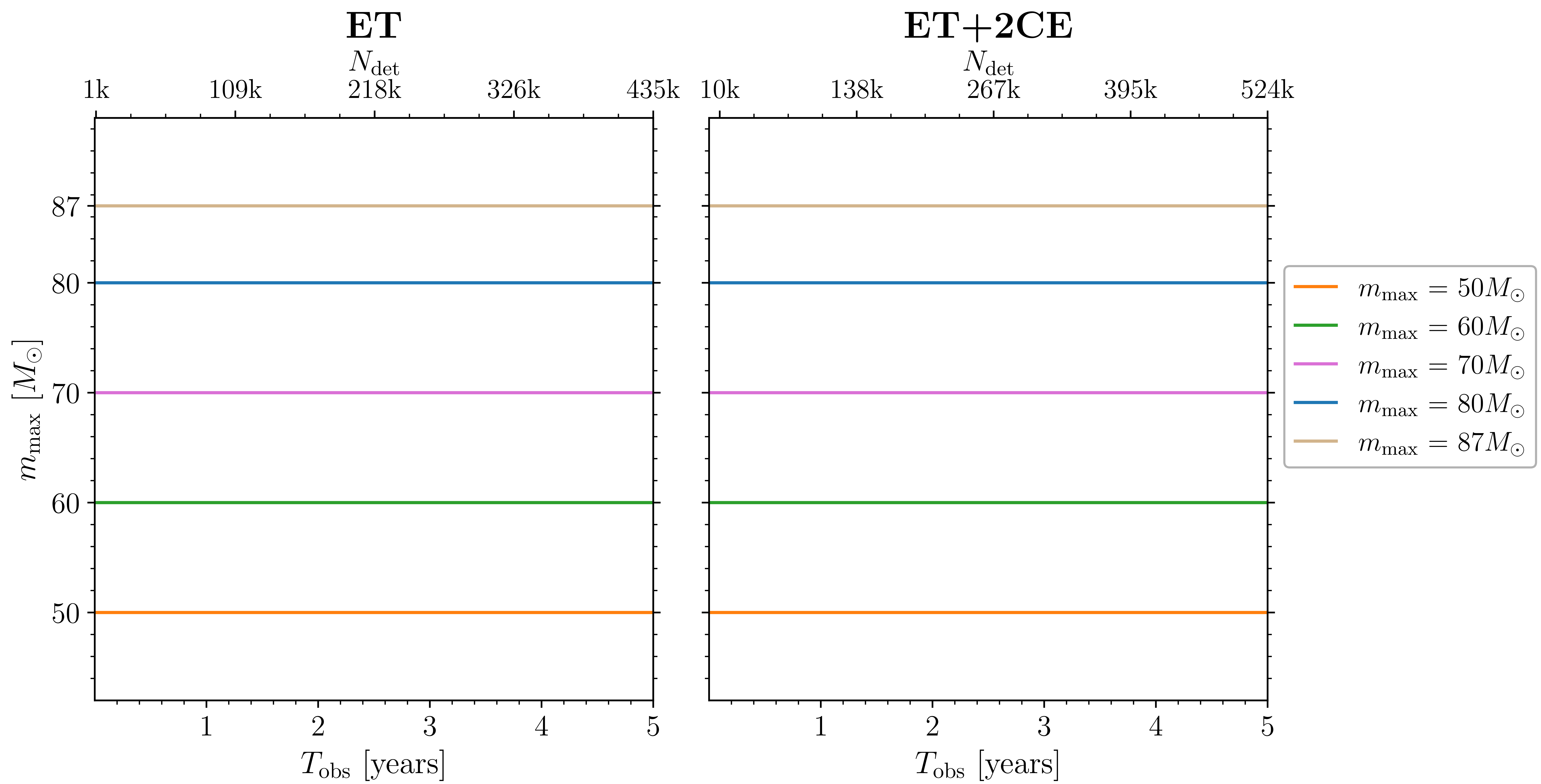
Preliminary

Variation of $m_{\rm max}$ vs $T_{\rm obs}$ = 12 months



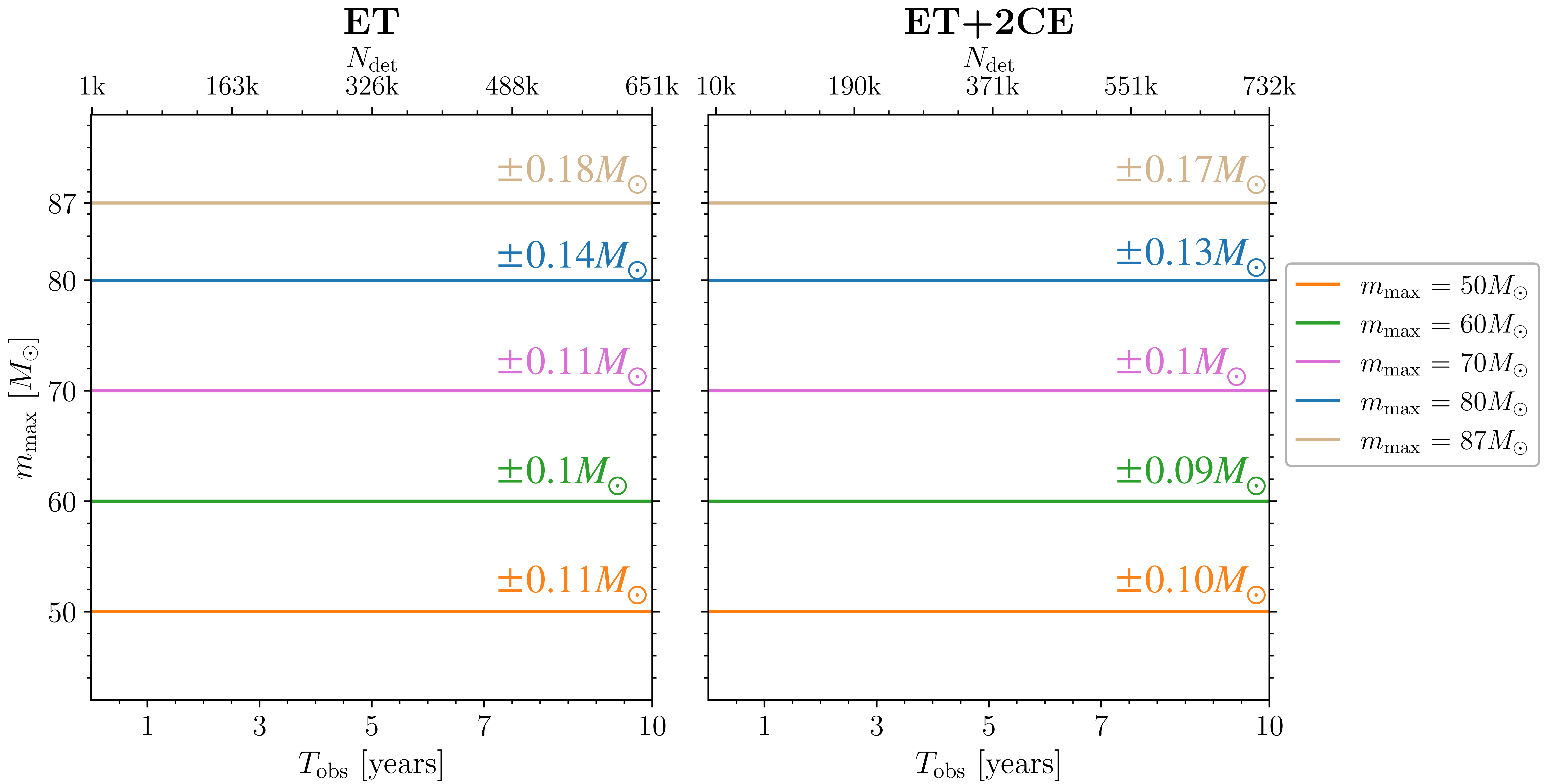
Preliminary

Variation of $m_{\rm max}$ vs $T_{\rm obs}$ = 5 years



Preliminary

Variation of $m_{\rm max}$ vs $T_{\rm obs}$ = 10 years



Preliminary

Conclusions

- We developed a (not yet public) Fisher code for population analysis with selection effects that enable the use of parametric (differentiable) models.
- Our forecast show the outstanding constraining power of 3G detectors
- After just a few years of observation, these detectors are projected to constrain hyperparameters with percent-level accuracy

Future work

- Exploring the correlations between parameters
- Adding cosmology
- Perform hierarchical test of GR
- Other ideas?

Back up slides

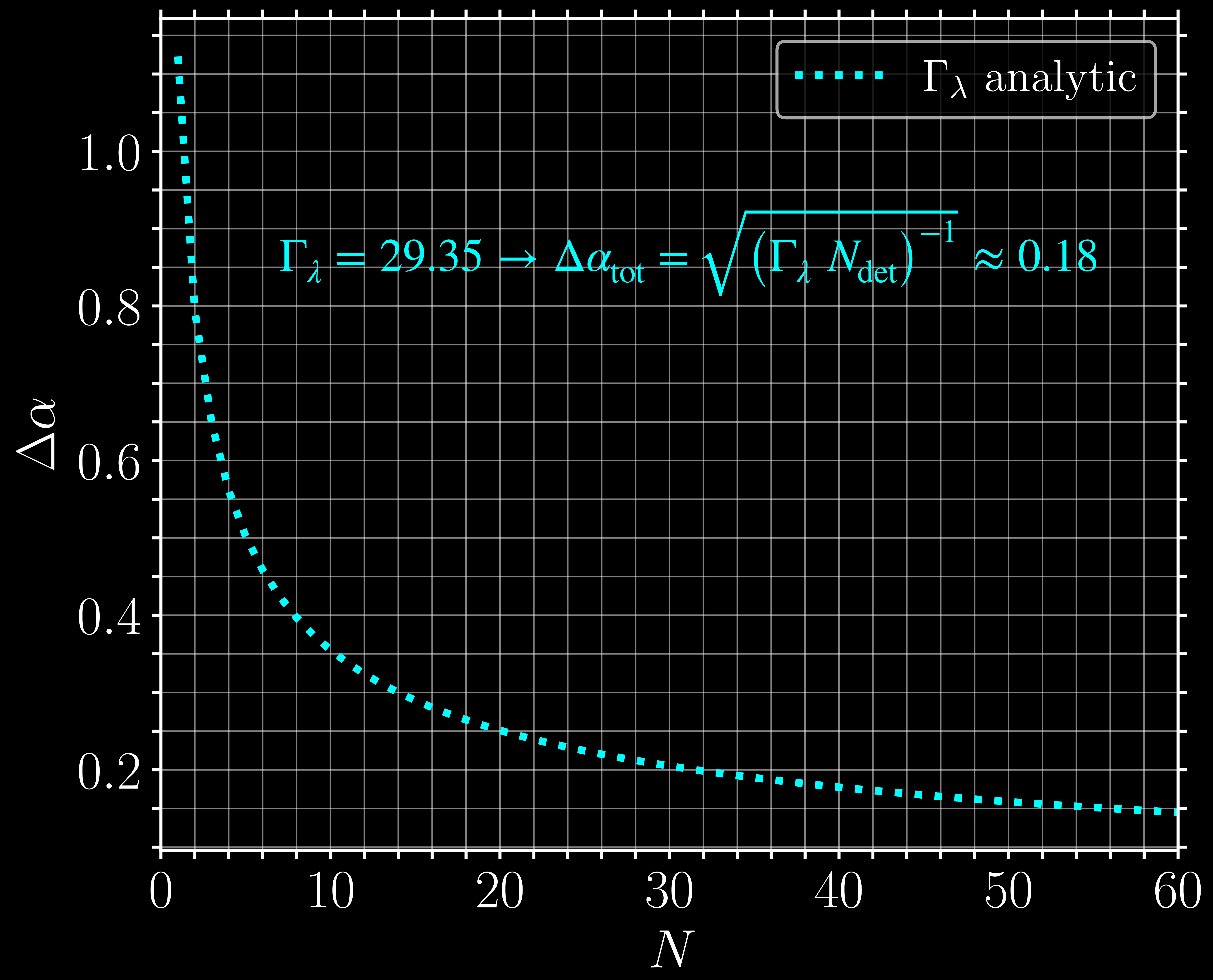
Power law of SMBHs with 1 parameter and 1 hyperparameter

[Gair et al. (2023) MNRAS 519 2736]

$$p(M_1 \mid \alpha) = \frac{\alpha}{M_{\max}^{\alpha} - M_{\min}^{\alpha}} M_1^{\alpha-1}$$

- ★ 1 parameter $\theta = M_1$
- ★ 1 hyperparameter $\lambda = \alpha$ with $\alpha_{\rm true} \approx 0$
- ★ $M_{\min} = 10^4 M_\odot$
- ★ $M_{\max} = 10^7 M_\odot$

- ★ $d_{th} = 5 \times 10^5 M_\odot$
- ★ $\Gamma = \frac{1}{\sigma^2}$ with $\sigma = 0.1$
- ★ $N_{\rm obs} = 100$
- ★ $N_{\rm det} = 39$



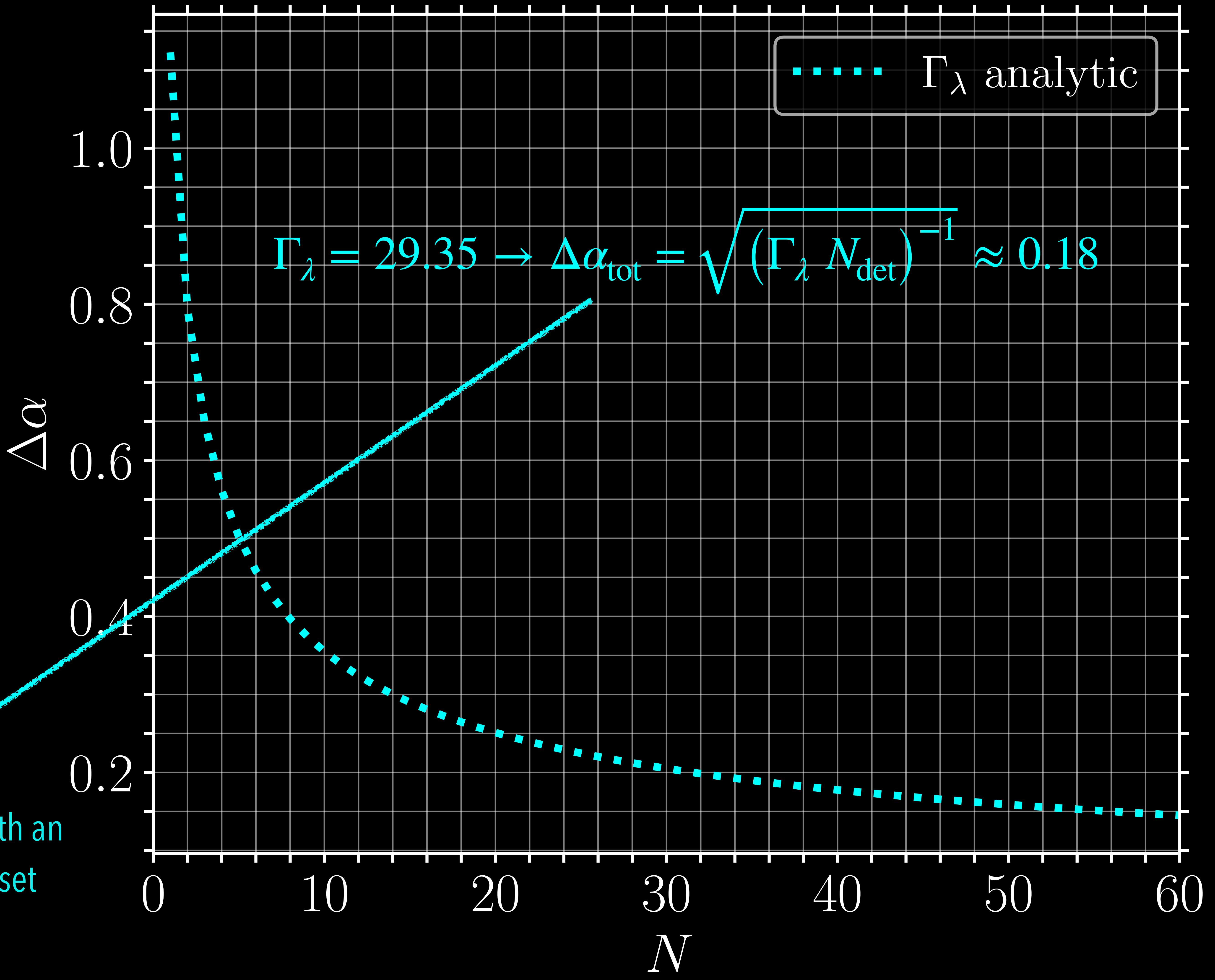
Power law of SMBHs with 1 parameter and 1 hyperparameter

[Gair et al. (2023) MNRAS 519 2736]

$$p(M_1 \,|\, \alpha) = \frac{\alpha}{M_{\max}^{\alpha} - M_{\min}^{\alpha}} M_1^{\alpha-1}$$

- ★ 1 parameter $\theta = M_1$
- ★ 1 hyperparameter $\lambda = \alpha$ with $\alpha_{\mathrm{true}} \approx 0$
- ★ $M_{\min} = 10^4 M_\odot$
- ★ $M_{\max} = 10^7 M_\odot$

- ★ $d_{th} = 5 \times 10^5 M_\odot$
- ★ $\Gamma = \frac{1}{\sigma^2}$ with $\sigma = 0.1$
- ★ $N_{\mathrm{obs}} = 100$
- ★ $N_{\mathrm{det}} = 39$



Fisher predictions were validated with an MCMC analysis for the same data set

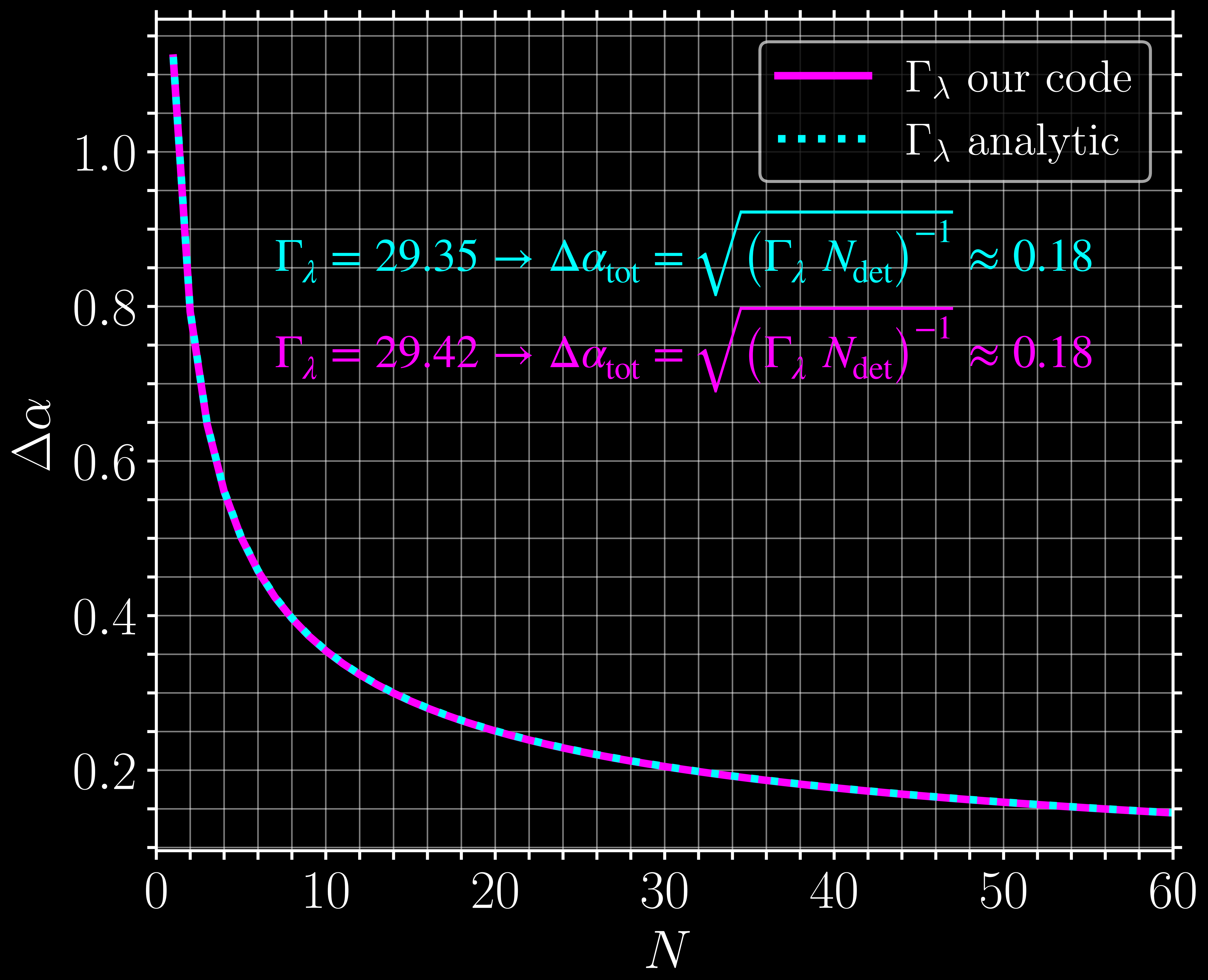
Power law of SMBHs with 1 parameter and 1 hyperparameter

[Gair et al. (2023) MNRAS 519 2736]

$$p(M_1 | \alpha) = \frac{\alpha}{M_{\max}^{\alpha} - M_{\min}^{\alpha}} M_1^{\alpha-1}$$

- ★ 1 parameter $\theta = M_1$
- ★ 1 hyperparameter $\lambda = \alpha$ with $\alpha_{\rm true} \approx 0$
- ★ $M_{\min} = 10^4 M_\odot$
- ★ $M_{\max} = 10^7 M_\odot$

- ★ $d_{th} = 5 \times 10^5 M_\odot$
- ★ $\Gamma = \frac{1}{\sigma^2}$ with $\sigma = 0.1$
- ★ $N_{\rm obs} = 100$
- ★ $N_{\rm det} = 39$



Power Law (PL) mass function with smoothing

$$p\left(M_1 \mid \vec{\lambda}\right) \propto M_1^{-\alpha}\ S(M_1, M_{\min}, \sigma_l, M_{\max}, \sigma_h)$$

$$p\left(M_2 \mid M_1, \vec{\lambda}\right) \propto M_2^{\beta}\ S(M_2, M_{\min}, \sigma_l, M_{\max}, \sigma_h)$$

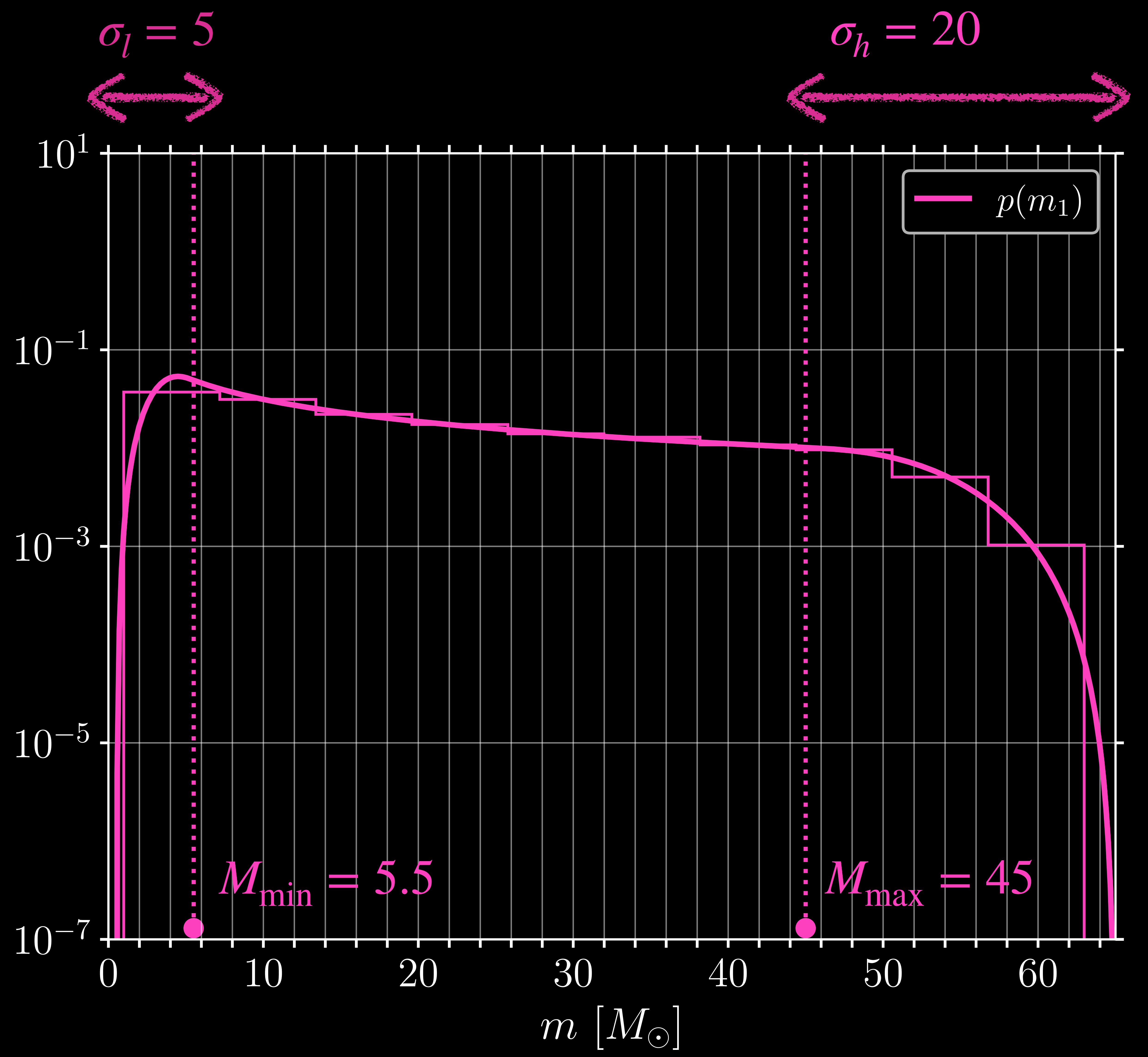
6 hyperparameter $\vec{\lambda}$:

- α : Spectral index for the PL of the primary mass distribution ($\alpha_{true} = 0.75$)
- β: Spectral index for the PL of the mass ratio distribution ($\beta_{true} = 0.1$)
- $M_{\max}$, $M_{\min}$: Maximum and minimum mass of the PL component of the primary mass distribution
- σ_h , σ_l : Width of the smoothing component at the upper and lower edge of the mass distribution

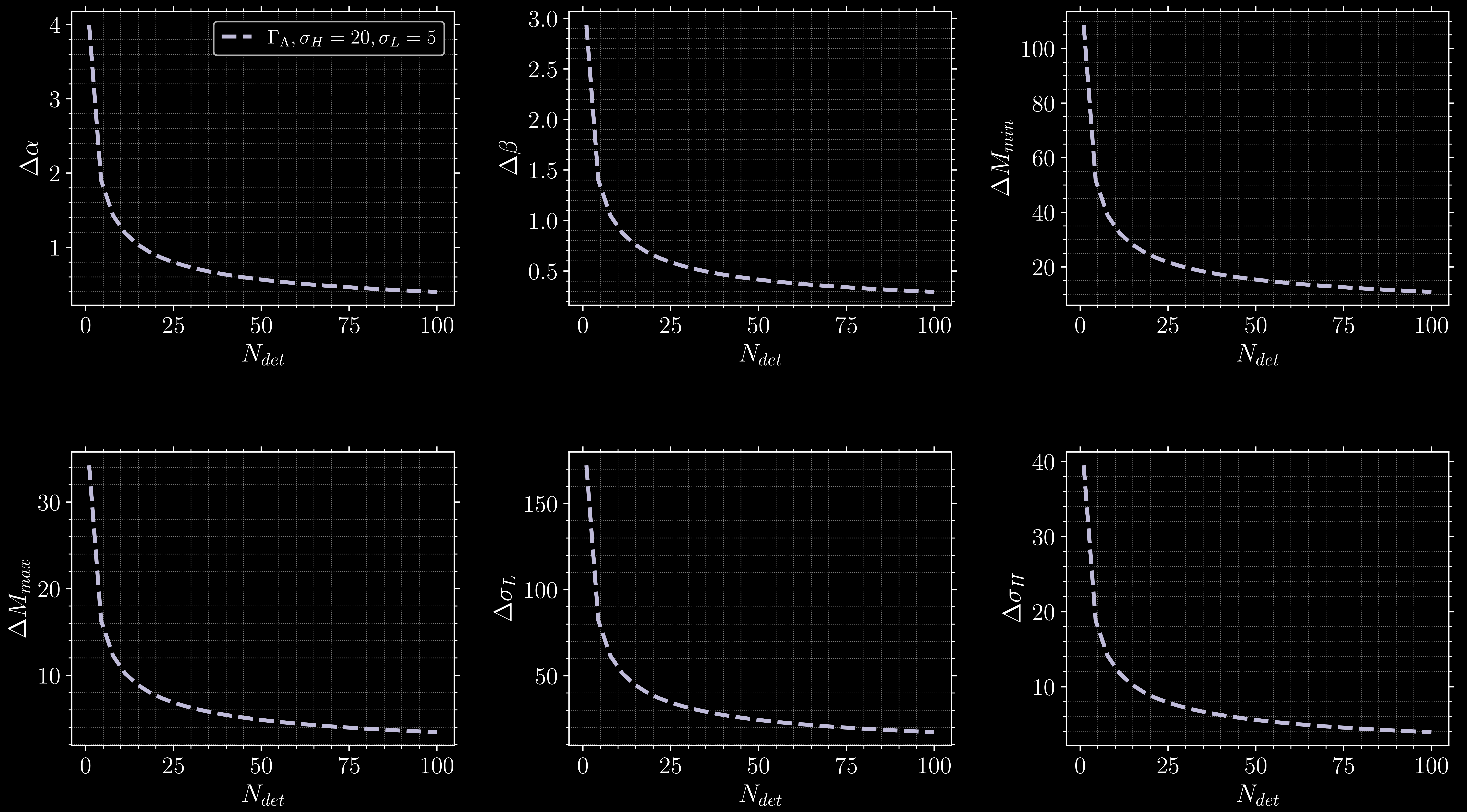
O4 sentivity curve

IMRPhenomHM waveform model

$\rho_{th=20}$



PowerLaw mass function with smoothing



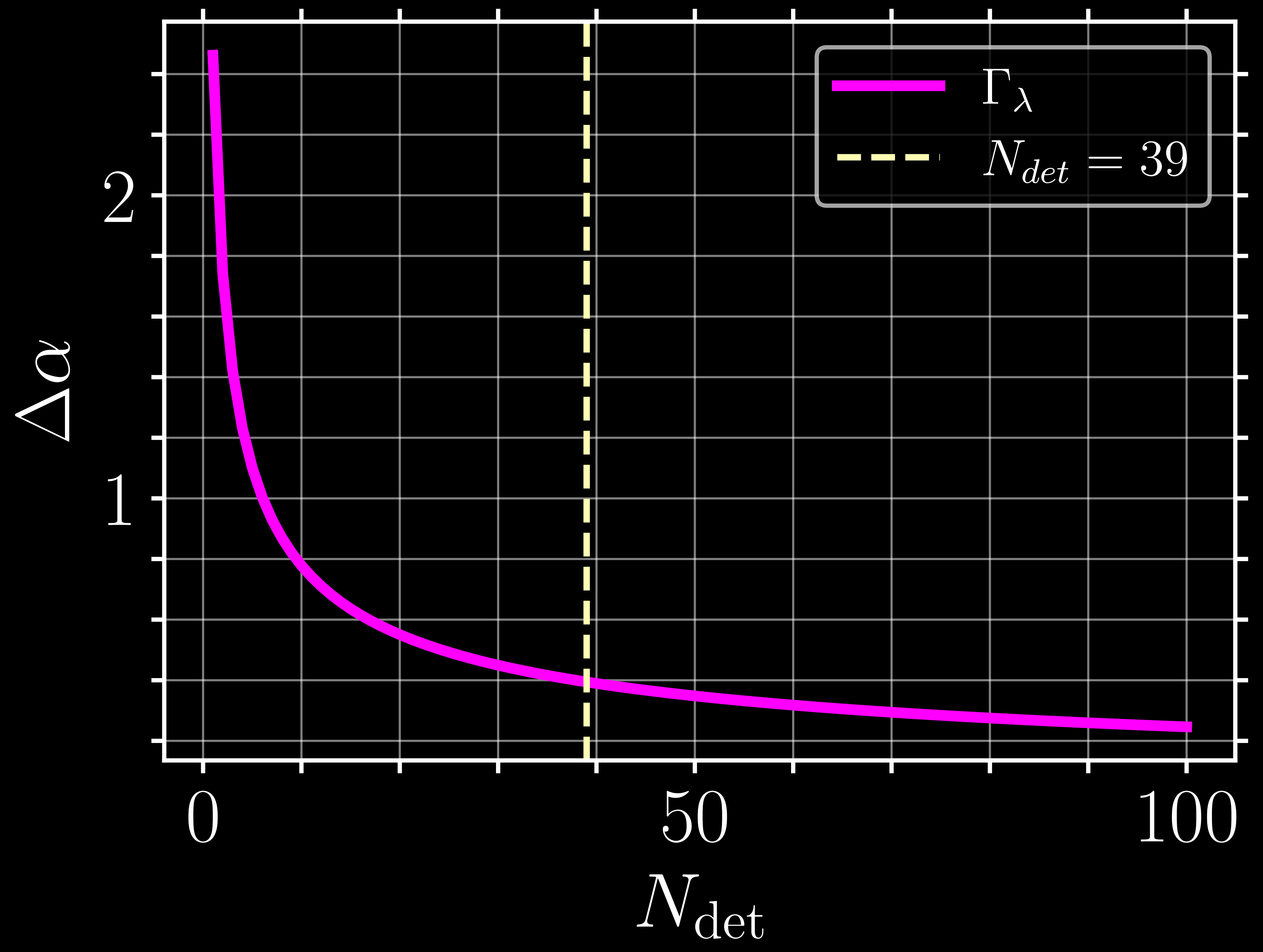
Population model with 2 parameters and 2 hyperparameters

$$p(M_1 | \alpha) = \frac{\alpha}{M_{\max}^{\alpha} - M_{\min}^{\alpha}} M_1^{\alpha-1}$$

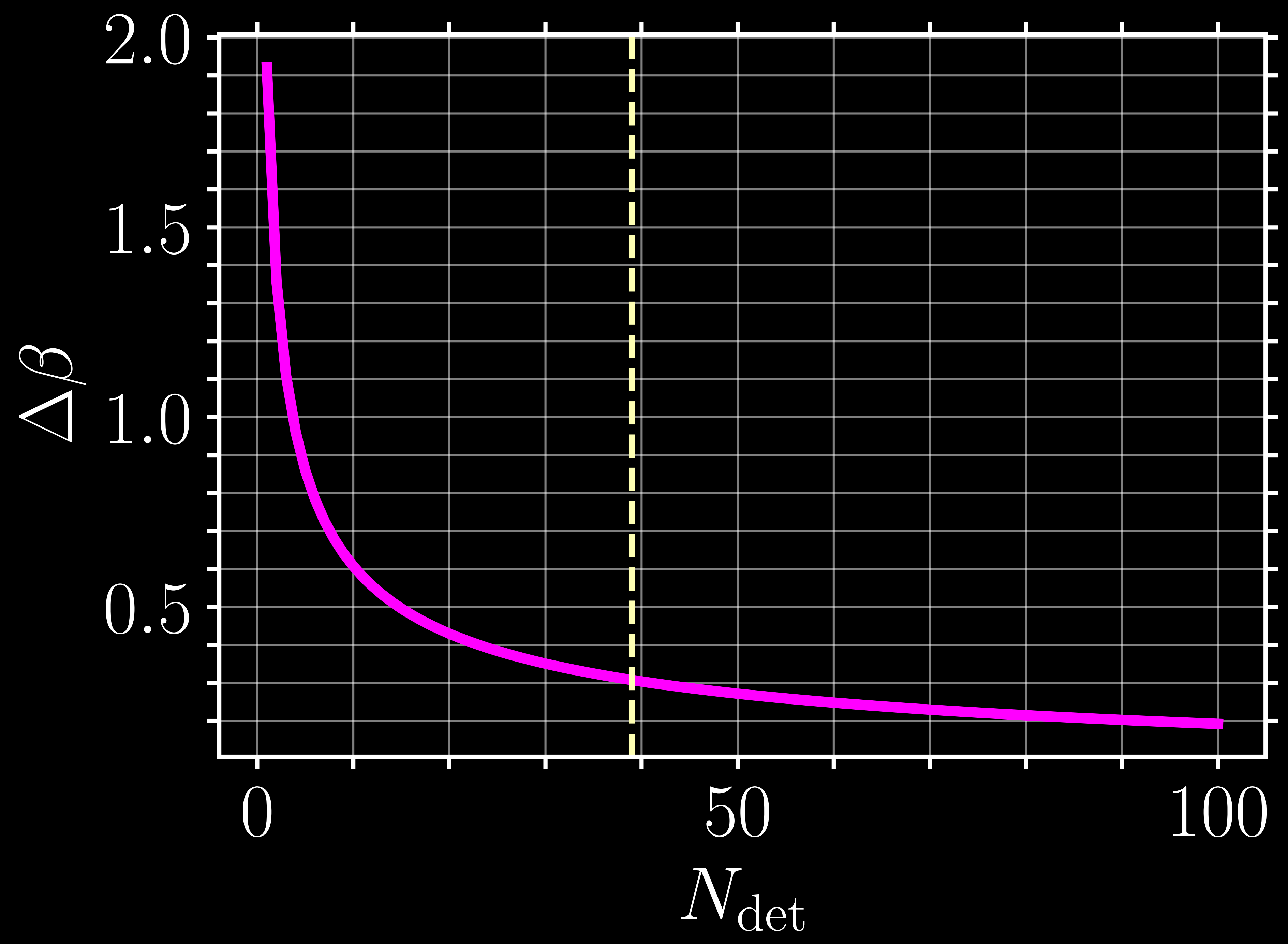
$$p(M_2 | \beta, M_1) \sim \left(\frac{M_2}{M_1}\right)^{\beta}$$

- ★ 2 parameters $\overrightarrow{\theta} = \{M_1, M_2\}$
- ★ 2 hyperparameters $\overrightarrow{\lambda} = \{\alpha, \beta\}$ with $\alpha_{\text{true}} \approx 0$ and $\beta_{\text{true}} \approx 1.1$
  (Spectral indexes for the PL of the primary (mass ratio) distributions)
- ★ Ndet=39

$$\Delta\alpha_{\text{tot}} = \sqrt{\left(\Gamma_\lambda\ N_{\text{det}}\right)^{-1}} \approx 0.39$$



$$\Delta\beta_{\text{tot}} = \sqrt{\left(\Gamma_\lambda\ N_{\text{det}}\right)^{-1}} \approx 0.31$$



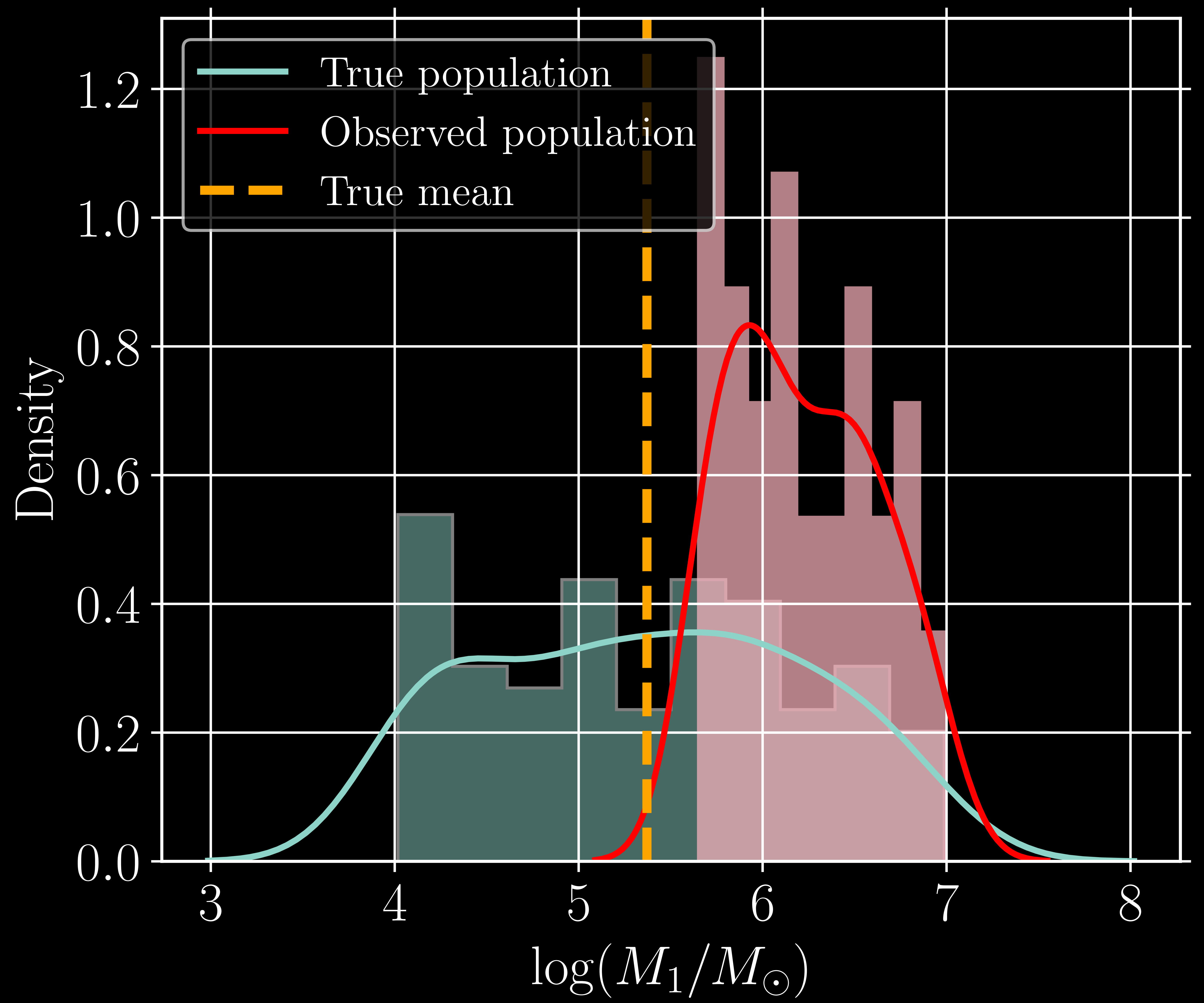
Population model with 1 parameter and 1 hyperparameter

[Gair et al. (2023) MNRAS 519 2736]

$$p(M_1 \,|\, \alpha) = \frac{\alpha}{M_{\max}^{\alpha} - M_{\min}^{\alpha}} M_1^{\alpha - 1}$$

- ★ 1 parameter $\theta = M_1$
- ★ 1 hyperparameter $\lambda = \alpha$ with $\alpha_{\rm true} \approx 0$
- ★ $M_{\min} = 10^4 M_\odot$
- ★ $M_{\max} = 10^7 M_\odot$

- ★ $d_{th} = 5 \times 10^5 M_\odot$
- ★ $\Gamma = \frac{1}{\sigma^2}$ with $\sigma = 0.1$
- ★ $N_{\rm obs} = 100$
- ★ $N_{\rm det} = 39$



Population model with 1 parameter and 1 hyperparameter

[Gair et al. (2023) MNRAS 519 2736]

$$p(M_1\,|\,\alpha) = \frac{\alpha}{M_{\max}^{\alpha} - M_{\min}^{\alpha}} M_1^{\alpha-1}$$

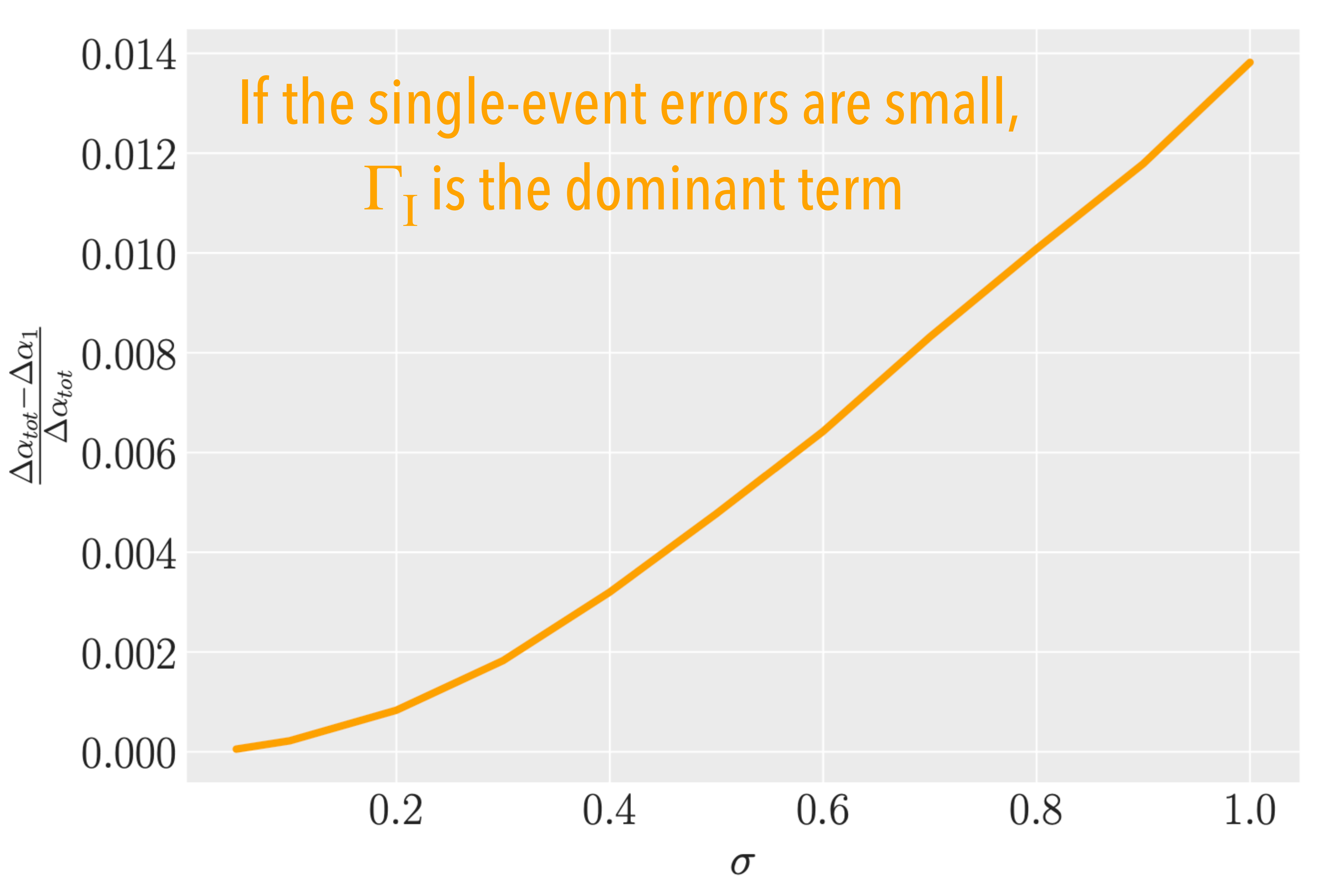
- ★ 1 parameter $\theta = M_1$
- ★ 1 hyperparameter $\lambda = \alpha$ with $\alpha_{\rm true} \approx 0$
- ★ $M_{\min} = 10^4 M_\odot$
- ★ $M_{\max} = 10^7 M_\odot$

- ★ $d_{th} = 5 \times 10^5 M_\odot$
- ★ $\Gamma = \frac{1}{\sigma^2}$ with $\sigma = 0.1$
- ★ $N_{\rm obs} = 100$
- ★ $N_{\rm det} = 39$

$$\Gamma_\lambda = 29.35 \rightarrow \Delta\alpha_{\rm tot} = \sqrt{(\Gamma_\lambda\, N_{\rm det})^{-1}} \approx 0.18$$

$$\Gamma_{\rm I} = 29.36 \rightarrow \Delta\alpha_{\rm I} = \sqrt{(\Gamma_{\rm I}\, N_{\rm det})^{-1}} \approx 0.18$$

$$\Gamma_{\rm II} + \Gamma_{\rm III} + \Gamma_{\rm IV} + \Gamma_{\rm V} \approx 10^{-13}$$



Population model with 2 parameter and 2 hyperparameter

- ★ 2 parameter $\overrightarrow{\theta} = \{M_1, M_2\}$
- ★ 2 hyperparameter $\overrightarrow{\lambda} = \{\alpha, \beta\}$ with $\alpha_{\text{true}} \approx 0$ and $\beta_{\text{true}} \approx 1.1$
- ★ Ndet=39

$$\Delta\alpha_{\text{tot}} = \sqrt{\left(\Gamma_\lambda\, N_{\text{det}}\right)^{-1}} \approx 0.39$$

$$\Delta\alpha_{\text{I}} = \sqrt{\left(\Gamma_{\text{I}}\, N_{\text{det}}\right)^{-1}} \approx 0.23$$

$$\Delta\beta_{\text{tot}} = \sqrt{\left(\Gamma_\lambda\, N_{\text{det}}\right)^{-1}} \approx 0.31$$

$$\Delta\beta_{\text{I}} = \sqrt{\left(\Gamma_{\text{I}}\, N_{\text{det}}\right)^{-1}} \approx 0.18$$