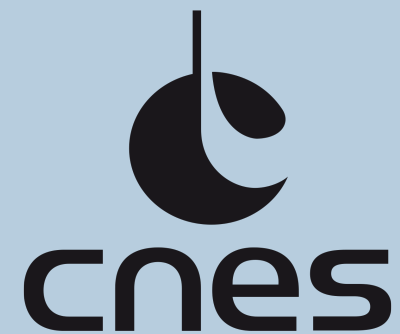




UNIVERSITÉ
DE TOULOUSE



additional structure in the observed black hole population and implications for cosmology

Vasco Gennari

Apr 10, 2025

ACME Workshop, Toulouse

L2T

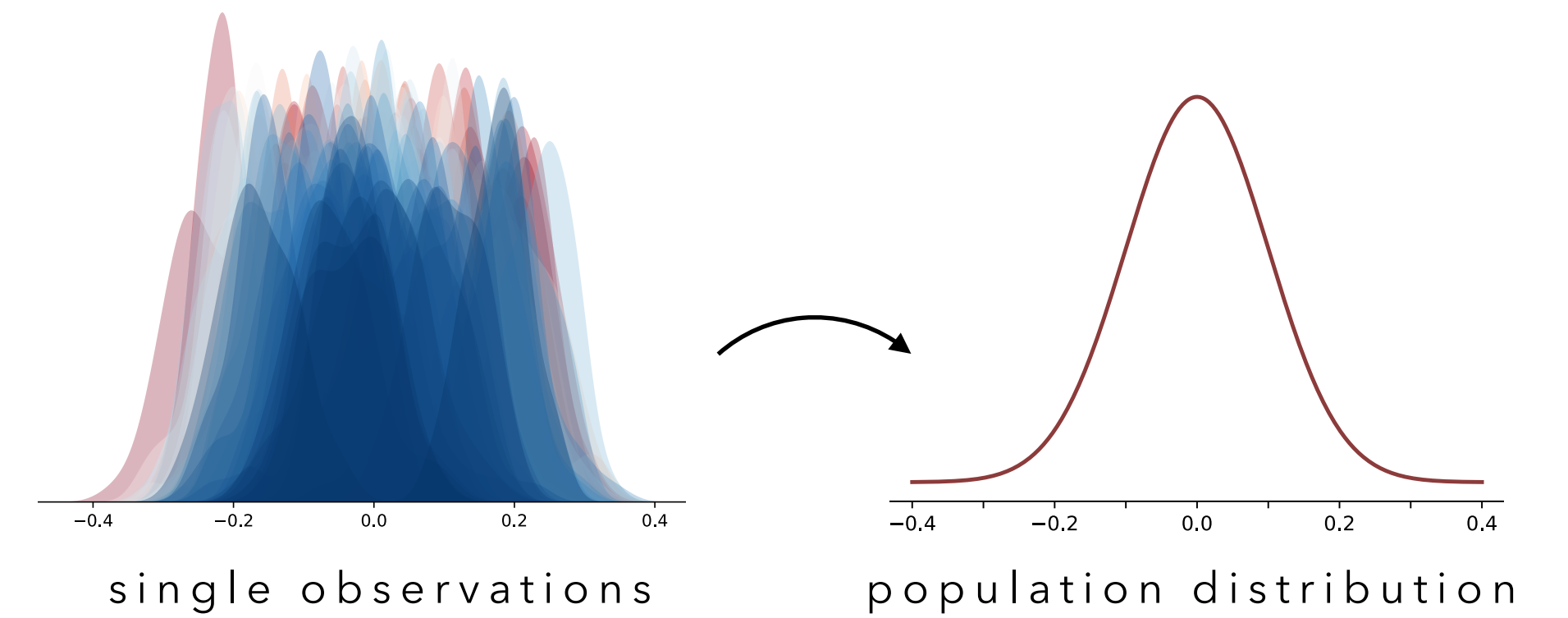


1. population studies

STATISTICAL FRAMEWORK

[1809.02063, 2007.05579, 1809.03815]

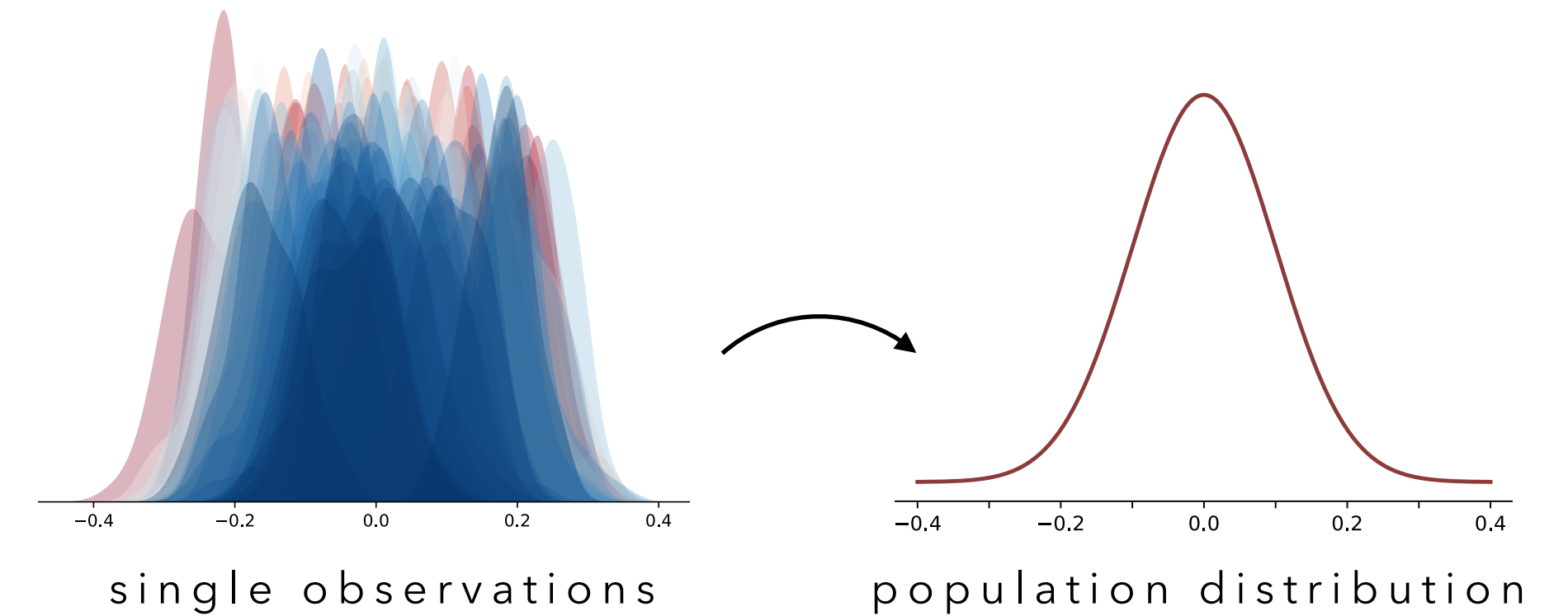
combine multiple measurements to find the most likely intrinsic probability distribution from which the observed events are drawn



STATISTICAL FRAMEWORK

[1809.02063, 2007.05579, 1809.03815]

combine multiple measurements to find the most likely intrinsic probability distribution from which the observed events are drawn



- we use Bayesian analysis

$$p(\mathbf{\Lambda}|\{\mathbf{d}\}) \propto \mathcal{L}_H(\{\mathbf{d}\}|\mathbf{\Lambda}) p(\mathbf{\Lambda})$$

Diagram illustrating the Bayesian analysis equation:

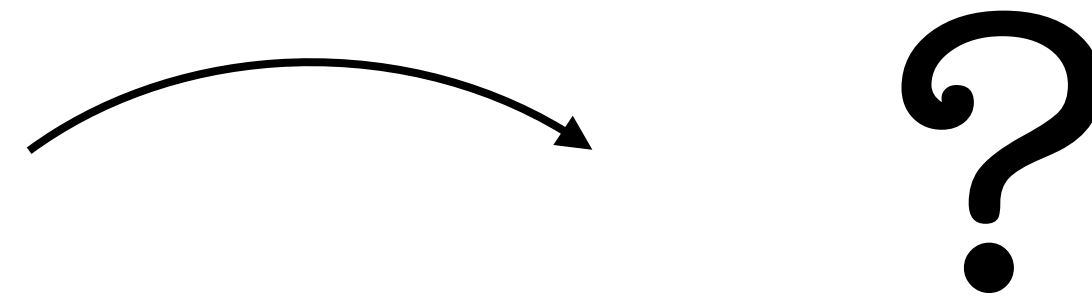
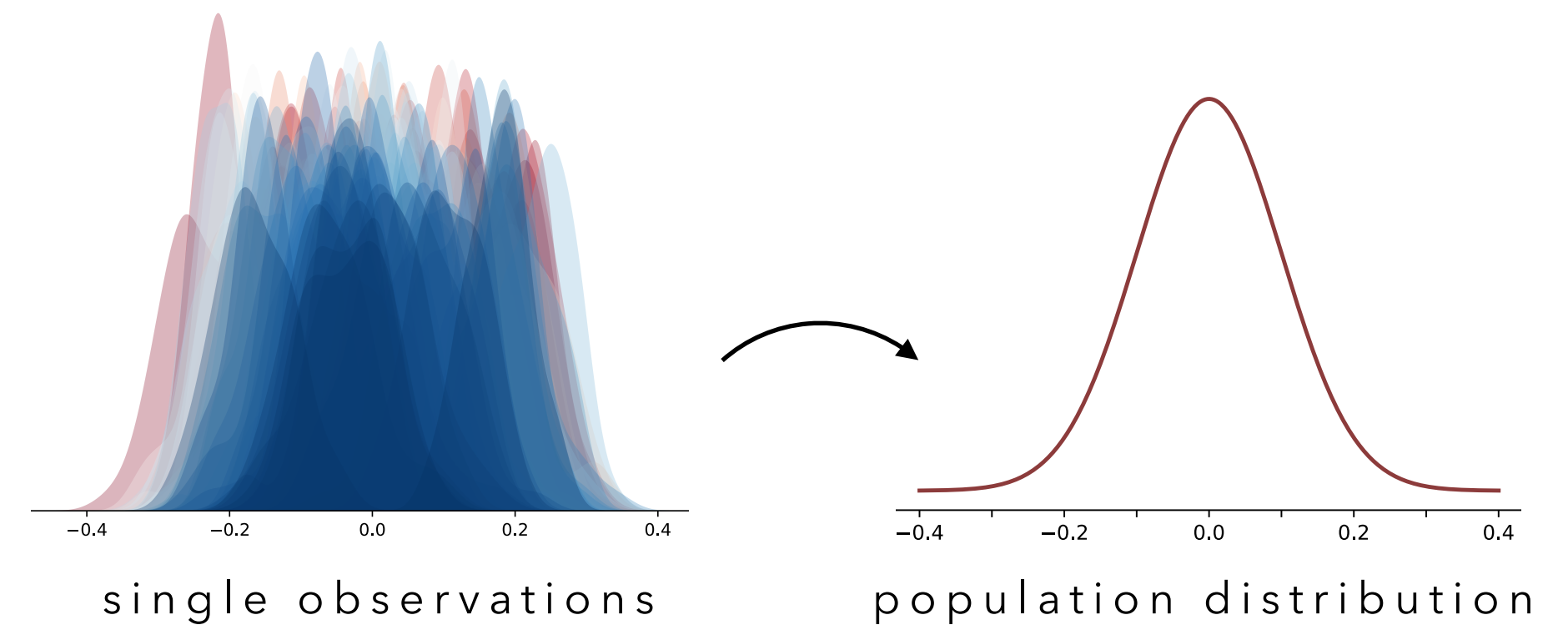
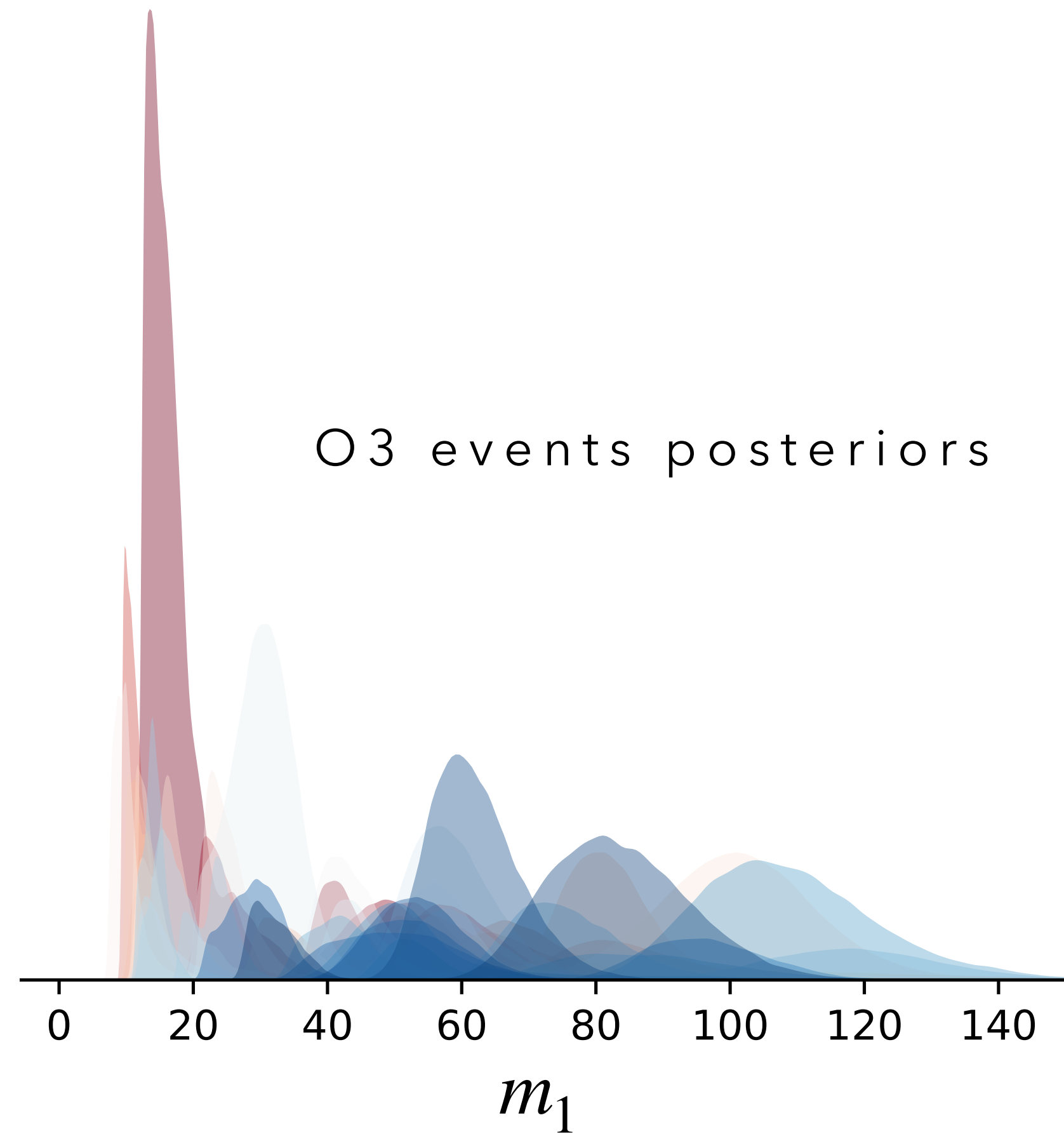
- $p(\mathbf{\Lambda}|\{\mathbf{d}\})$ is labeled as the **posterior**.
- $\mathcal{L}_H(\{\mathbf{d}\}|\mathbf{\Lambda})$ is labeled as the **(hierarchical) likelihood**.
- $p(\mathbf{\Lambda})$ is labeled as the **prior**.

$$p(\text{model} | \text{data}) \longleftrightarrow p(\text{data} | \text{model})$$

functional form
for the BH
distribution

GW events
to be
combined

BLACK HOLES POPULATION

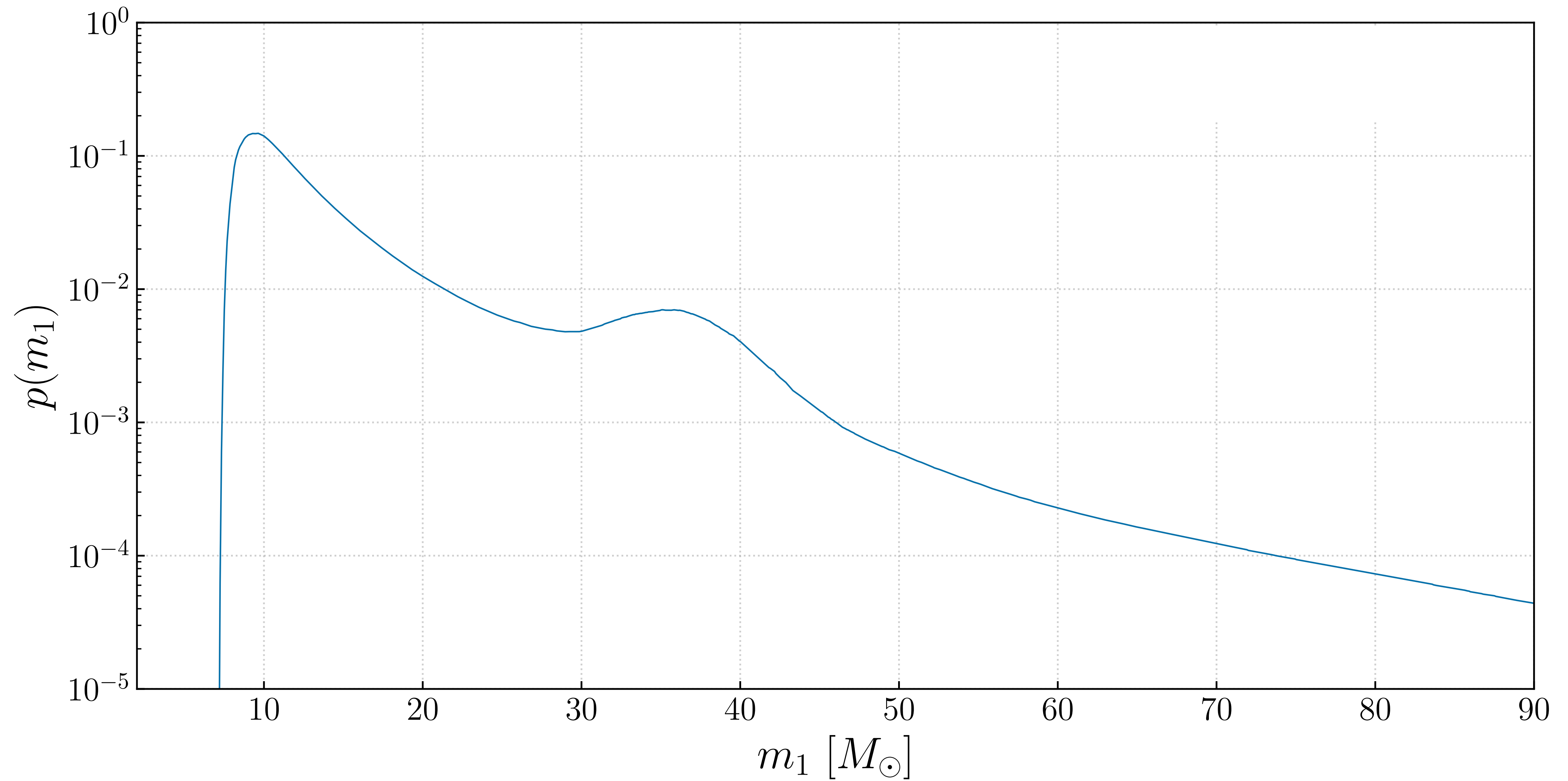


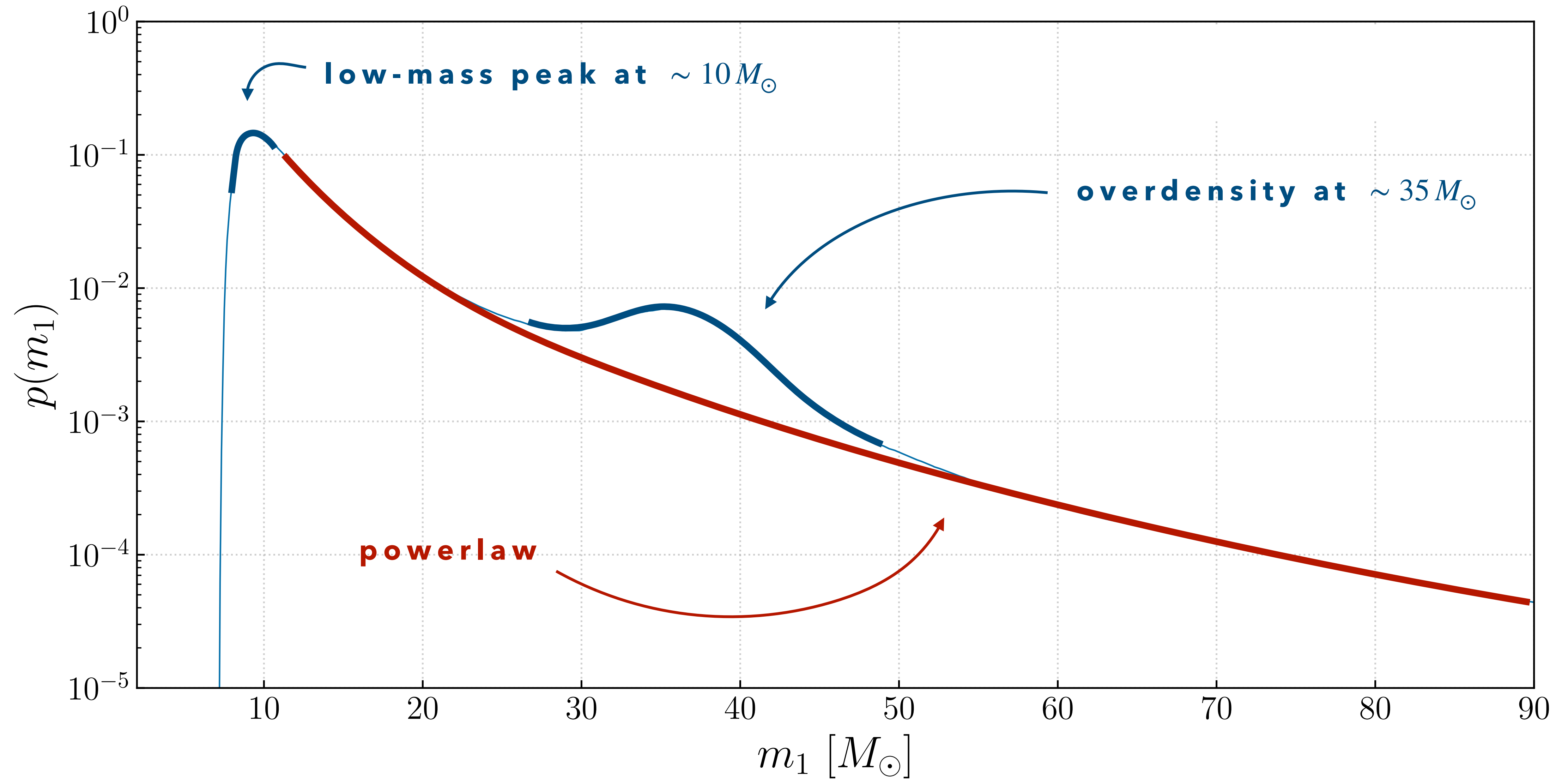
what is the predicted shape of the
astrophysical BH distribution?

→ we don't know in advance!



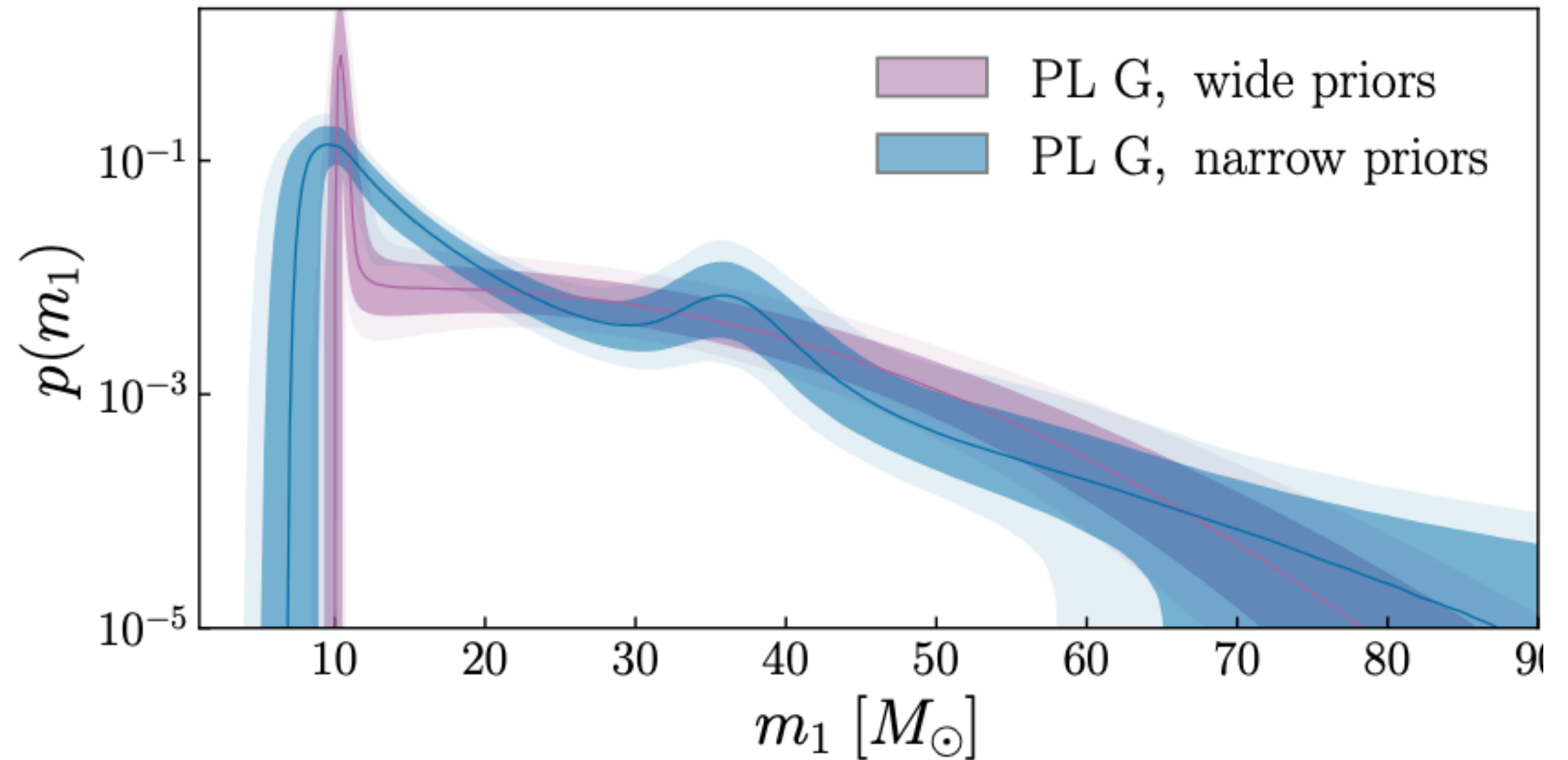
2. real data





O3 DATA 2 FEATURES

mass model
Powerlaw
+ Gaussian



- results depend on the prior bounds
- with wide priors, find sharp low-mass peak and loose the $\sim 35 M_\odot$ overdensity
- the pink analysis is statistically preferred by Bayes factor ($\ln B \simeq 5$)

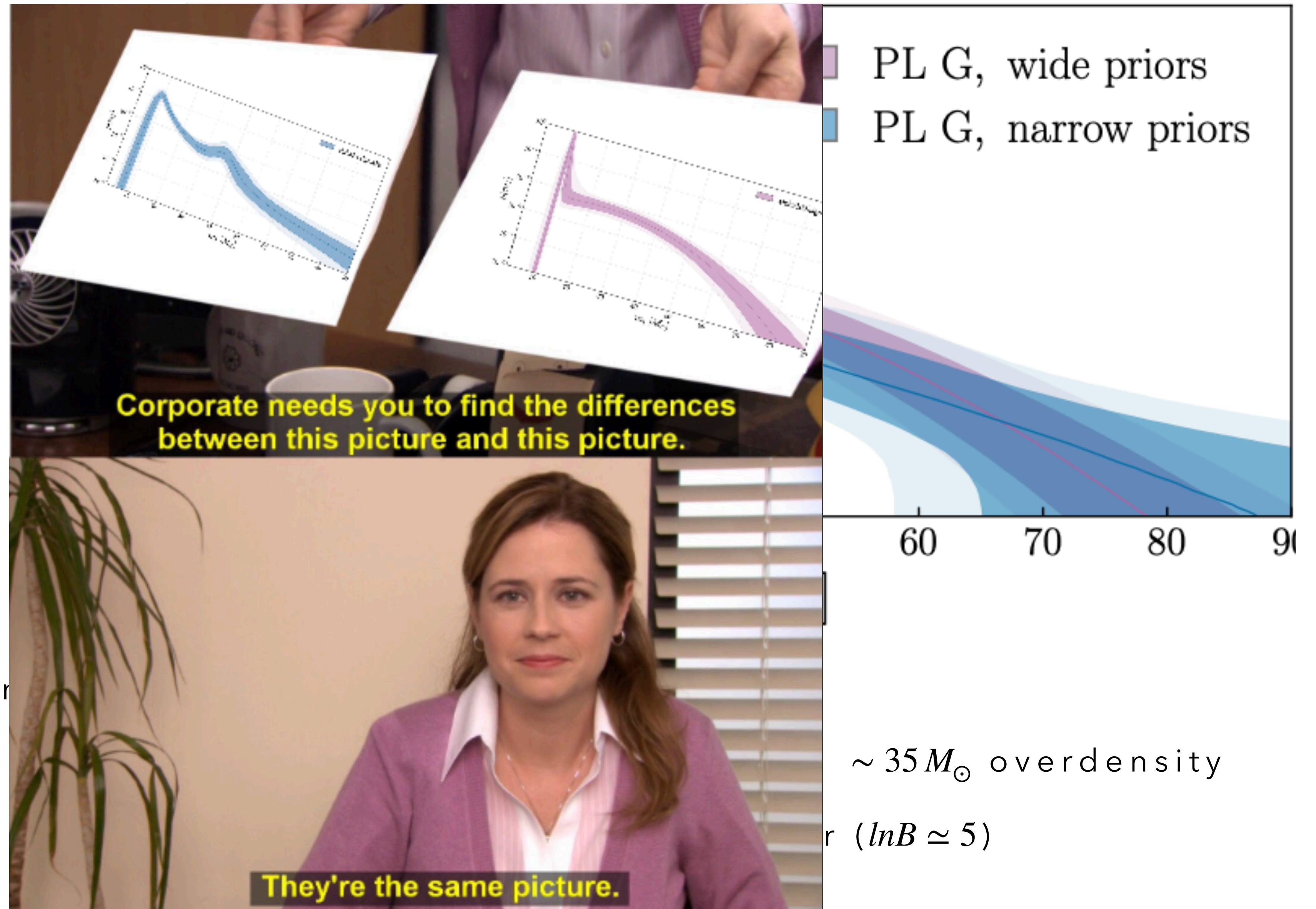
O3 DATA 2 FEATURES

mass model

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- results depend on
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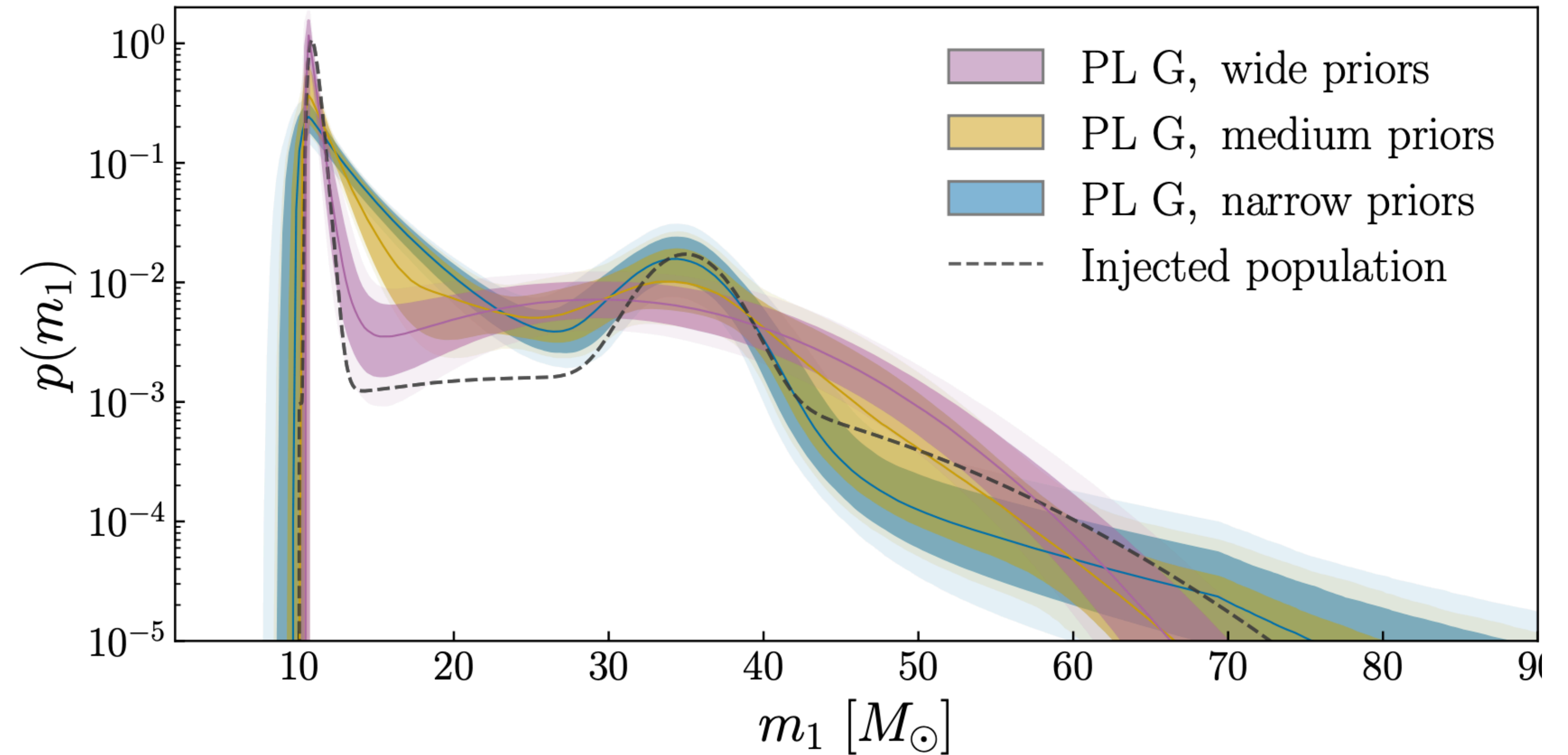


SIMULATED DATA

mass model

Powerlaw

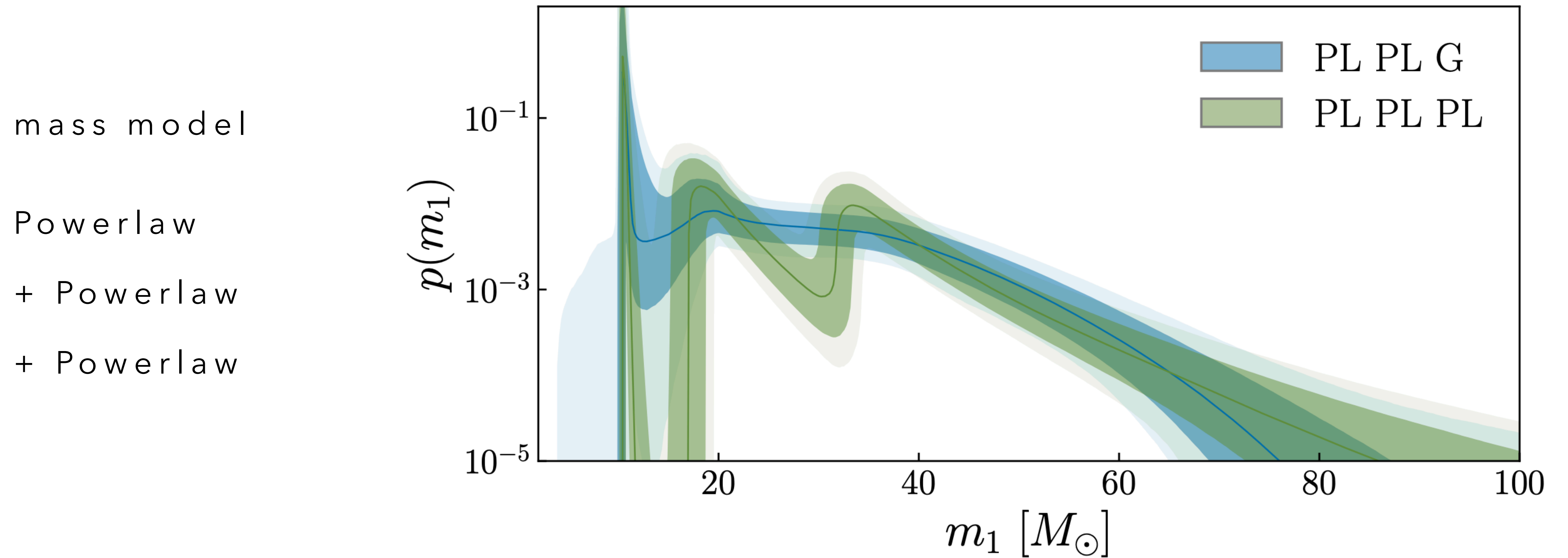
+ Gaussian



- simulate data from a population with both $10M_\odot$ peak and $\sim 35M_\odot$ overdensity
- reproduce the results on real data (bimodal hierarchical likelihood)

can we resolve both features simultaneously?

O3 DATA 3 FEATURES



- additional features resolve both the sharp $10 M_\odot$ and $\sim 35 M_\odot$ peaks
- evidence for additional structure at $\sim 15 - 20 M_\odot$
- the PL-PL-PL is slightly preferred over the wide priors PL-G ($\ln B \simeq 0.3$)

O3 DATA 3 FEATURES

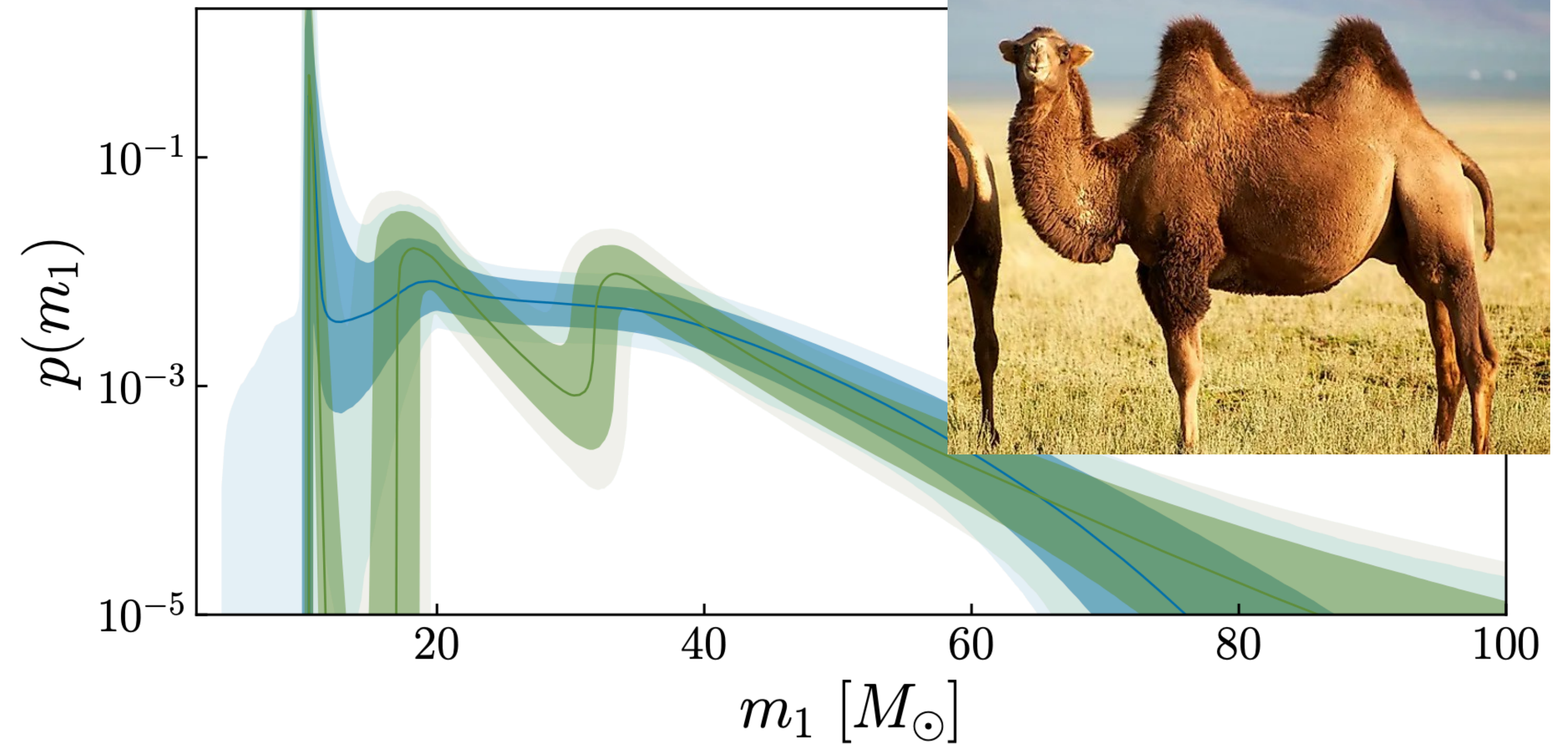
mass model

Powerlaw

+ Powerlaw

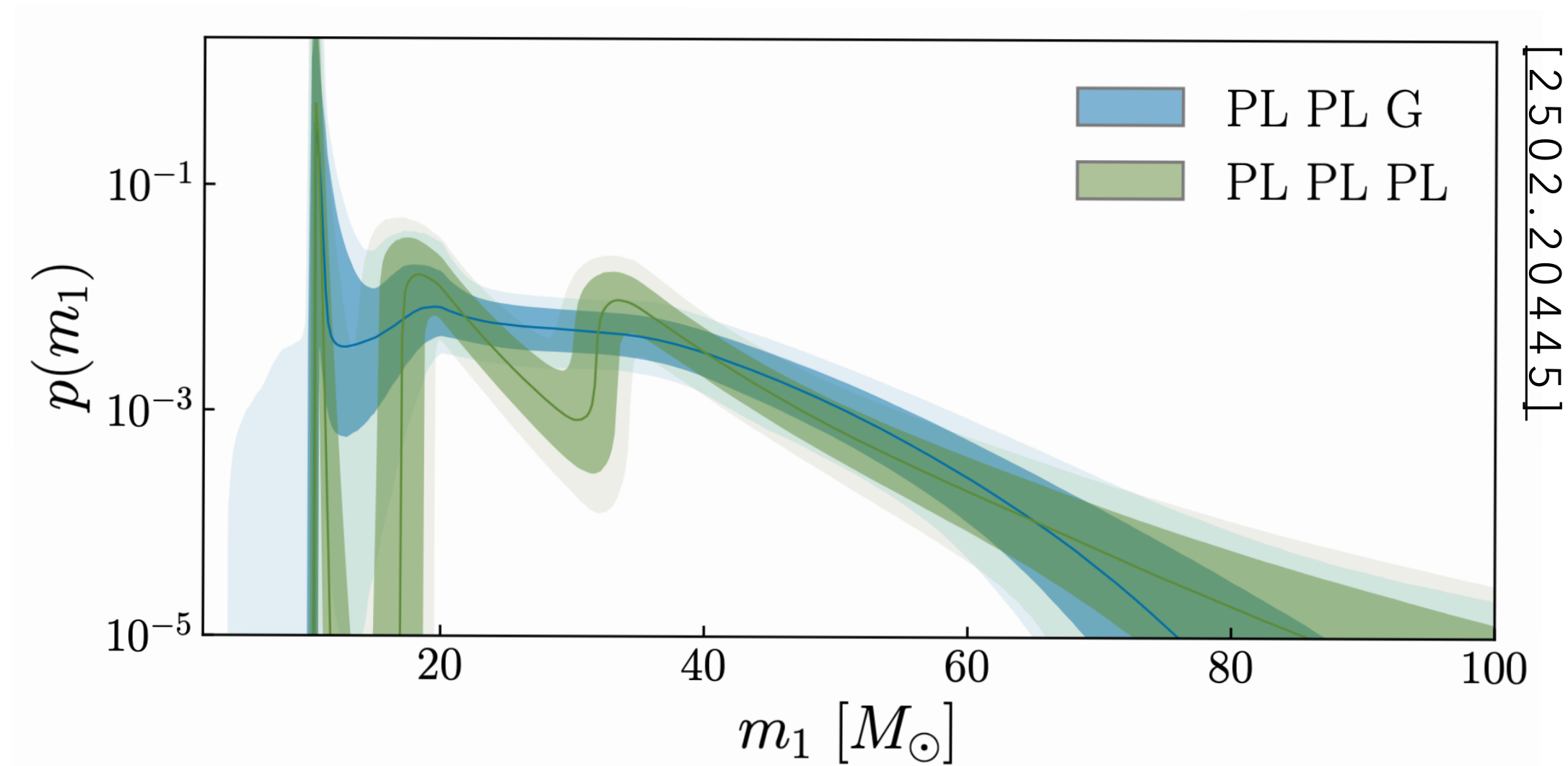
+ Powerlaw

(a.k.a. the **camel**)

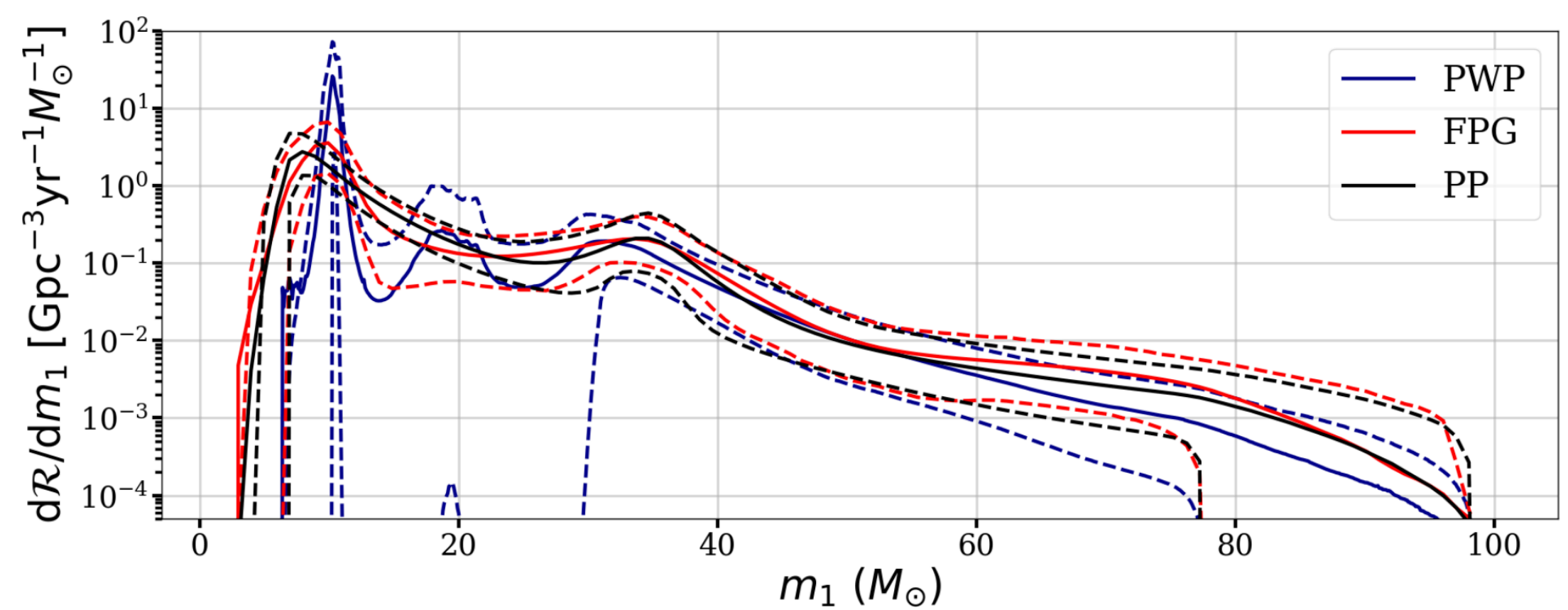


- additional features resolve both the sharp $10 M_\odot$ and $\sim 35 M_\odot$ peaks
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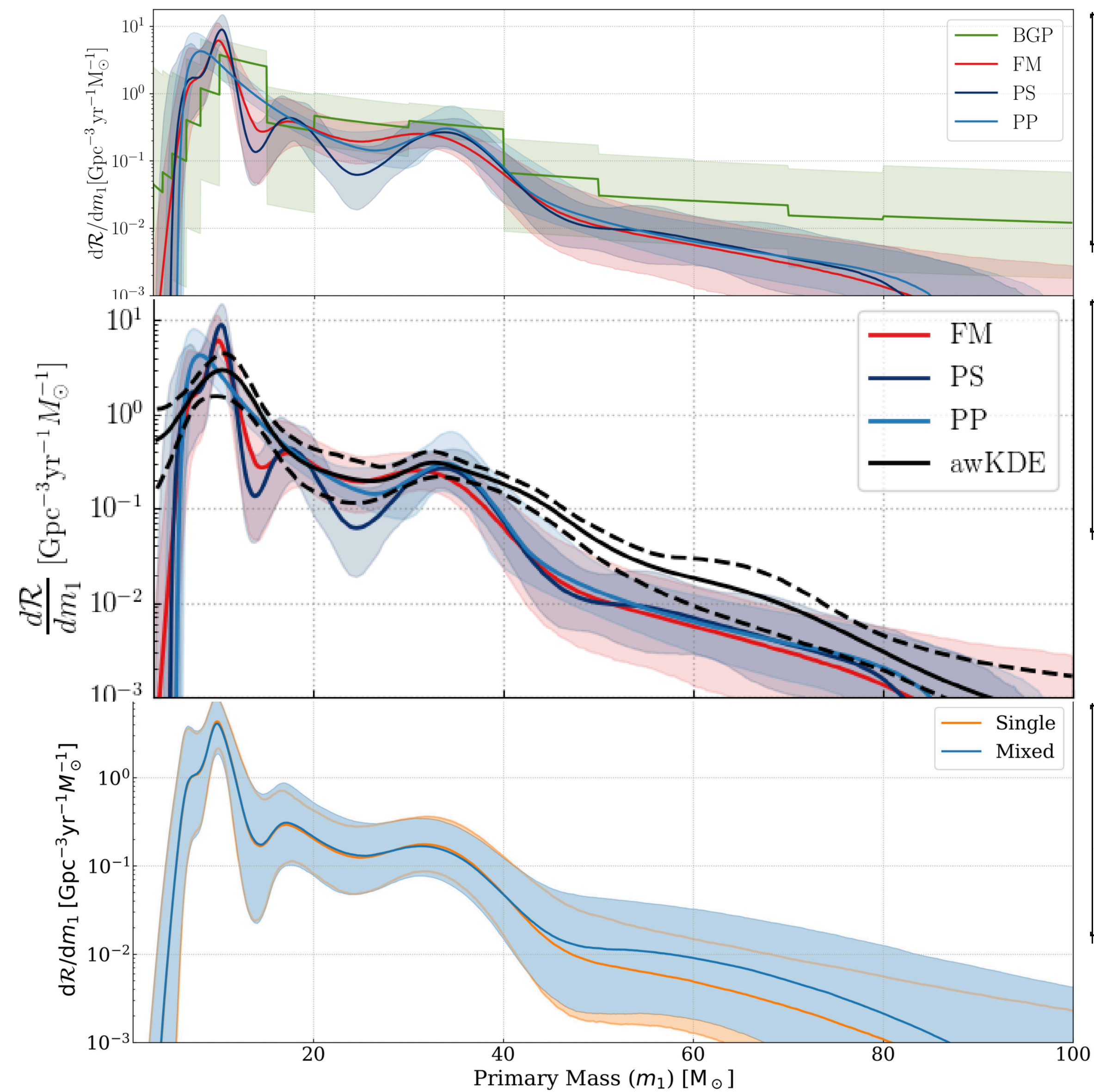
NON-PARAMETRIC COMPARISON see also [2301.00834]



[2502.20445]



[2305.08909]



[2111.03634]

[2112.12659]

[2111.13991]

INTERPRETATION

- are the sharp $10M_{\odot}$ peak and the $15M_{\odot}$ drop physical?
 - likely model-induced biases, but that's what we have today
 - future data with more events will tell us more

INTERPRETATION

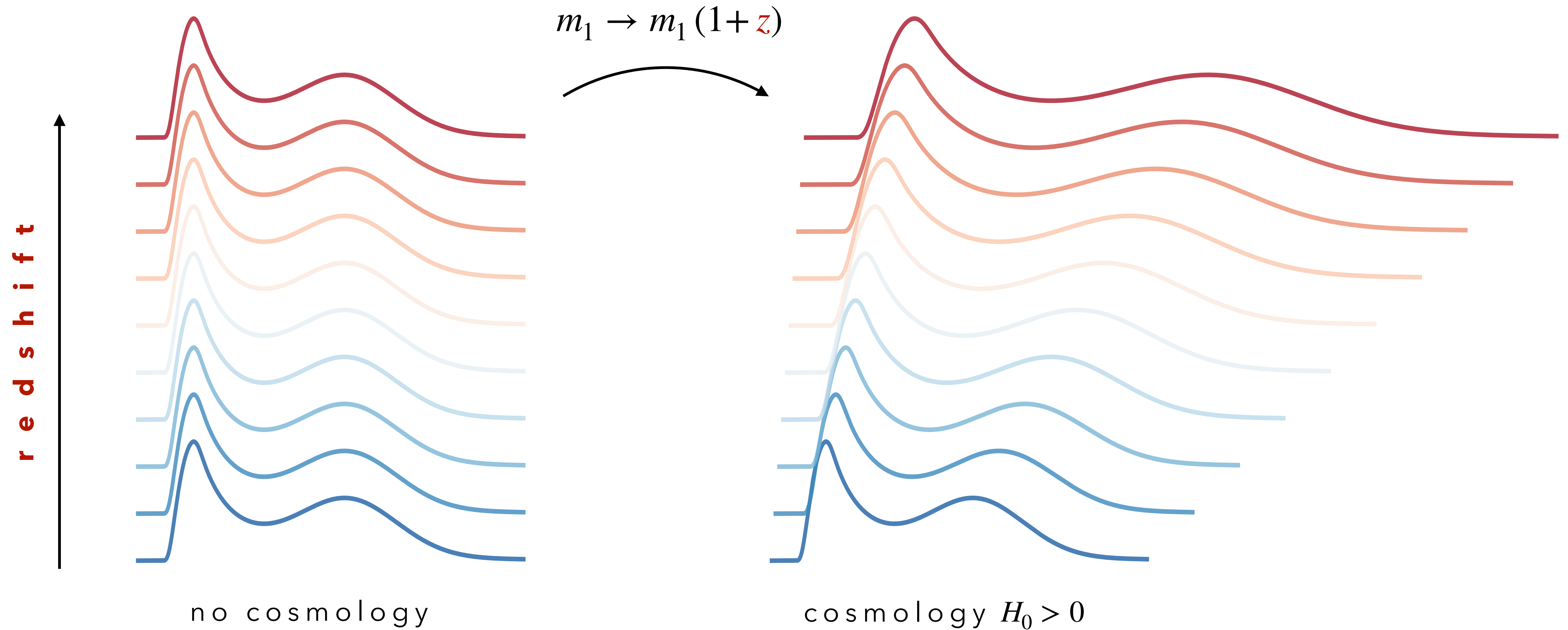
- are the sharp $10M_{\odot}$ peak and the $15M_{\odot}$ drop physical?
 - likely model-induced biases, but that's what we have today
 - future data with more events will tell us more

what can we use these results for?

3. cosmology

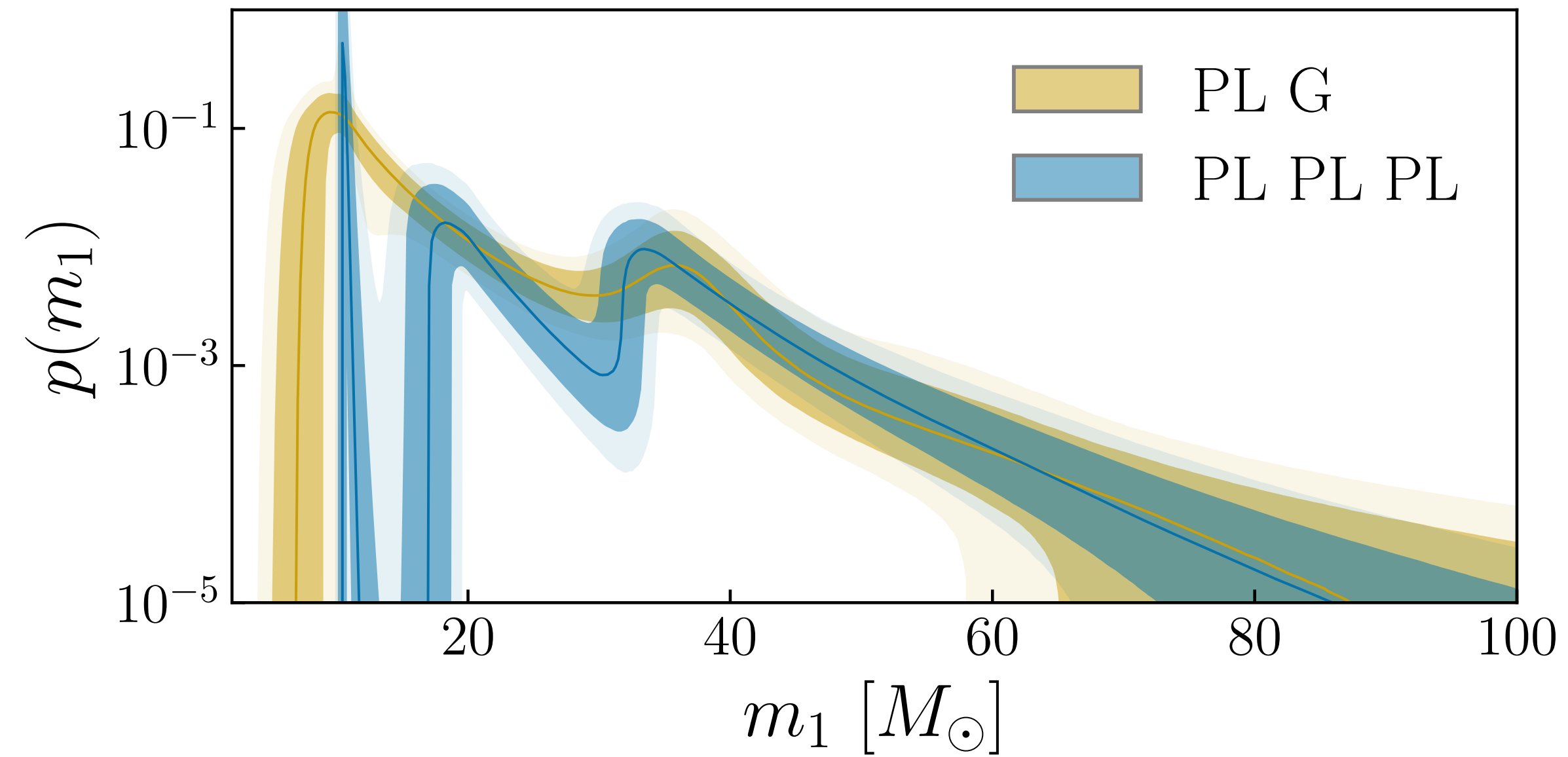
SPECTRAL SIRENS IN 1 SLIDE

features in the population contain information on redshift



COSMOLOGY WITH 3 FEATURES

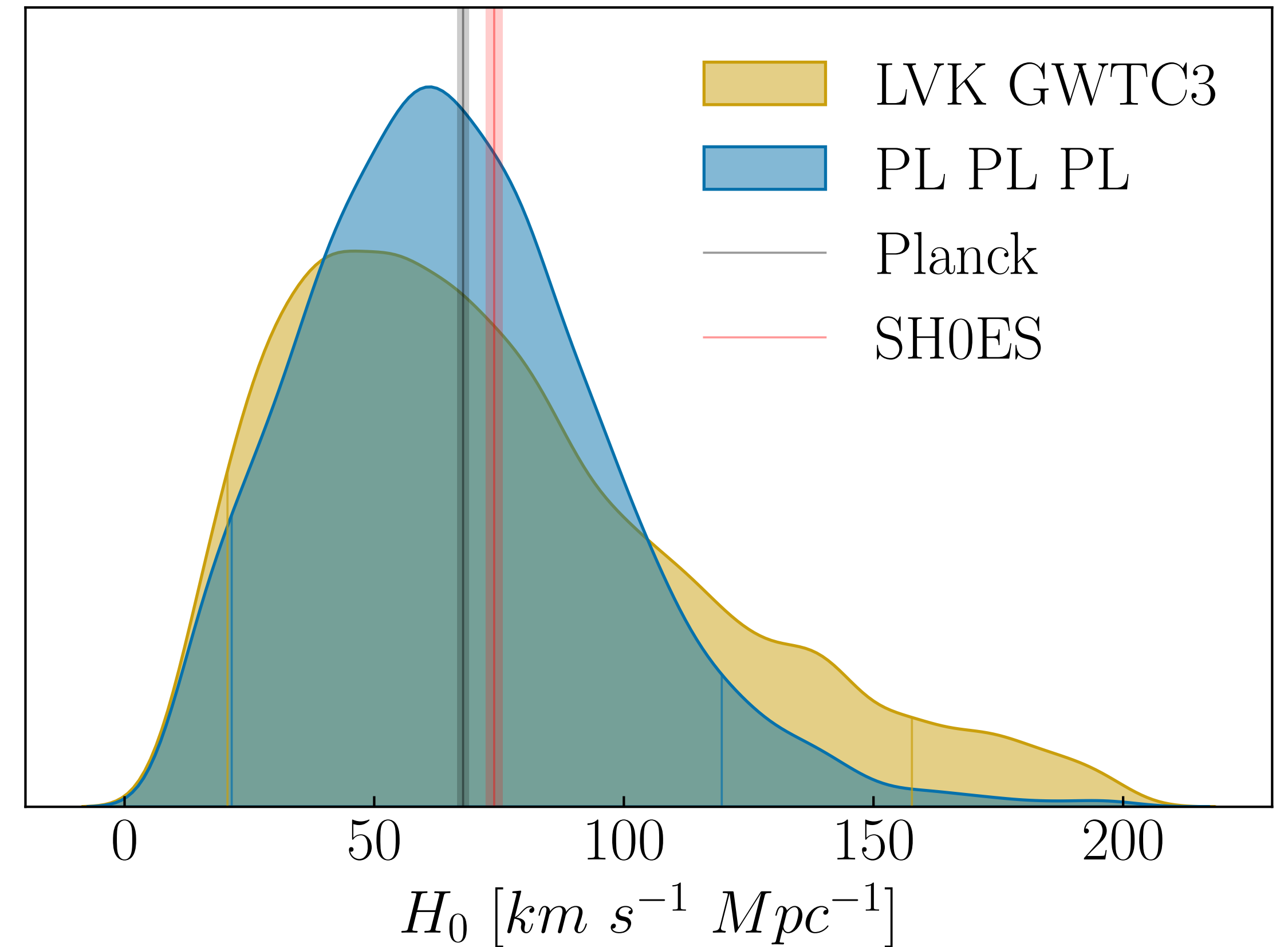
primary BH distribution



$\sim 30\%$ improvement just by
changing the mass model

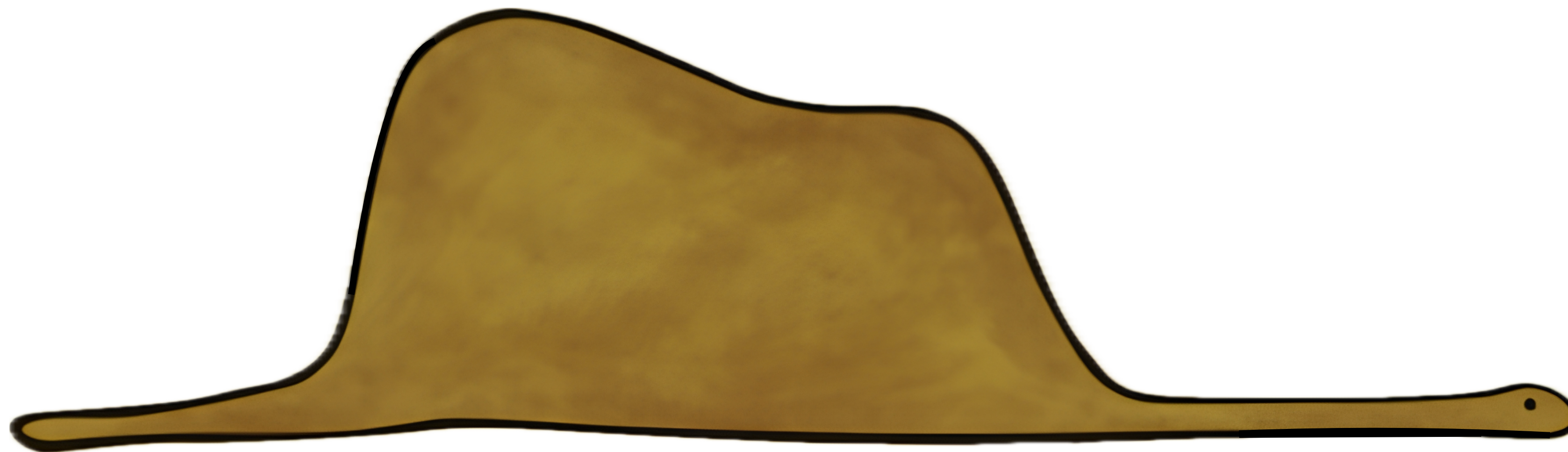
$$H_0 = 66^{+91}_{-46} \longrightarrow H_0 = 64^{+55}_{-42}$$

PRELIMINARY



CONCLUSIONS

- the population of black holes contains crucial information on *astrophysics* and cosmology
- the current fiducial Powerlaw-Gaussian model provides prior-dependent results
- multiple features resolve additional structure in agreement with more agnostic analyses
- such additional structure allows to improve current constraints on cosmology with only gravitational waves



ceci n'est pas une mass function.

backup slides

MODEL SETUP

$$\mathcal{L}_H(\{\mathbf{x}\}|\mathbf{\Lambda}) \propto e^{-N_{\text{exp}}(\mathbf{\Lambda})} \prod_i^{N_{\text{gw}}} T_{\text{obs}} \int d\boldsymbol{\theta} dz \mathcal{L}_{\text{gw}}(\mathbf{x}_i | \boldsymbol{\theta}, \mathbf{\Lambda}) \left[\frac{d\mathcal{N}}{d\boldsymbol{\theta} dz dt_d}(\mathbf{\Lambda}) \right]$$

$\mathcal{R}(z | \mathbf{\Lambda}) \left[p_{\text{pop}}(\boldsymbol{\theta} | z, \mathbf{\Lambda}) \right] \frac{1}{1+z} \frac{dV_c}{dz}$
 $\downarrow$
 $p_{\text{pop}}(m_1, q | z, \mathbf{\Lambda}) = p_{\text{pop}}(m_1 | z, \mathbf{\Lambda}) p_{\text{pop}}(q | \mathbf{\Lambda})$

- evolving parametrization

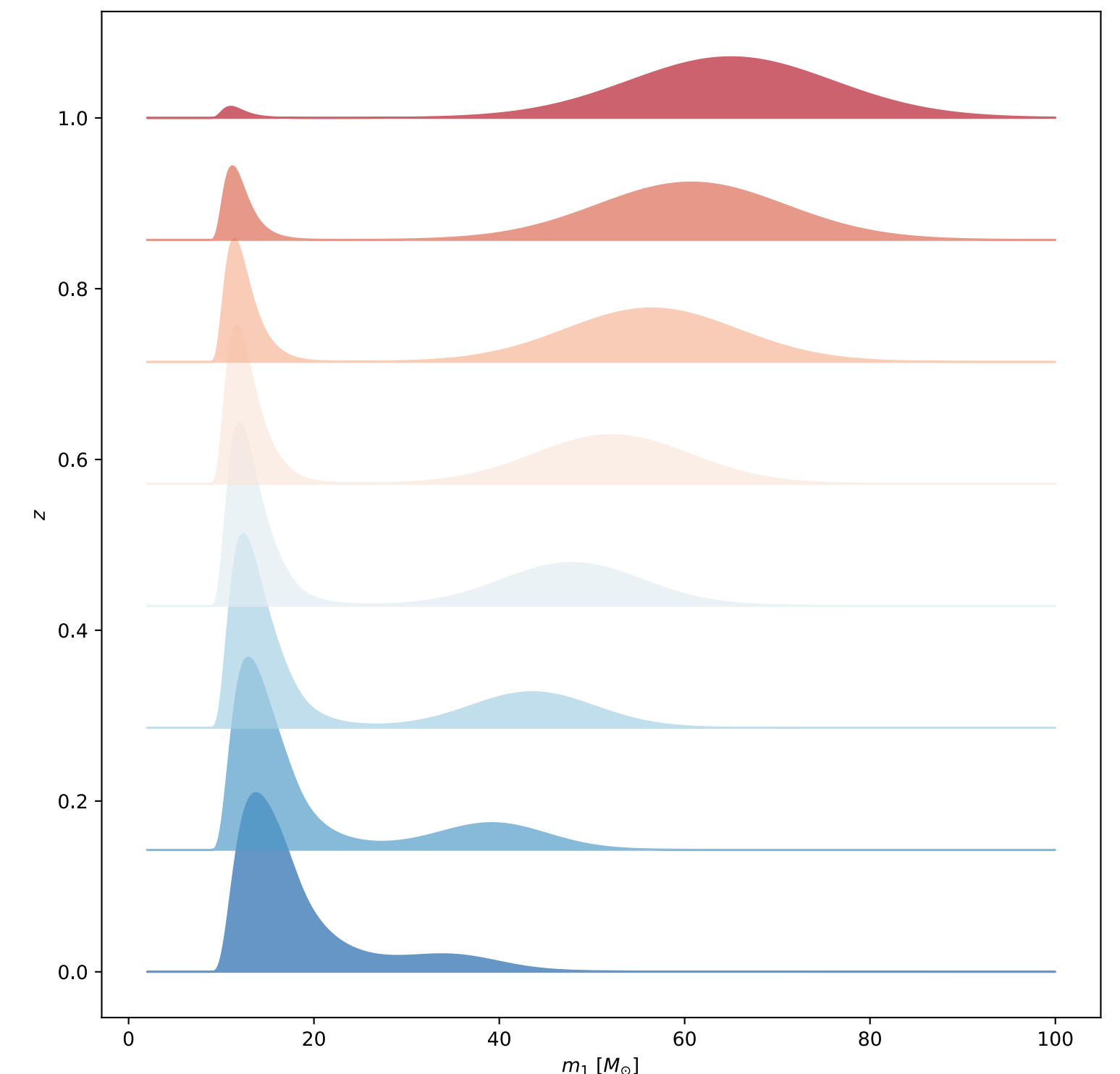
- evolution of each feature

- evolving mixture

$$p_{\text{pop}}(m_1 | z, \mathbf{\Lambda}) \sim \lambda(z) PL[\mathbf{\Lambda}_1(\mathbf{f}_1(z))] + [1 - \lambda(z)] G[\mathbf{\Lambda}_2(\mathbf{f}_2(z))]$$

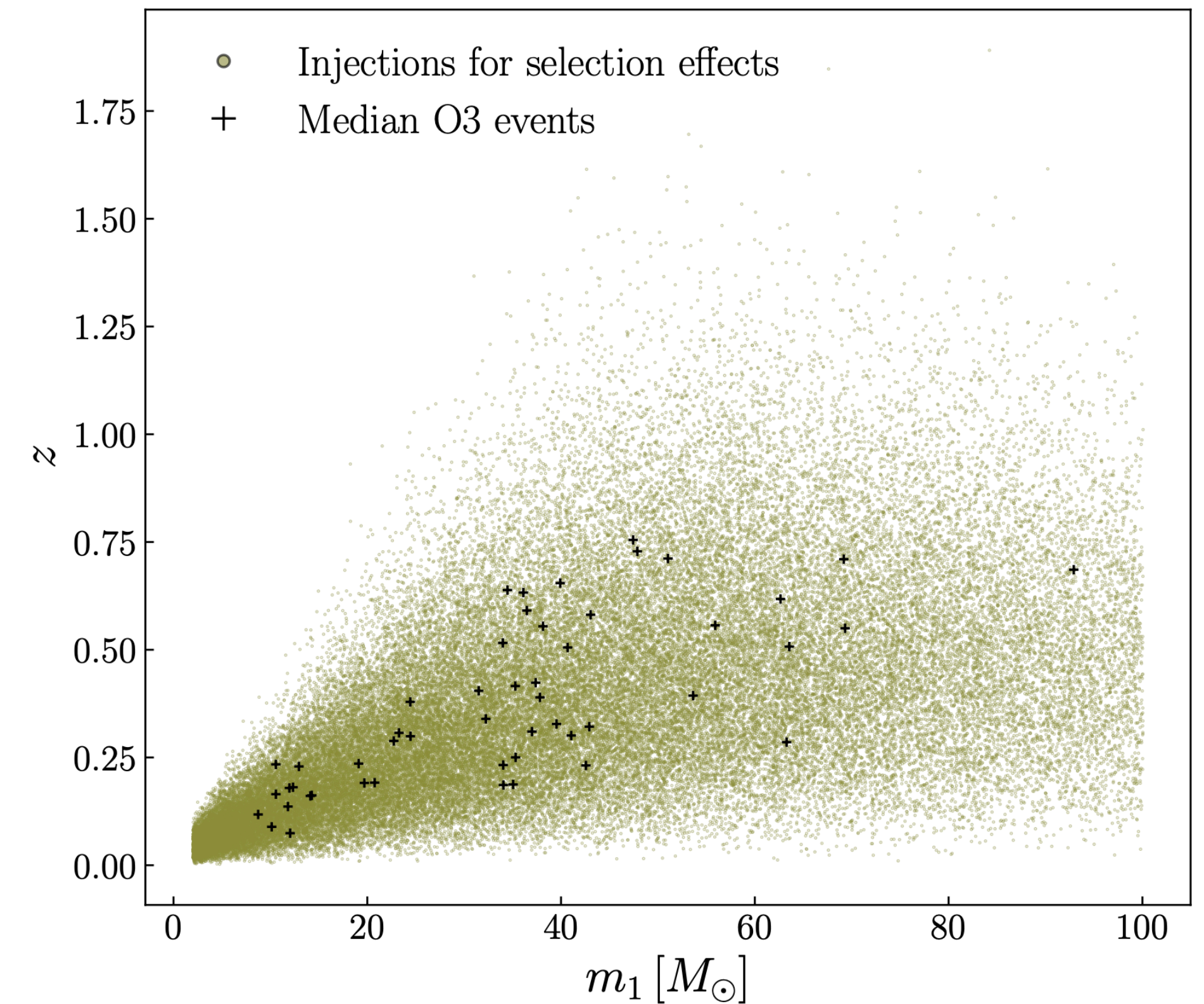
- we focus on **linear** redshift evolution

$$\mathbf{f}_i(z) = \mathbf{f}_{i,0} + \mathbf{f}_{i,1} z \quad \lambda(z) = (\lambda_1 - \lambda_0) z + \lambda_0$$



SETTINGS

- O3 data
 - 50 events (w/o GW190521 and GW190412)
- R&P O3 injections for selection effects
 - cut $IFAR > 4$
- ICAROGW pipeline
 - dynesty (2000 live points)
 - $N_{eff,PE} = 10, N_{eff,inj} = 200$
 - neglecting the spins
 - *fixed cosmology*



MODEL VALIDATION

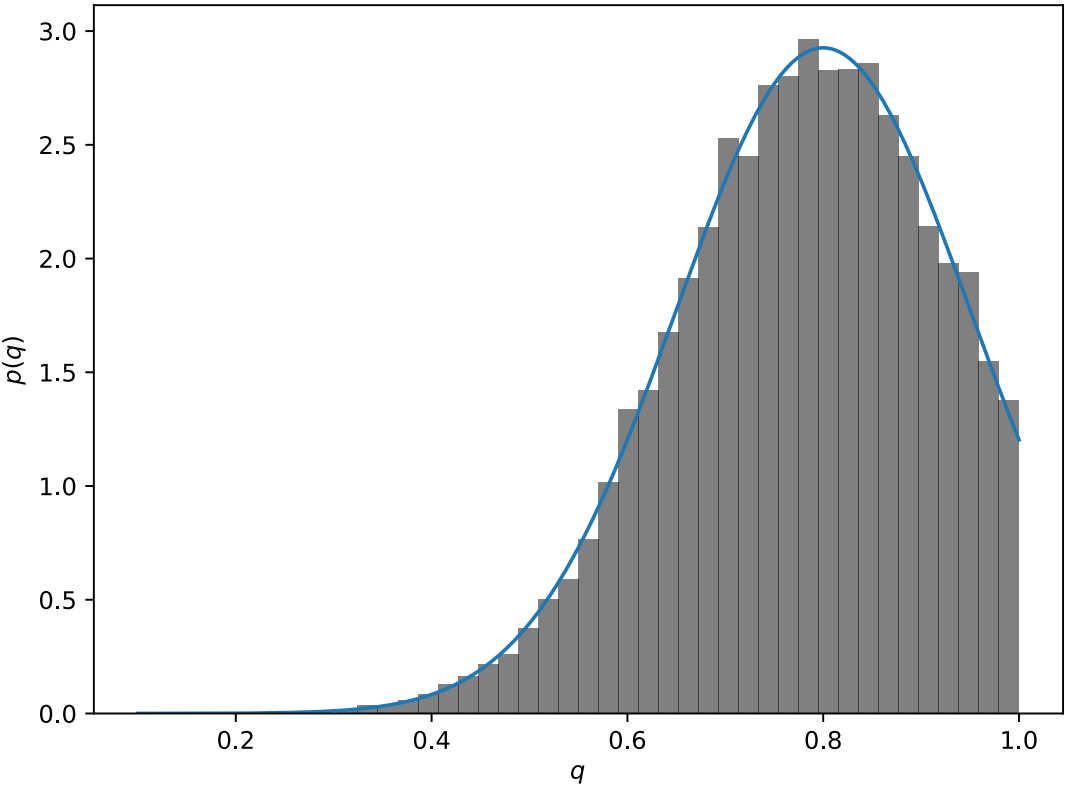
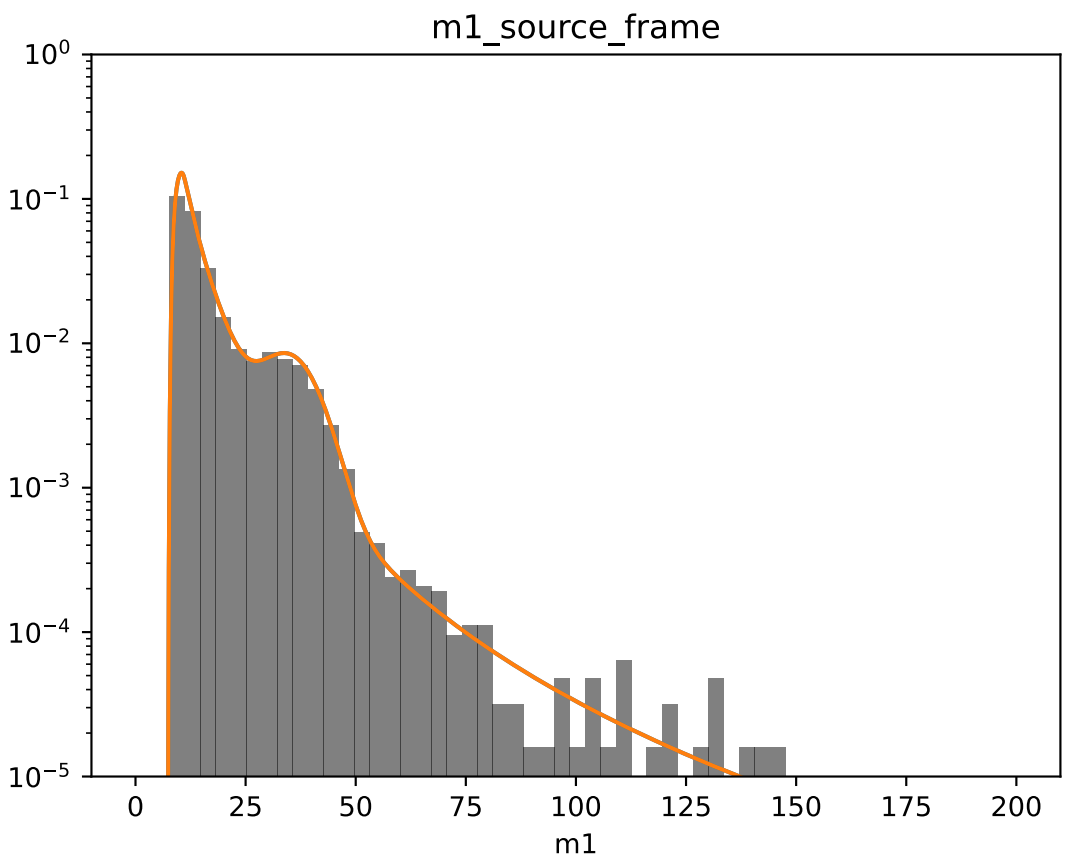
α	m_{min}	m_{max}	μ_{z_0}	σ_{z_0}	mix_{z_0}	δ_m	μ_q	σ_q	γ
3.8	7	150	35	6	0.9	5	0.8	0.15	0

- injections from **PowerLaw-Gaussian**

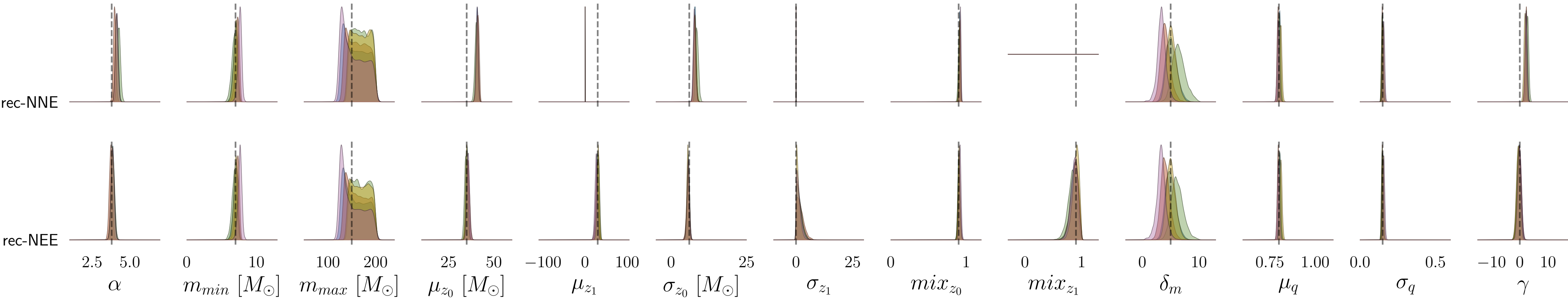
- a. stationary ($\mu_{z_1} = 0$)
 - b. evolving gaussian ($\mu_{z_1} = 30$)

- recovery

- a. non evolving ($\mu_{z_1} = 0$)
 - b. evolving ($\mu_{z_1} = [-80, 80]$)



$N_{events} \sim 1300$



MODELS & PRIORS

Primary stationary										Mass ratio & rate evolution			
Powerlaw-Gaussian wide priors α (−4, 200) $m_{\min}$ (1, 100) $m_{\max}$ (30, 200) δ_m (0, 10) μ (1, 60) σ (1, 30) mix (0, 1)										Gaussian (truncated) μ_q (0.1, 1) σ_q (0.01, 0.9)			
Powerlaw-Gaussian narrow priors α (−4, 12) $m_{\min}$ (1, 100) $m_{\max}$ (30, 200) δ_m (0, 10) μ (1, 60) σ (1, 6) mix (0, 1)										Madau-Dickinson γ (−50, 30) κ (−20, 10) z_p (0, 4) $\mathcal{R}_0$ (0, 100)			
Powerlaw-Gaussian-Gaussian α (−4, 200) $m_{\min}$ (1, 15) $m_{\max}$ (30, 200) μ_a (10, 20) σ_a (1, 30) μ_b (20, 60) σ_b (1, 30) mix $_{\alpha}$ (0, 1) mix $_{\beta}$ (0, 1)													
Powerlaw-Powerlaw-Gaussian α_a (−4, 200) $m_{\min_a}$ (1, 15) $m_{\max_a}$ (30, 200) α_b (−4, 20) $m_{\min_b}$ (10, 20) $m_{\max_b}$ (30, 200) μ (20, 60) σ (1, 30) mix $_{\alpha}$ (0, 1) mix $_{\beta}$ (0, 1)													
Powerlaw-Powerlaw-Powerlaw α_a (−4, 200) $m_{\min_a}$ (1, 15) $m_{\max_a}$ (30, 200) α_b (−4, 50) $m_{\min_b}$ (10, 20) $m_{\max_b}$ (30, 200) α_c (−4, 50) $m_{\min_c}$ (15, 60) $m_{\max_c}$ (30, 200) mix $_{\alpha}$ (0, 1) mix $_{\beta}$ (0, 1)													
Primary evolving													
Powerlaw-Gaussian α_{z_0} (−4, 200) $m_{\min_{z_0}}$ (1, 100) $m_{\max_{z_0}}$ (30, 200) μ_{z_0} (1, 60) σ_{z_0} (1, 30) mix $_{z_0}$ (0, 1) α_{z_1} (−200, 200) $m_{\min_{z_1}}$ (−100, 100) $m_{\max_{z_1}}$ 0 μ_{z_1} (−200, 200) σ_{z_1} (0, 200) mix $_{z_1}$ (0, 1)													
Powerlaw-Powerlaw-Powerlaw α_{az_0} (−4, 120) $m_{\min_{az_0}}$ (1, 20) $m_{\max_{az_0}}$ (30, 200) α_{bz_0} (−4, 20) $m_{\min_{bz_0}}$ (15, 25) $m_{\max_{bz_0}}$ (30, 200) α_{cz_0} (−4, 20) $m_{\min_{cz_0}}$ (25, 60) $m_{\max_{cz_0}}$ (30, 200) mix $_{\alpha_{z_0}}$ (0, 1) mix $_{\beta_{z_0}}$ (0, 1) α_{az_1} (−100, 100) $m_{\min_{az_1}}$ (−100, 100) $m_{\max_{az_1}}$ 0 α_{bz_1} (−100, 100) $m_{\min_{bz_1}}$ (−100, 100) $m_{\max_{bz_1}}$ 0 α_{cz_1} (−100, 100) $m_{\min_{cz_1}}$ (−100, 100) $m_{\max_{cz_1}}$ 0 mix $_{\alpha_{z_1}}$ (0, 1) mix $_{\beta_{z_1}}$ (0, 1)													

O3 DATA STATIONARY SUMMARY

stationary model	$\ln \mathcal{B}$	$\mathcal{L}_{\max}$
Powerlaw-Gaussian wide priors	0	-1277.3
Powerlaw-Gaussian narrow priors	-5.2 ± 0.2	-1280.3
Powerlaw-Gaussian-Gaussian	-1.1 ± 0.2	-1276.2
Powerlaw-Powerlaw-Gaussian	-1.1 ± 0.2	-1270.9
Powerlaw-Powerlaw-Powerlaw	0.3 ± 0.2	-1270.9

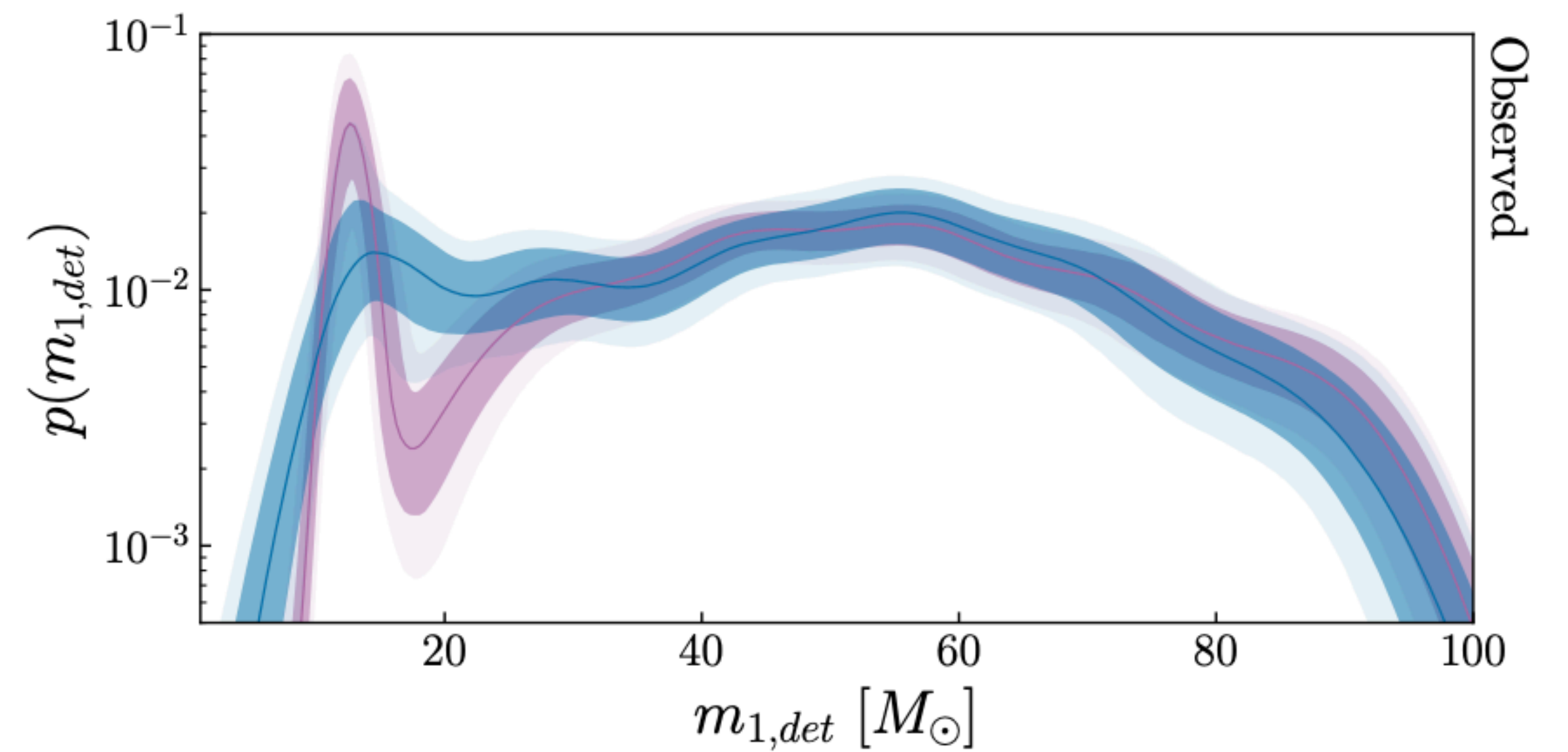
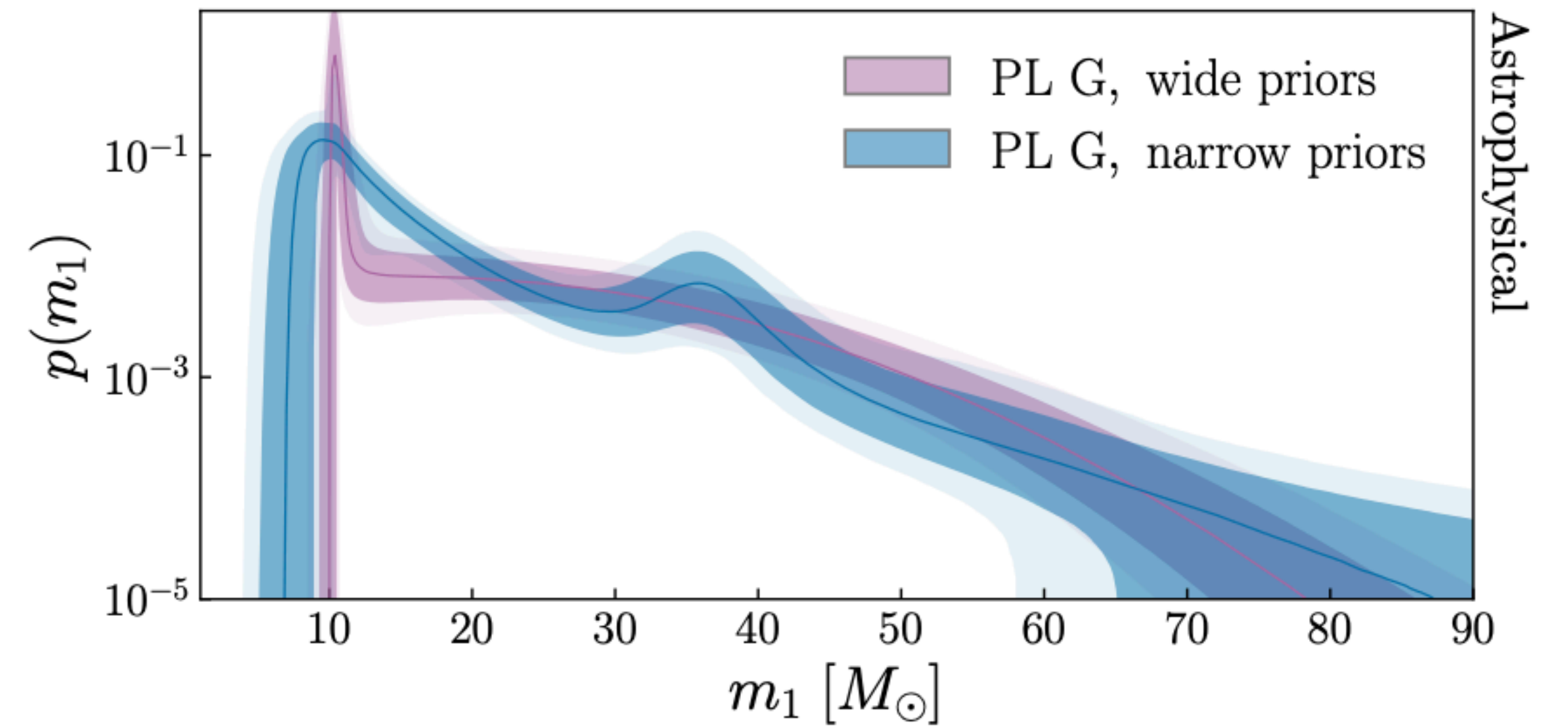
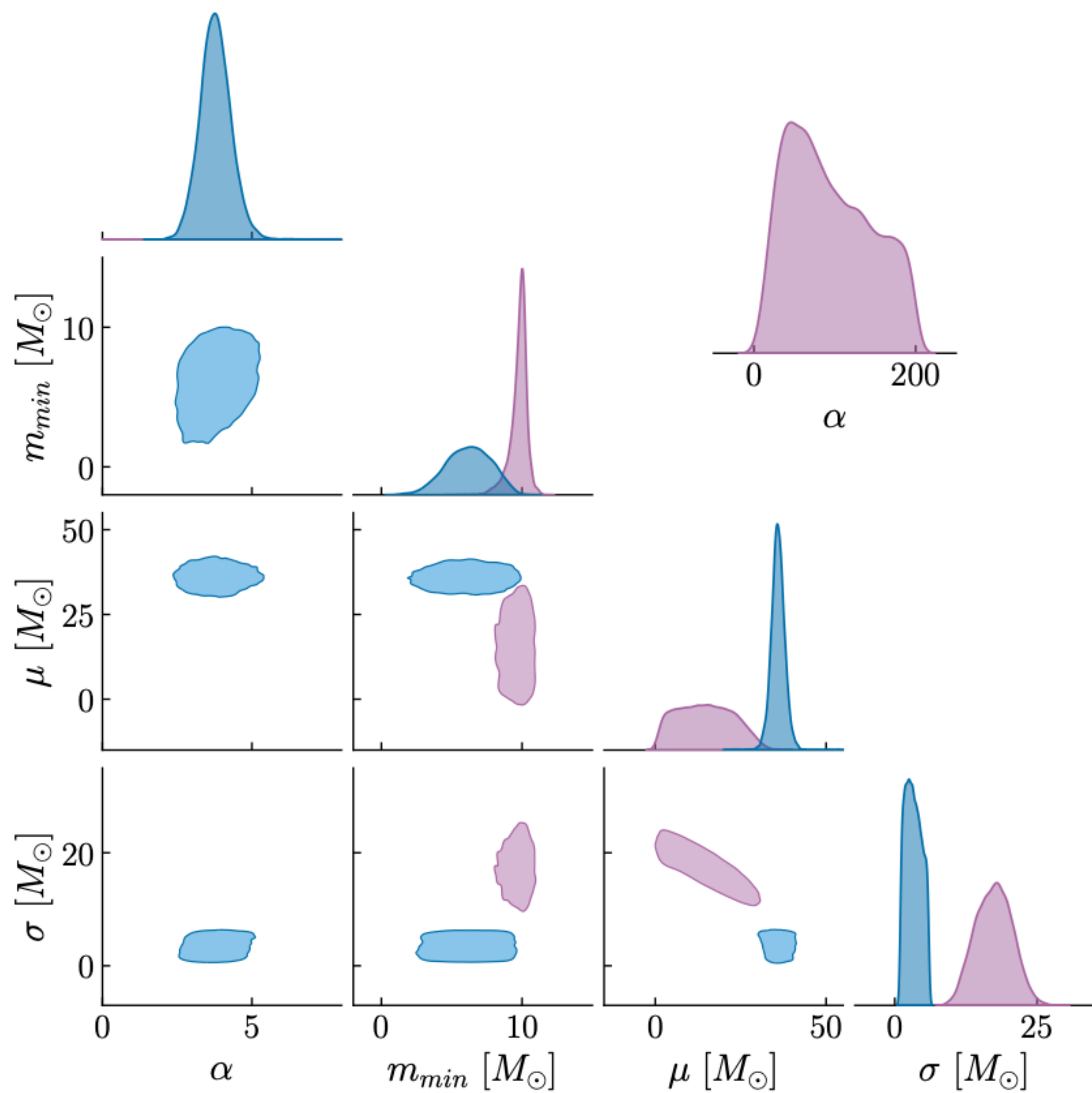
- PL-G results depend on prior bounds
 - wide priors are preferred by $\ln \mathcal{B} \sim 5$
 - reproduced with simulation
- 3-feature models can resolve additional substructure
 - PL-PL-PL comparable with (wide priors) PL-G ($\ln \mathcal{B} \sim 0.3$)
 - agreement with semi- and non-parametric literature

O3 DATA EVOLVING SUMMARY

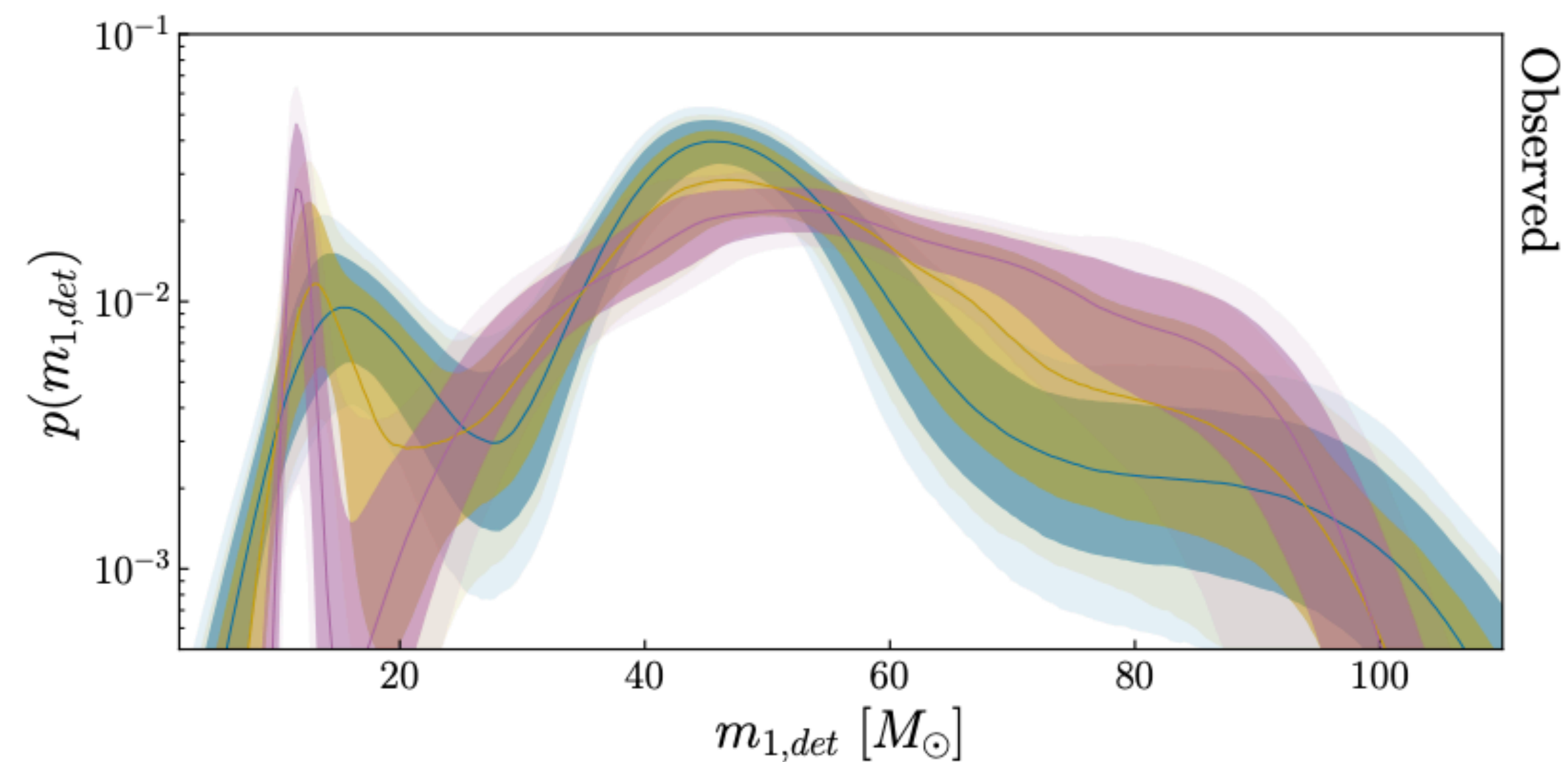
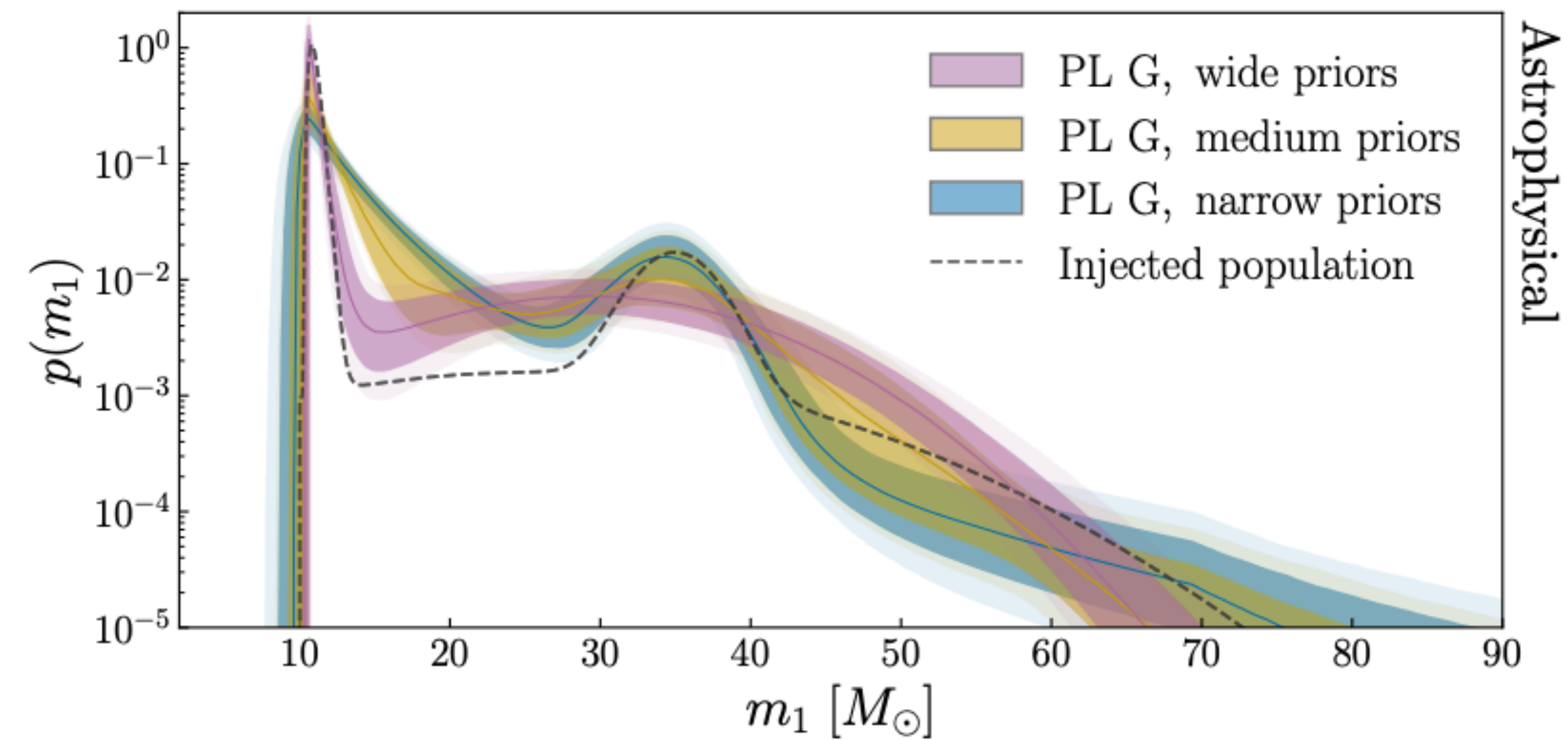
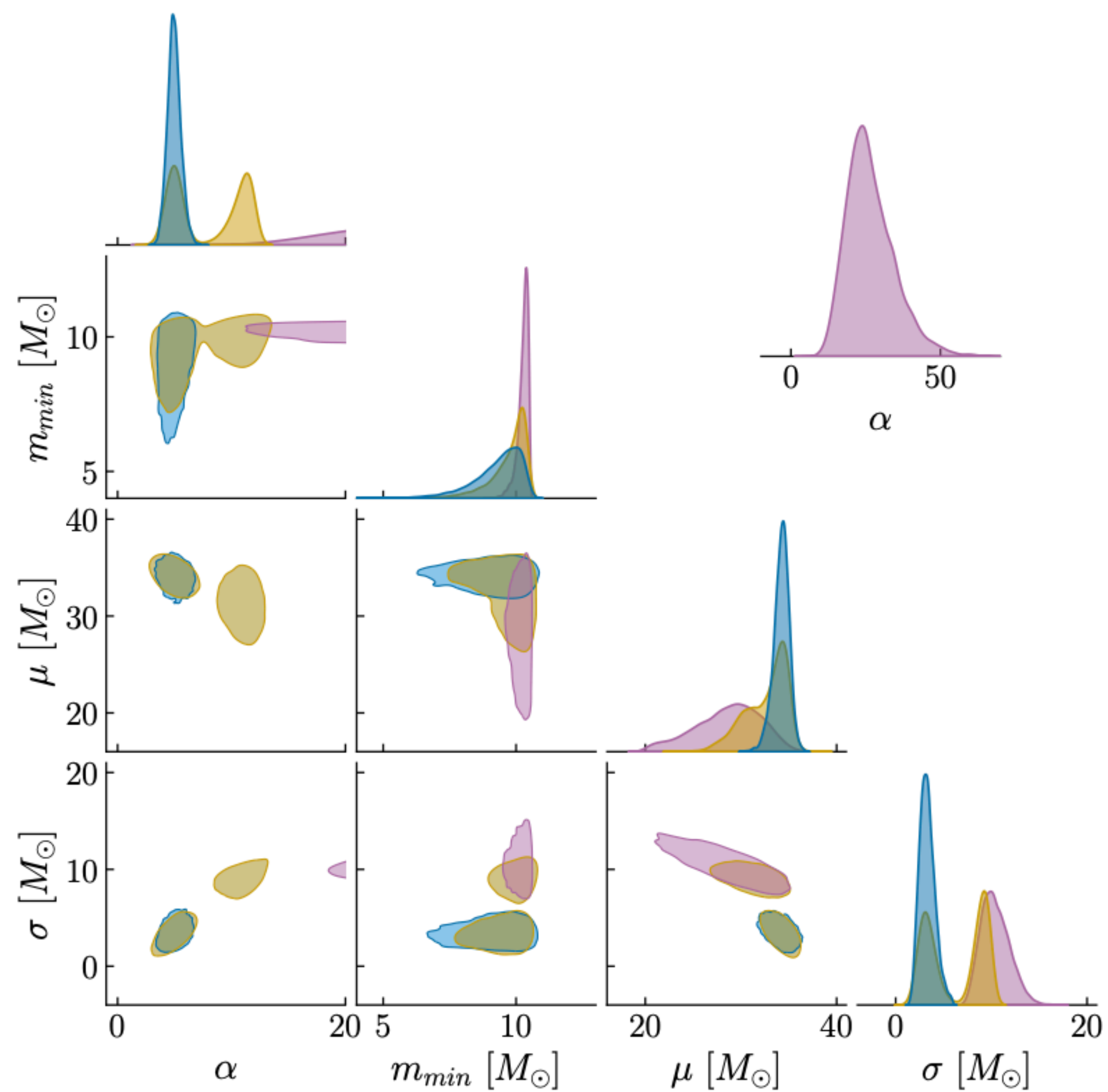
evolving	$\ln \mathcal{B}$	$\mathcal{L}_{\max}$
PL-G stationary	0	-1276.4
PL-G(z)	-3.1 ± 0.2	-1276.3
PL(z)-G	-1.9 ± 0.2	-1275.2
PL(z)-G(z)	-5.1 ± 0.2	-1275.3
PL-PL-PL stationary	0	-1270.9
PL-PL-PL(z)	-1.2 ± 0.2	-1272.5
PL-PL(z)-PL	-2.7 ± 0.2	-1273.2
PL(z)-PL-PL	-1.9 ± 0.2	-1272.3
PL(z)-PL(z)-PL(z)	-5.6 ± 0.2	-1271.5

- no support for redshift evolution
 - negative BF_s, evolving posteriors centered at zero
- interplay between evolution and selection effects
 - evolving features outside the detector horizon five same results

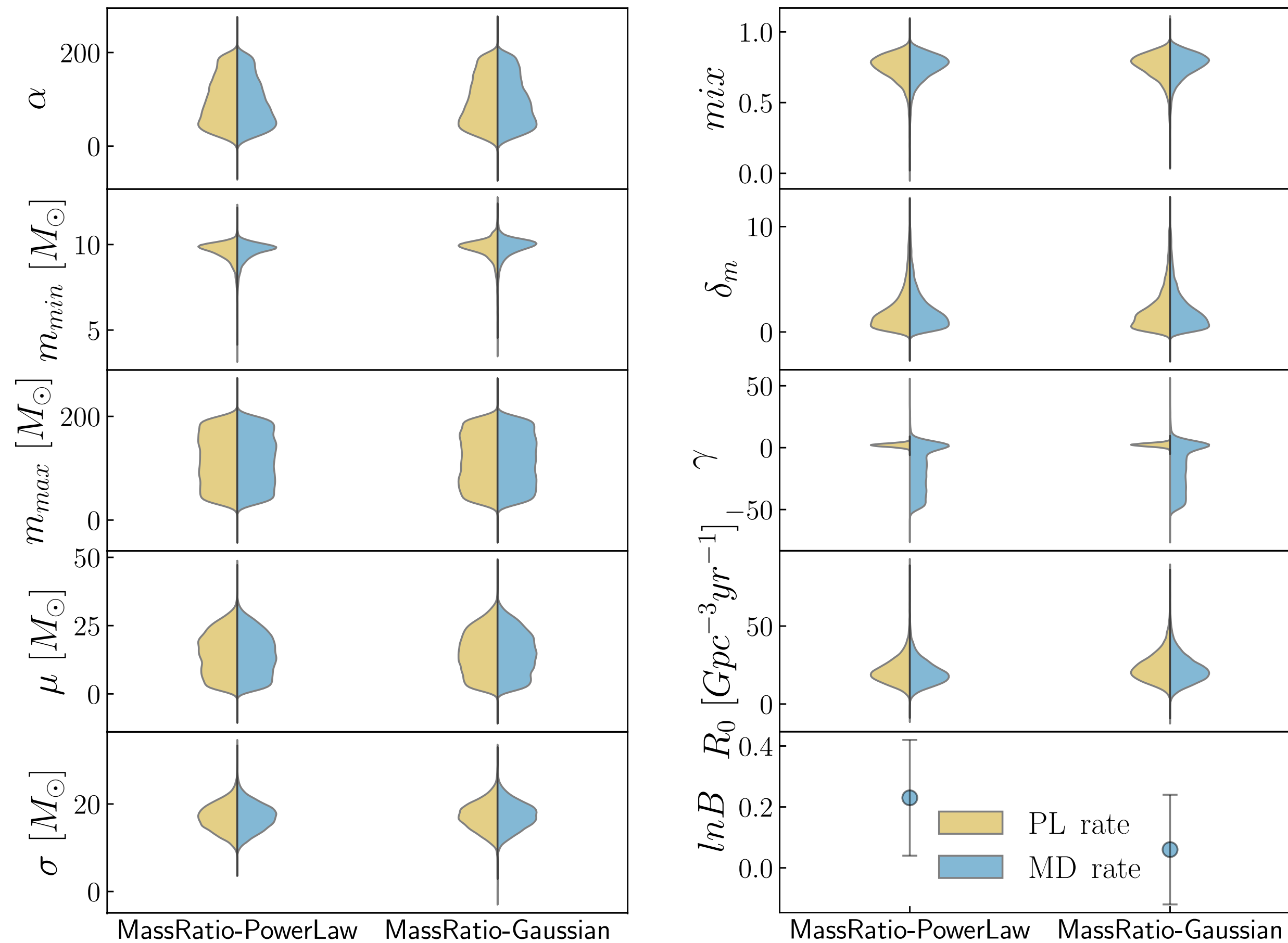
O3 DATA 2 FEATURES CORNER



SIMULATED DATA CORNER



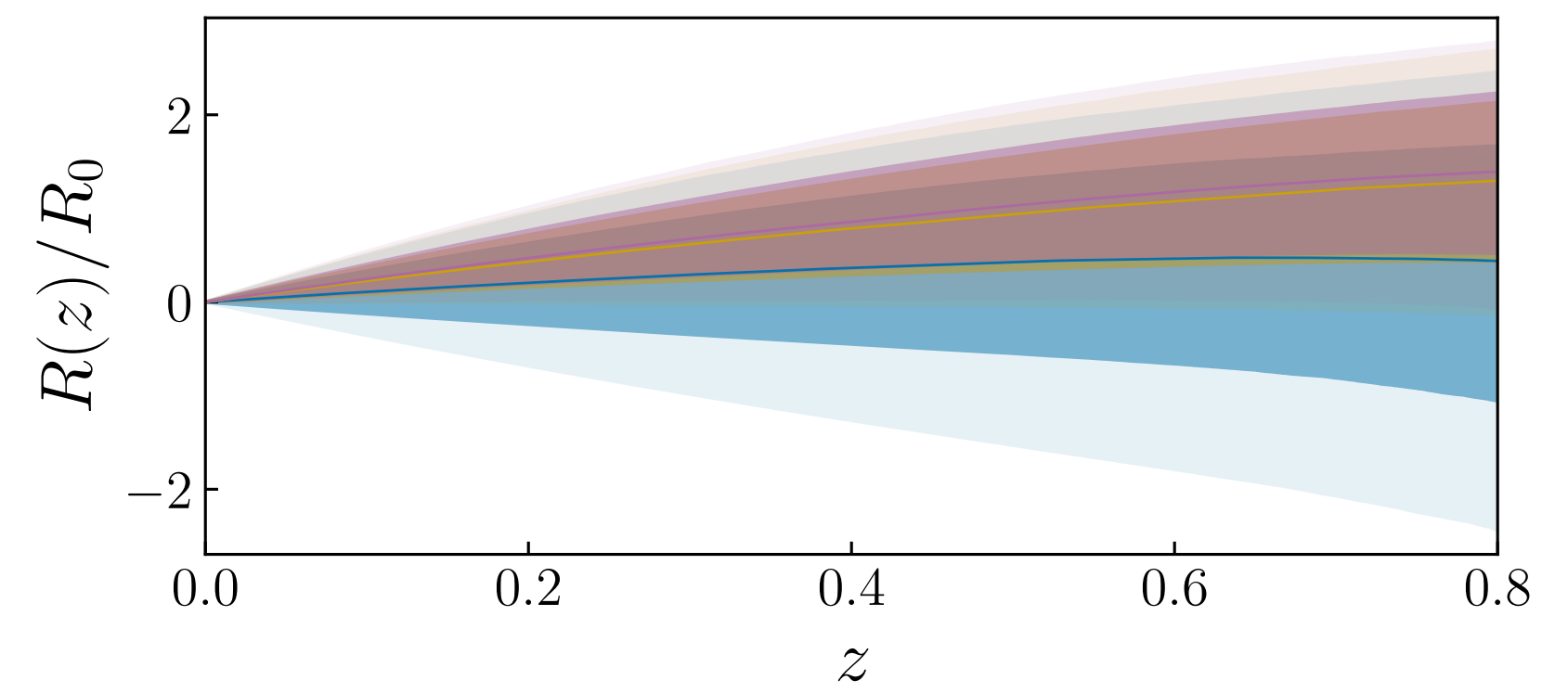
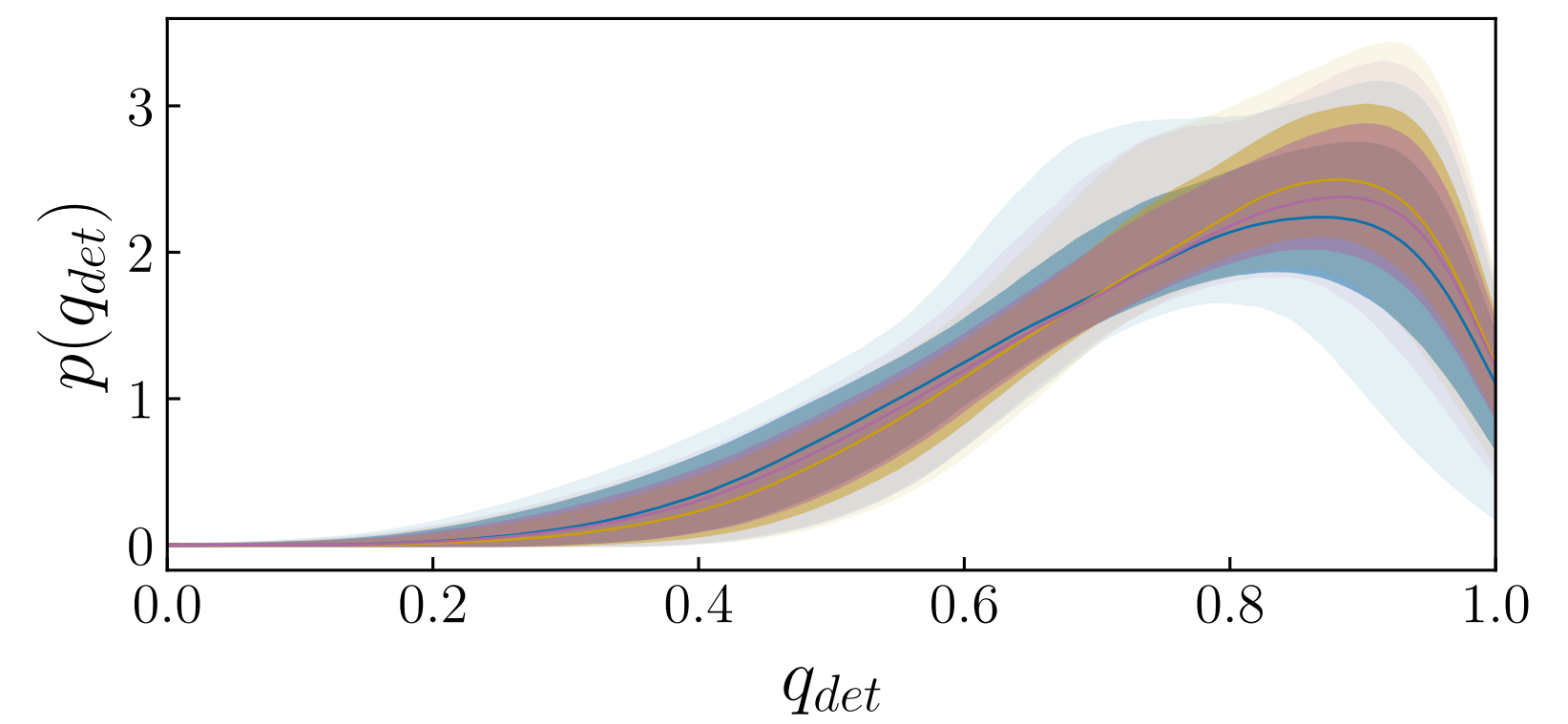
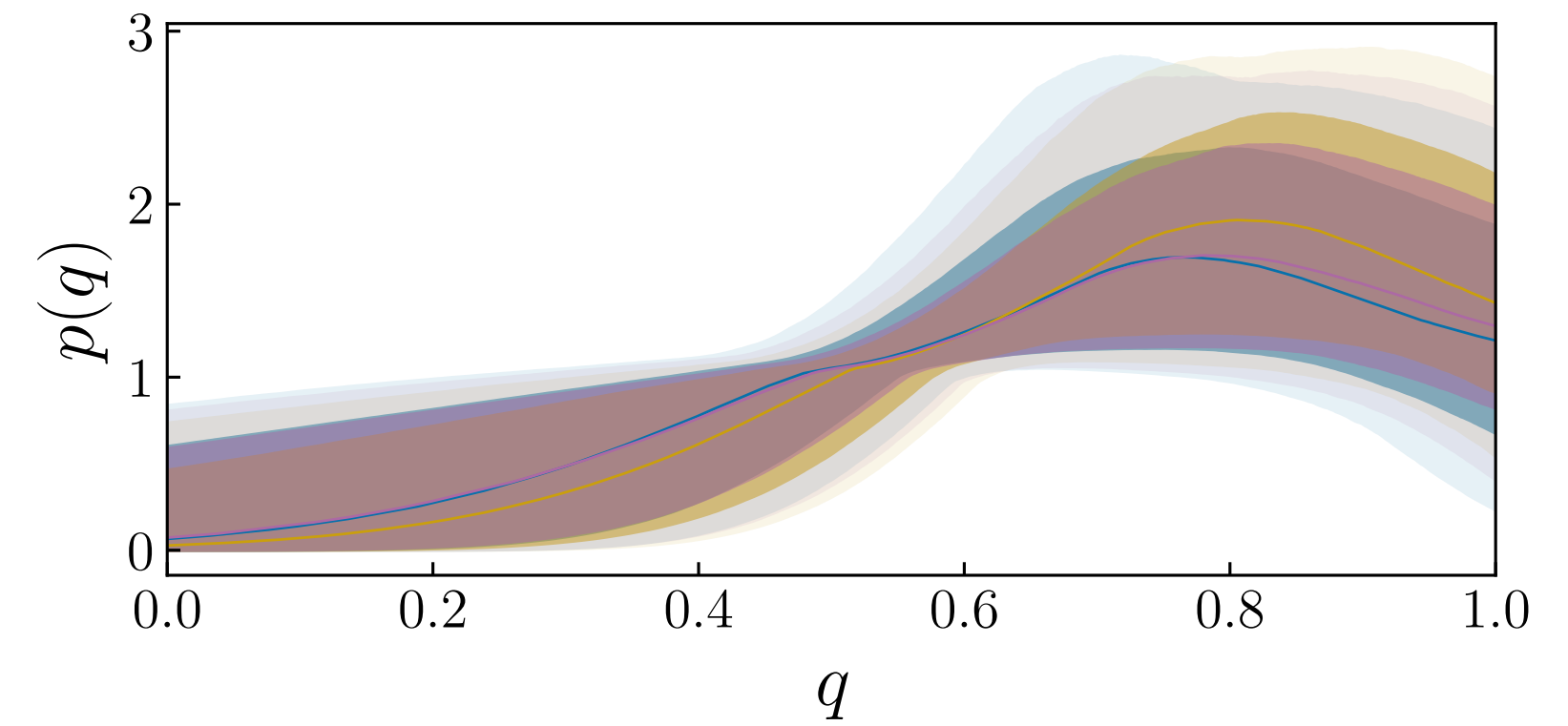
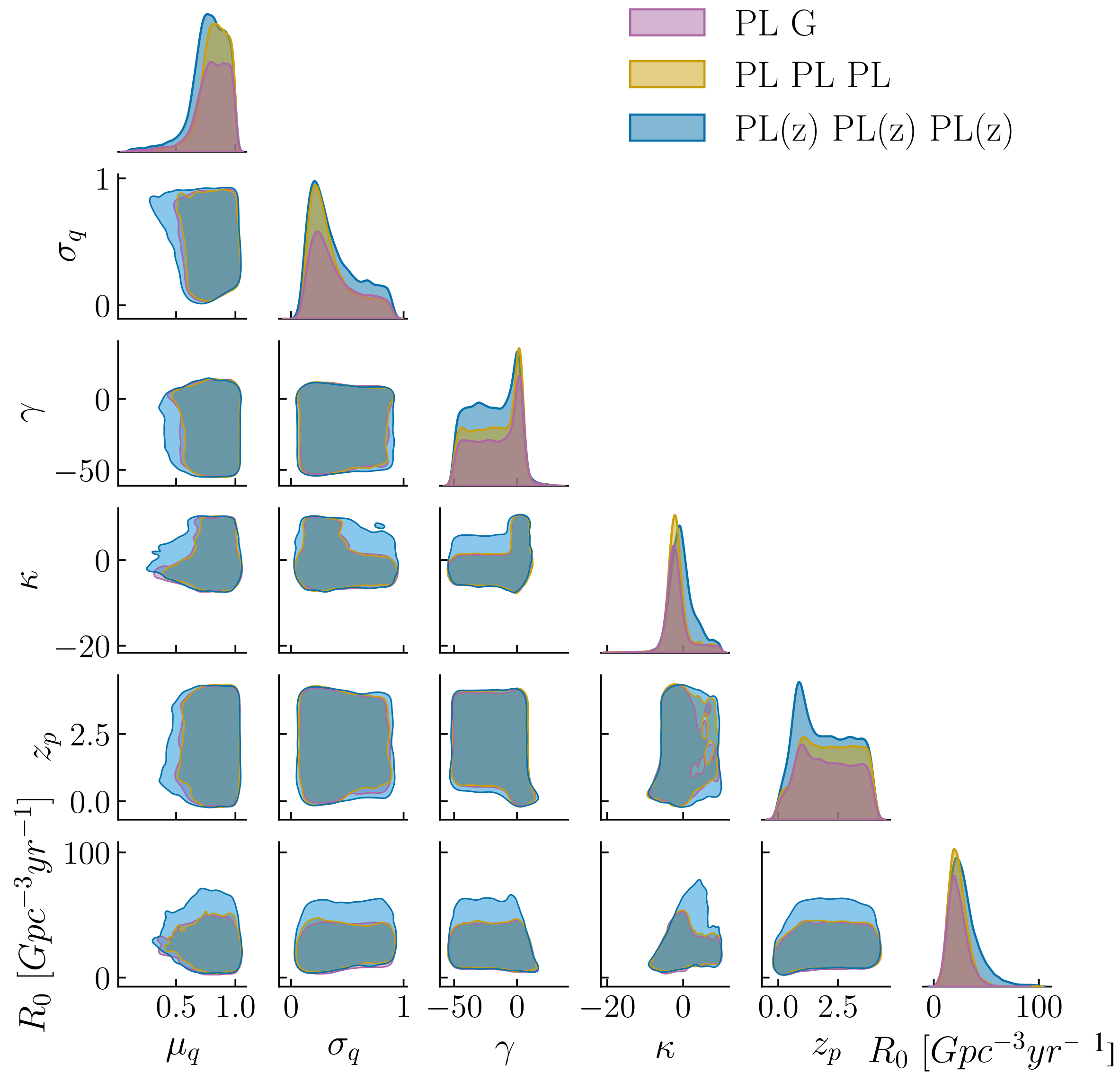
MASS RATIO & RATE EVOLUTION



- rate evolution
 - Madau-Dickinson has and Powerlaw are comparable
- mass ratio
 - Powerlaw and (truncated) Gaussian are comparable

since there is no strong preference for any model, we use the Madau-Dickinson for the rate and the Gaussian for the mass ratio, because are more flexible

O3 DATA MASS RATIO & RATE EVOLUTION

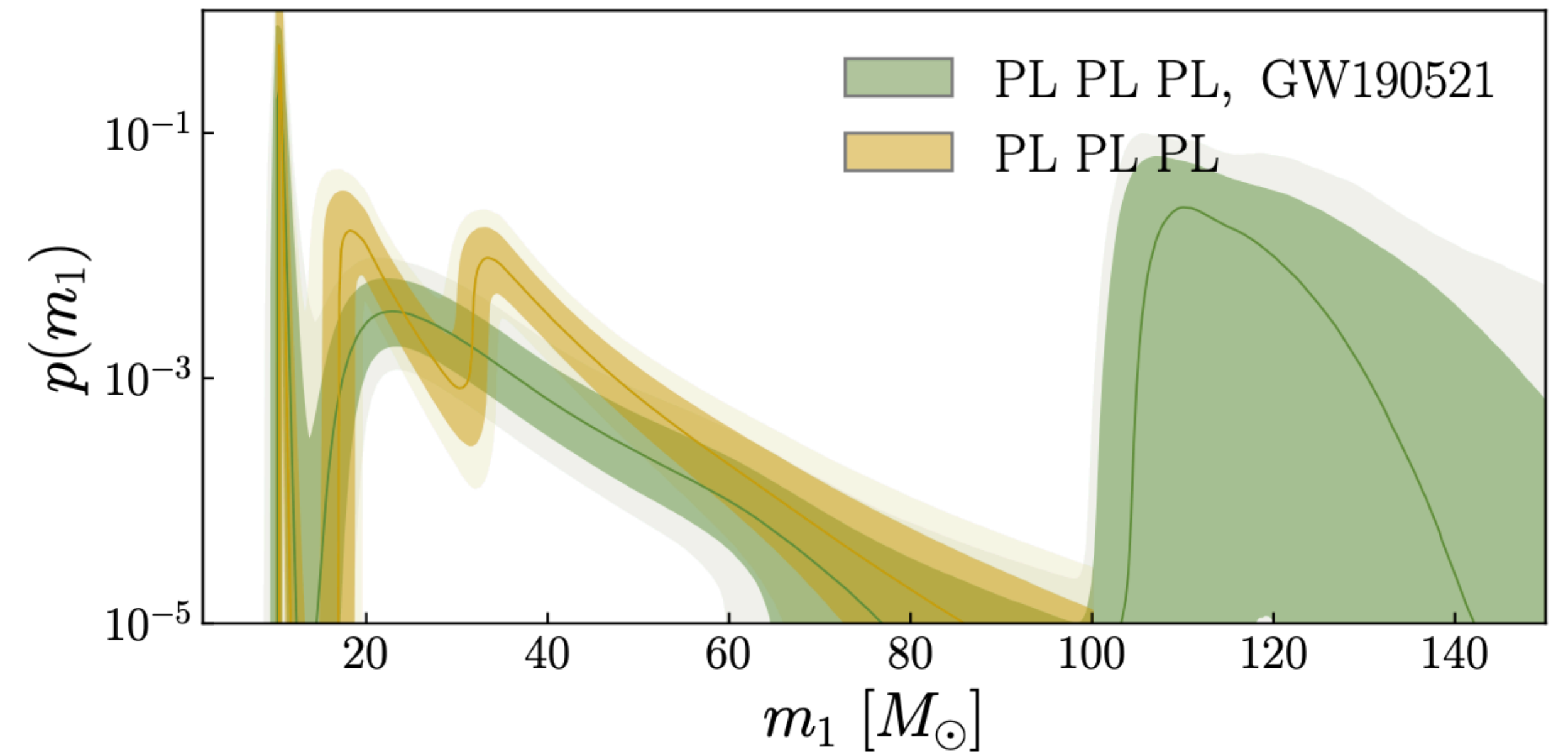
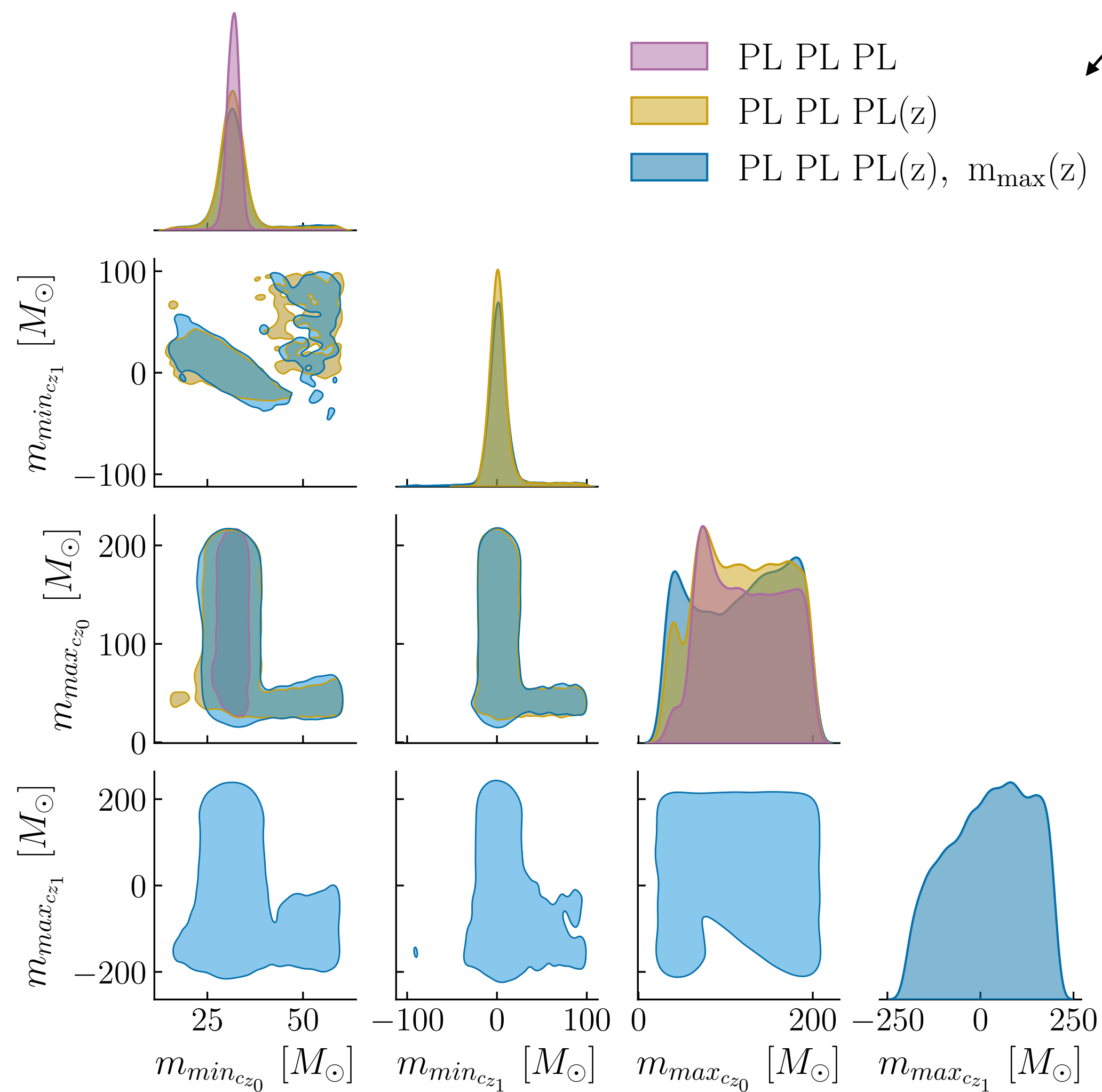


GW190521 and MAXIMUM MASS

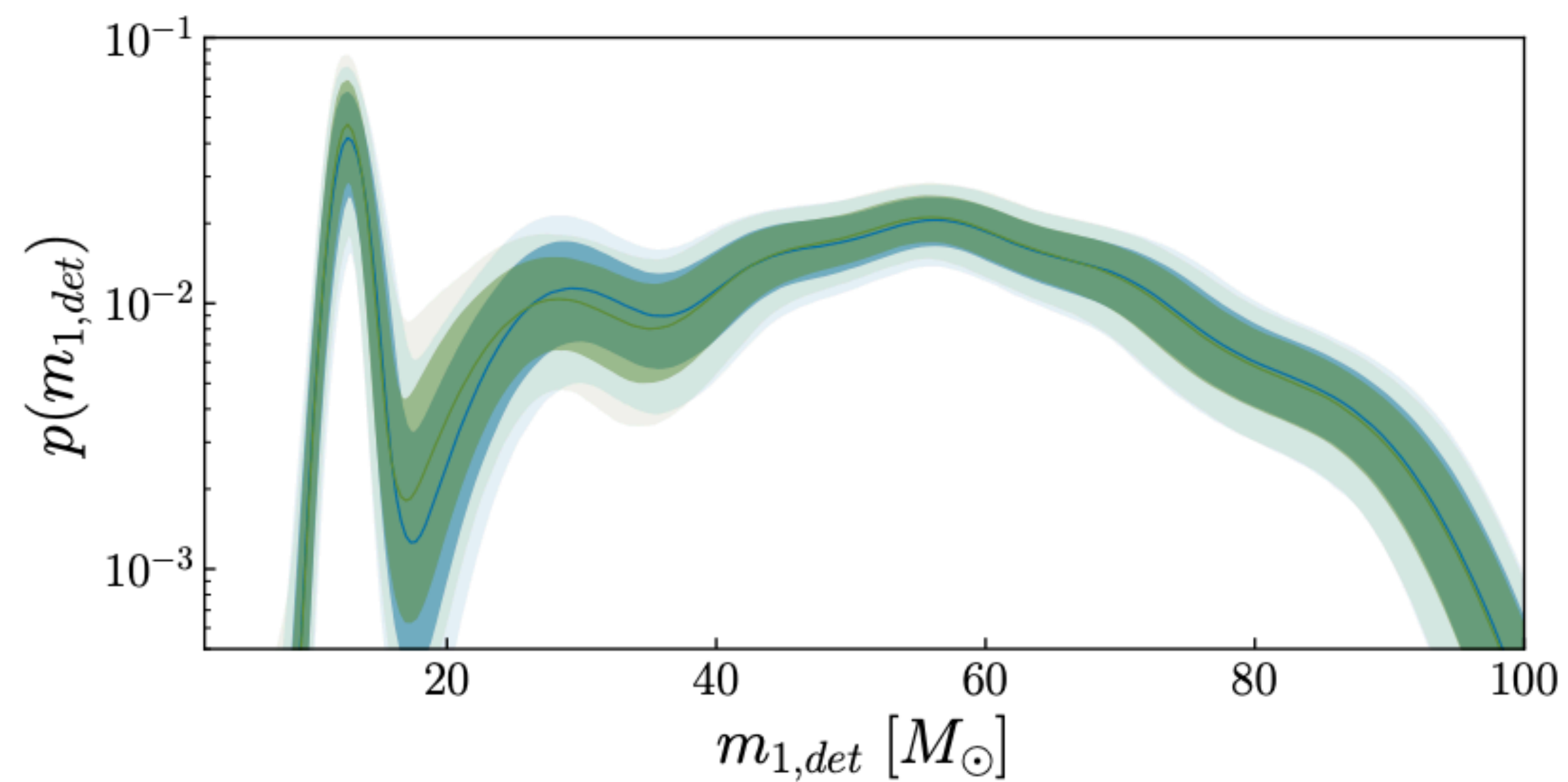
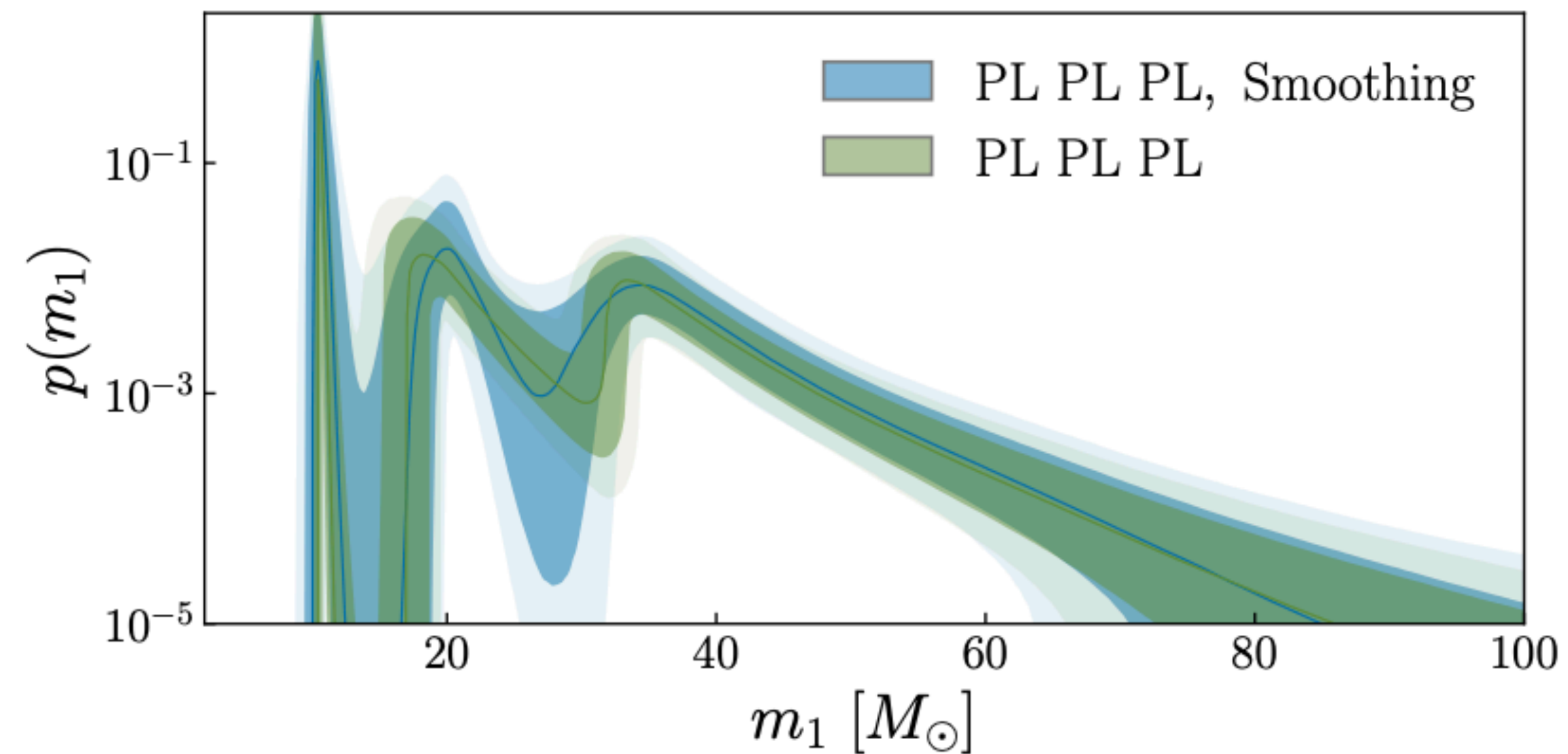
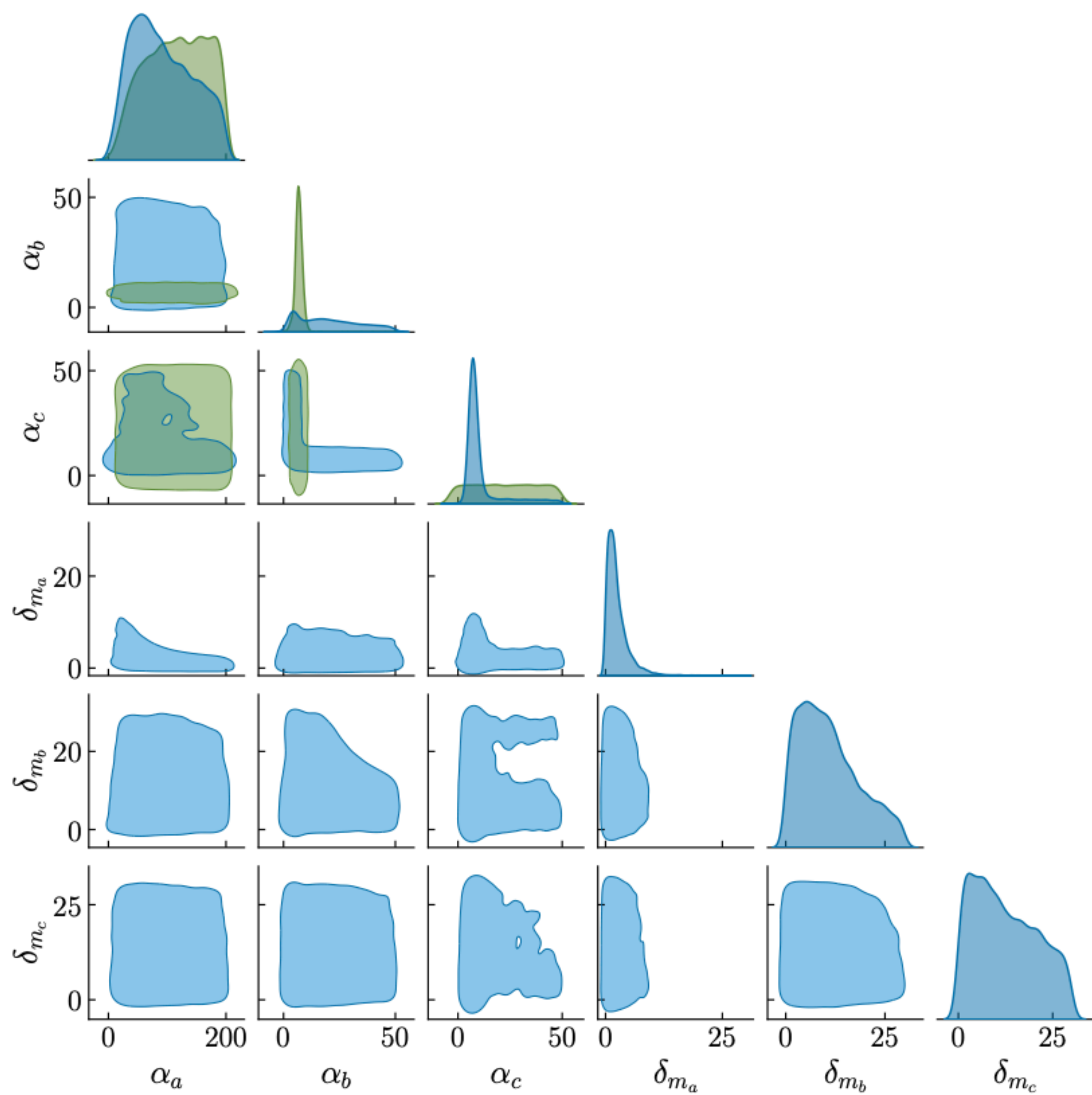
- weak support for evolution in m_{max_c} posteriors

$$(\ln B = -0.1 \pm 0.2)$$

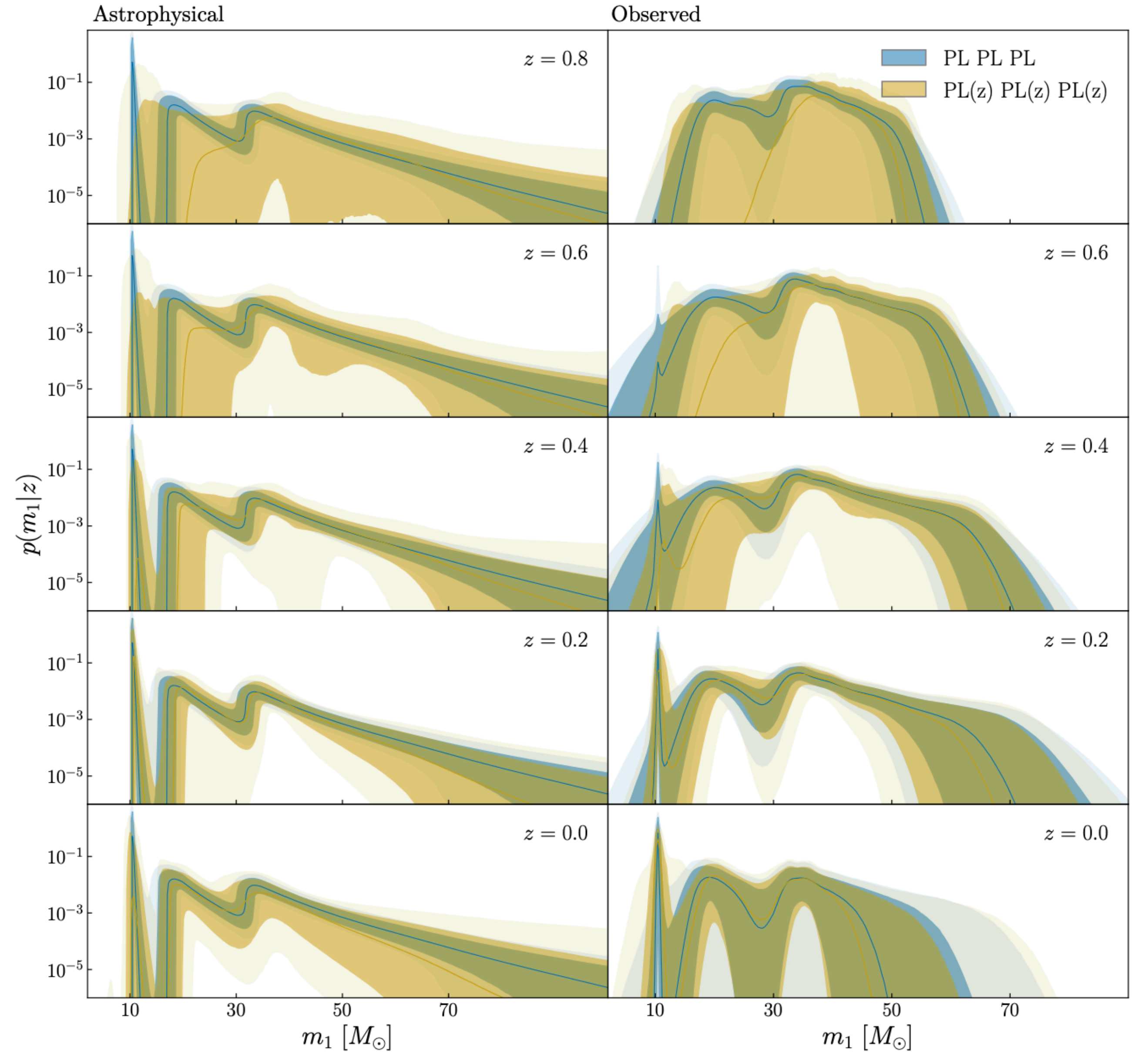
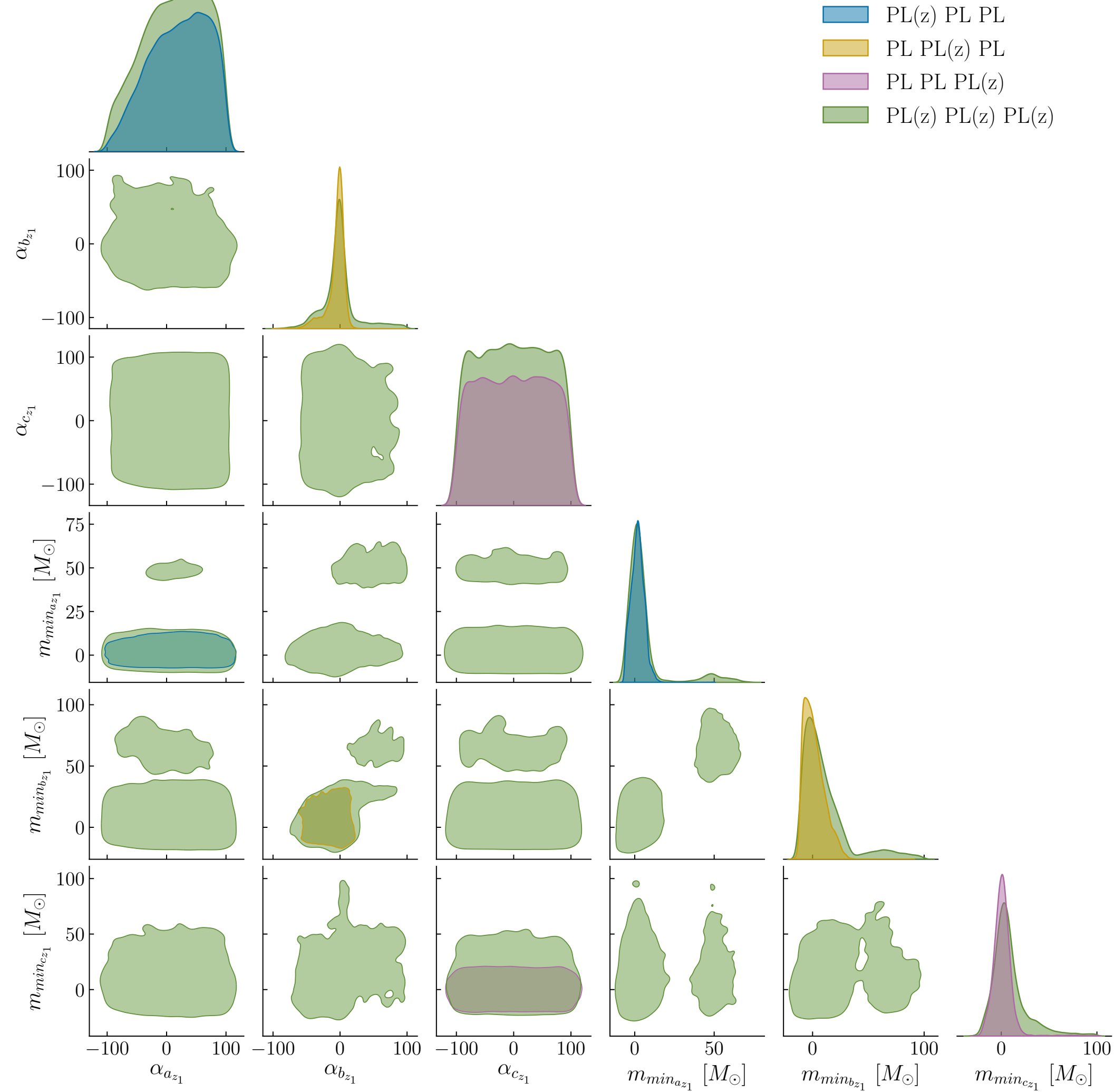
- problems with the Powerlaws including GW190521



POWERLAW SMOOTHING $\ln B = -1.9 \pm 0.2$



O3 DATA EVOLVING



O3 DATA EVOLVING $\text{mix}(z)$

