Binary Black Holes mergers from Population III stars

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1st TEONGRAV international workshop on theory of gravitational waves
16-20 September, 2024

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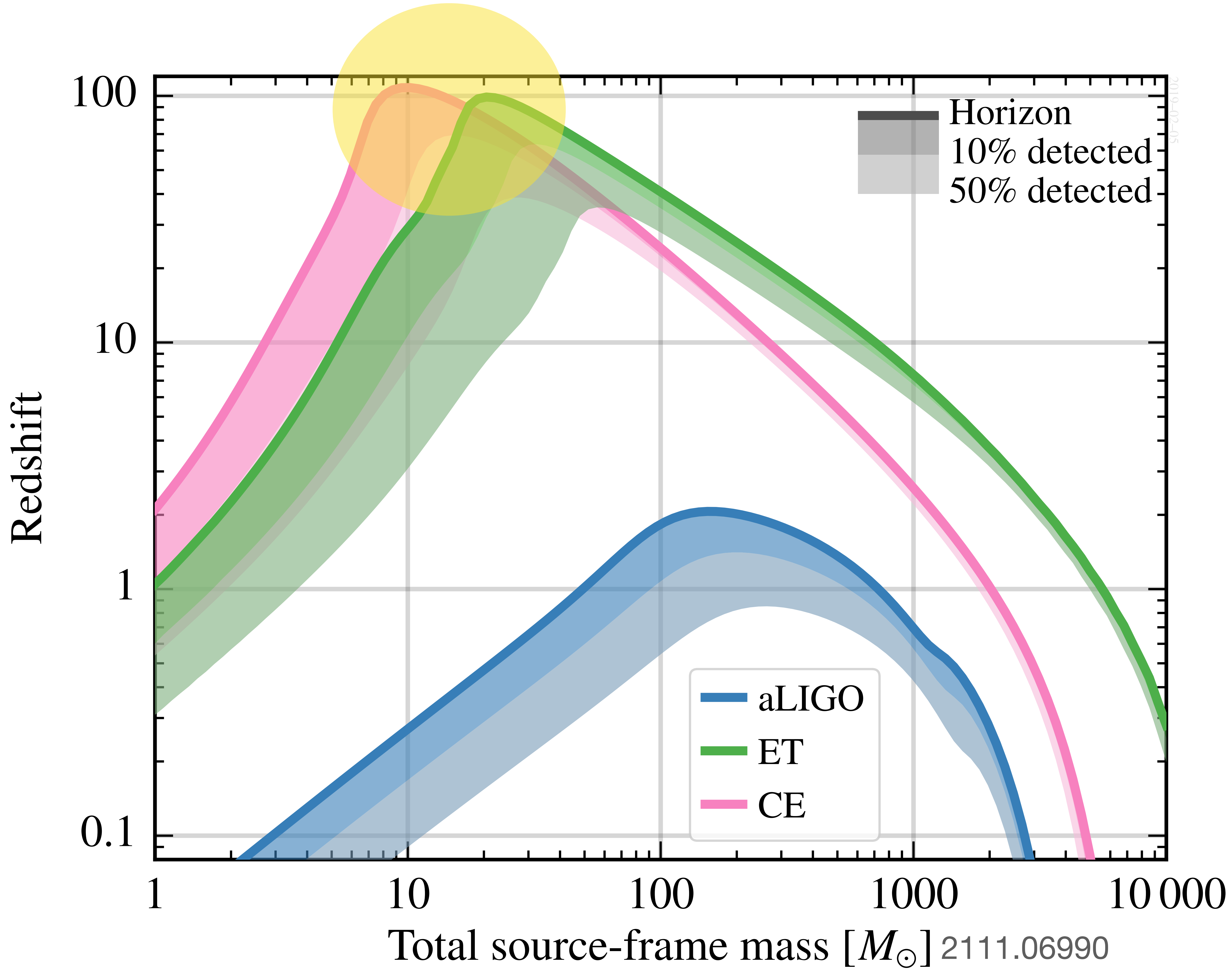
Third-generation detectors



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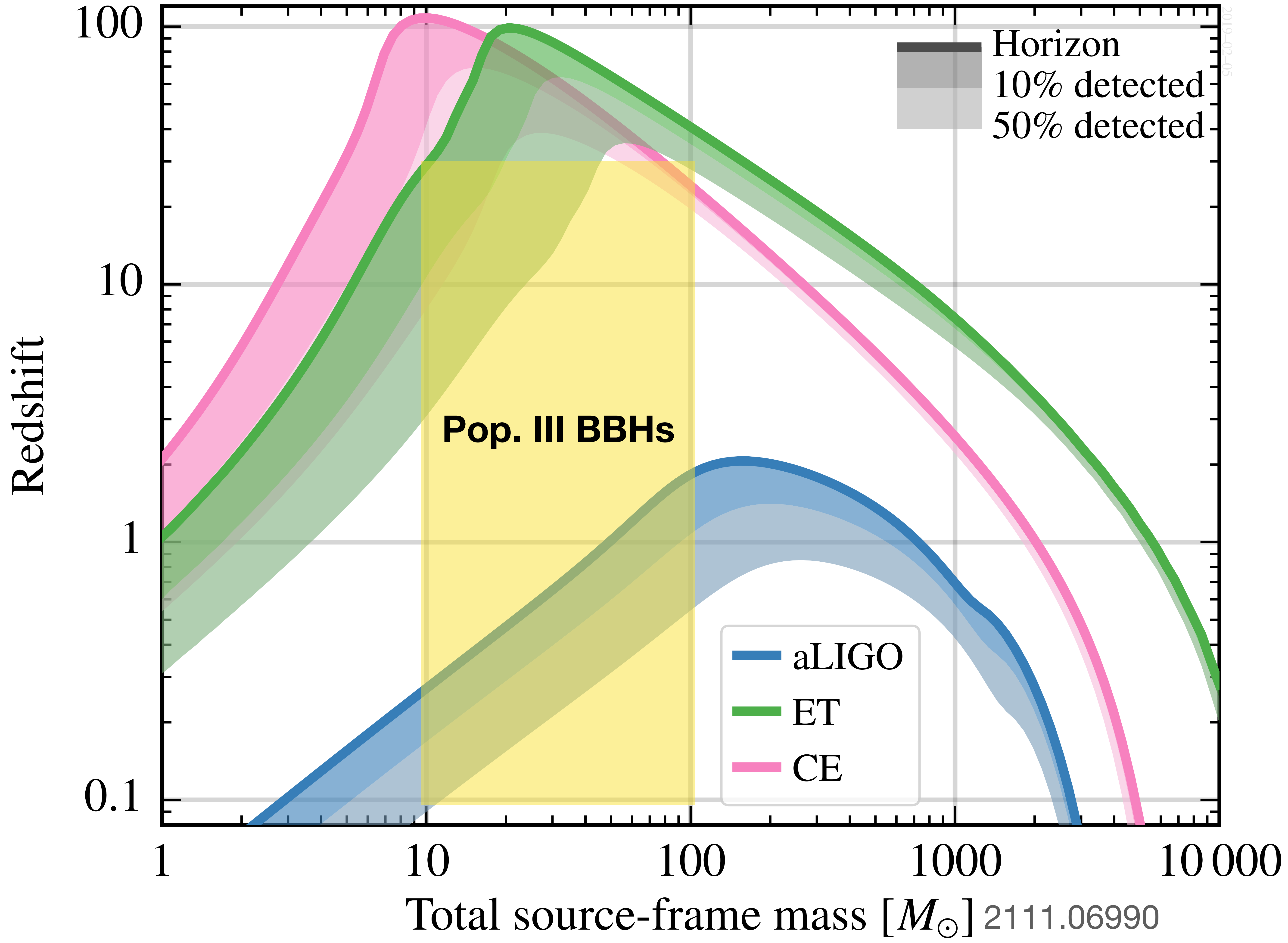
Ref. *Maggiore et al. 2020*, *Ng et al. 2021*, *2022*, *Branchesi et al. 2023*

BBHs from Pop. III stars



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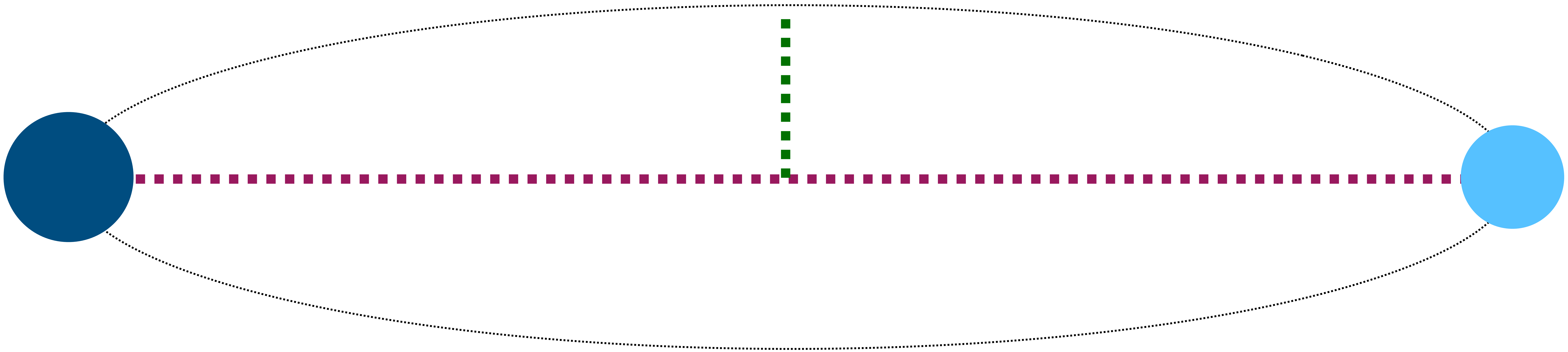
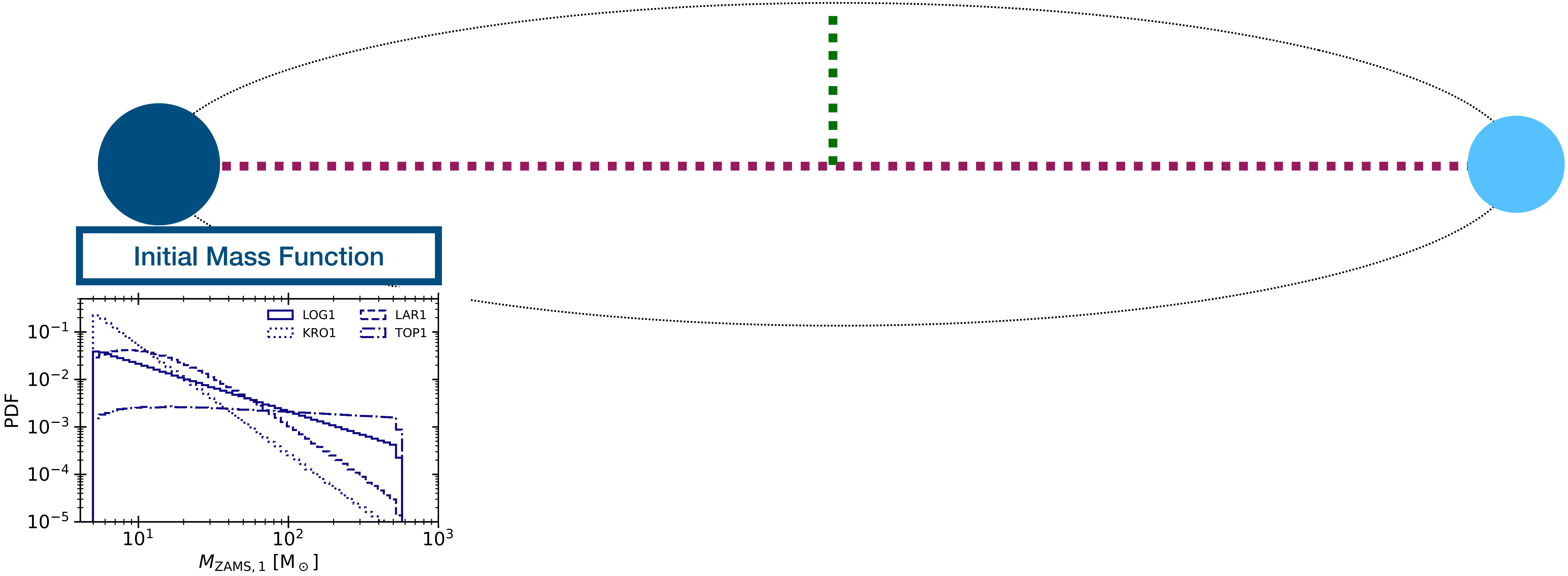
Population synthesis: SEVN



Costa et al. 2023 generated a new set of Pop. III stellar tracks

Initial conditions



Initial conditions

Initial conditions

COSMORATE

$$\mathcal{R}(z) = \int_{z_{\max}}^{z} \left[\int_{Z_{\min}}^{Z_{\max}} \mathrm{SFRD}(z', Z) \mathcal{F}(z', z, Z) \mathrm{d}Z \right] \frac{\mathrm{d}t(z')}{\mathrm{d}z'} \mathrm{d}z'$$

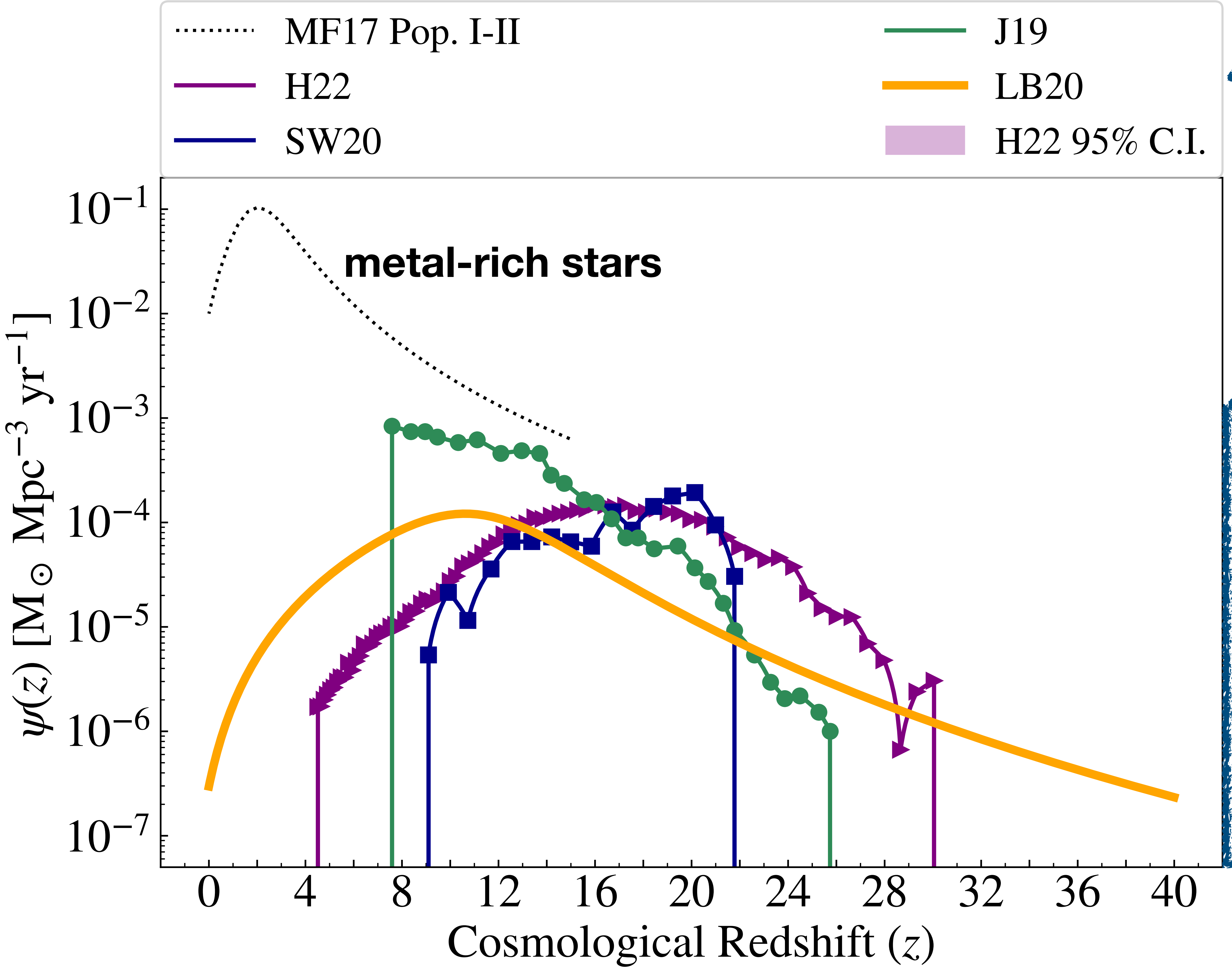
Evaluated from SEVN catalogs

COSMORATE

$$\mathcal{R}(z) = \int_{z_{\max}}^{z} \left[\int_{Z_{\min}}^{Z_{\max}} \mathrm{SFRD}(z', Z)\, \mathcal{F}(z', z, Z)\, \mathrm{d}Z \right] \frac{\mathrm{d}t(z')}{\mathrm{d}z'} \mathrm{d}z'$$

$$\mathrm{SFRD}(z, Z) = \psi(z)\, p(Z|z)$$

Evaluated from SEVN catalogs



4 different Pop. III SFRDs:

H22 - *Hartwig et al. 2022*

J19 - *Jaacks et al. 2019*

LB20 - *Liu & Bromm 2020*

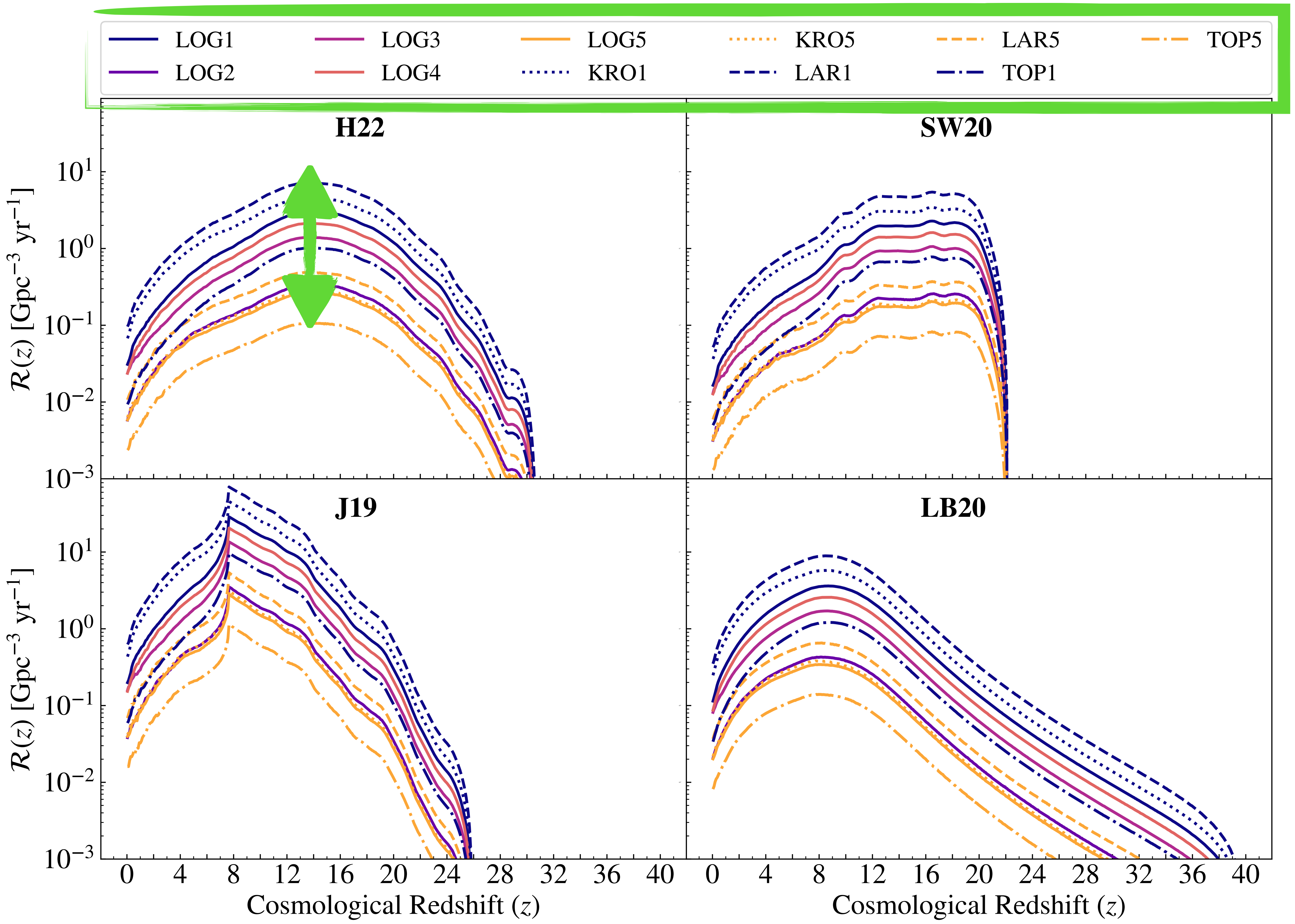
SW20 - *Skinner & Wise 2020*

different assumptions on baryonic physics + cosmic variance

Merger rate density

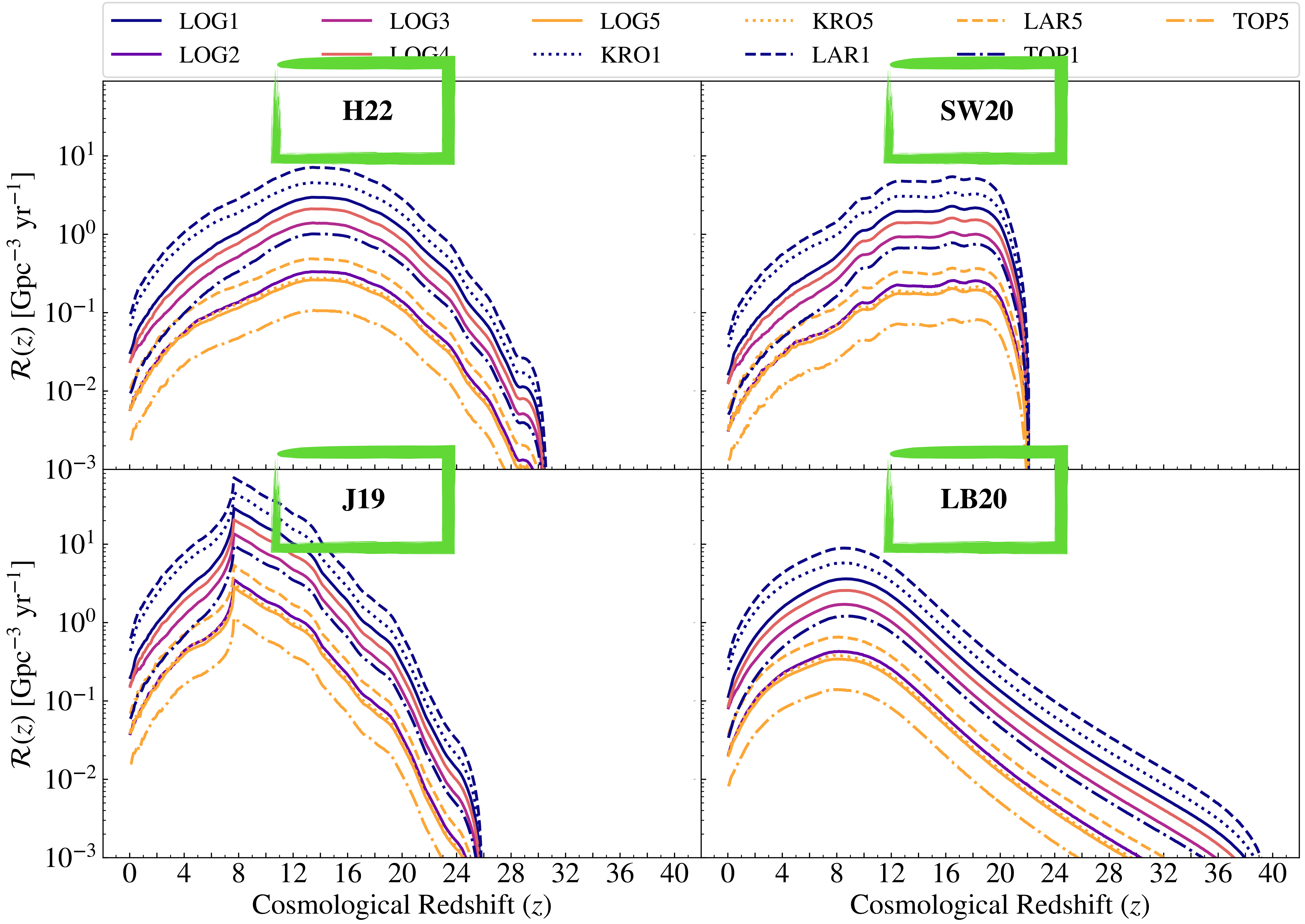
initial conditions

impact ~2 orders of magnitude

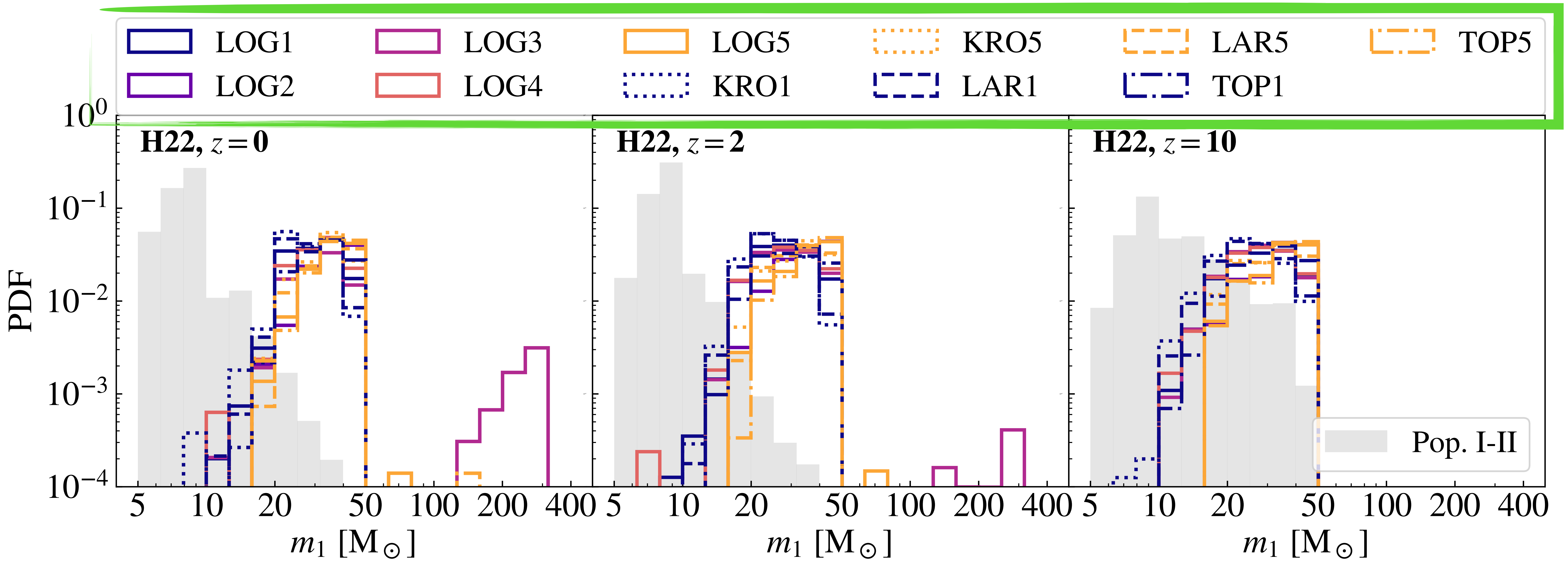


Merger rate density

star formation history impacts shape and normalisation

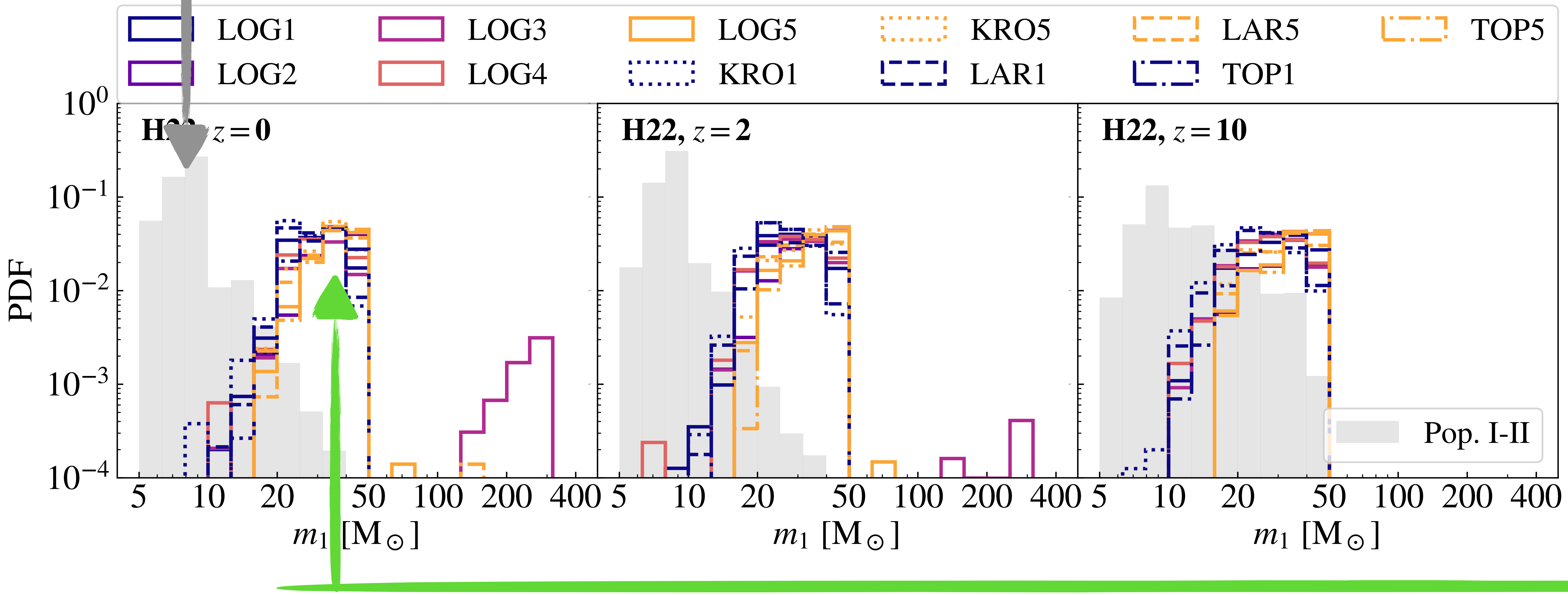


Primary mass



Primary mass

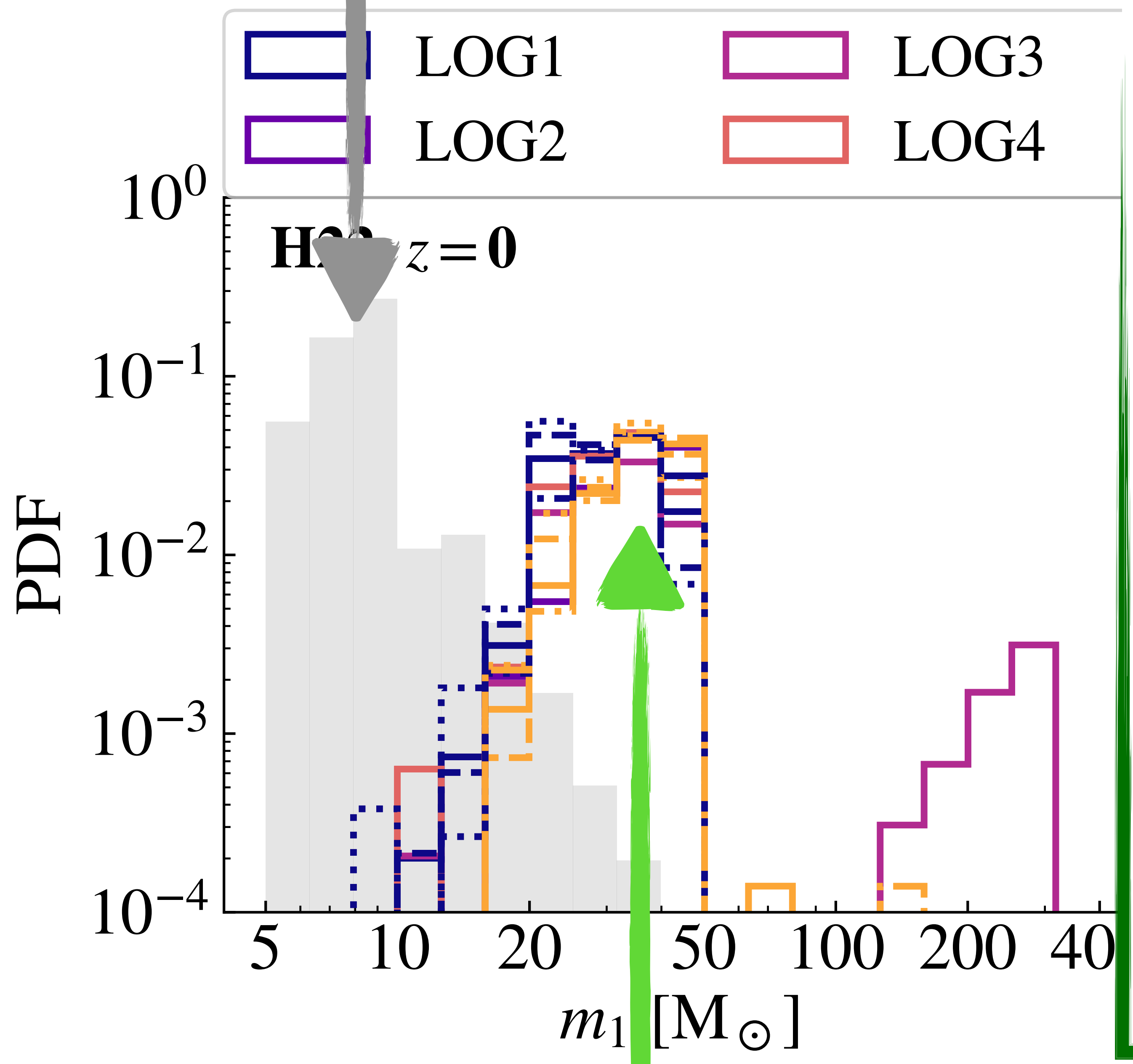
At $z = 0$, **Pop. I-II** BBHs show a **main peak at 8 – 10** $\mathrm{M}_\odot$

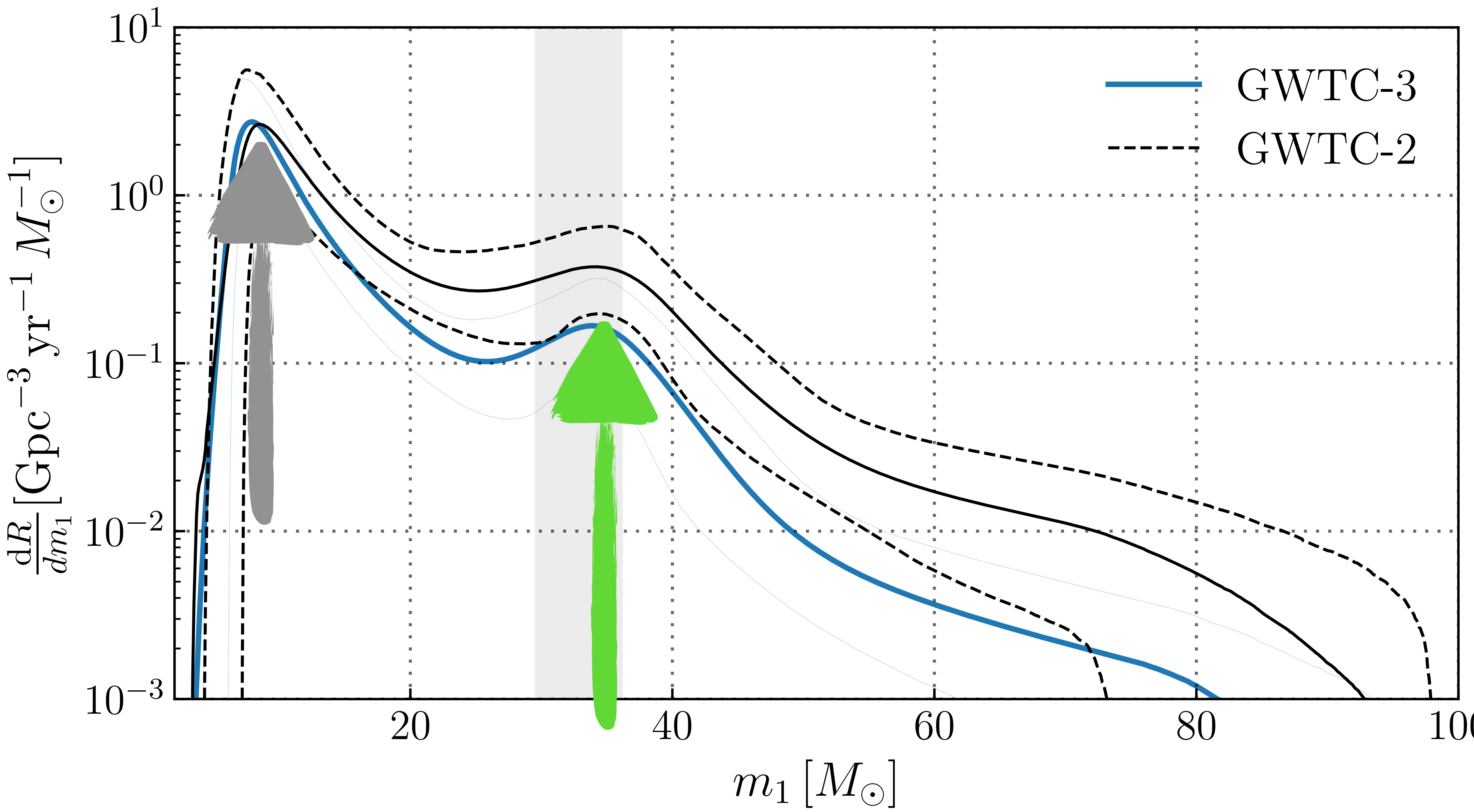


Pop. III BBHs show a **main peak at 30 – 35** $\mathrm{M}_\odot$

Primary mass

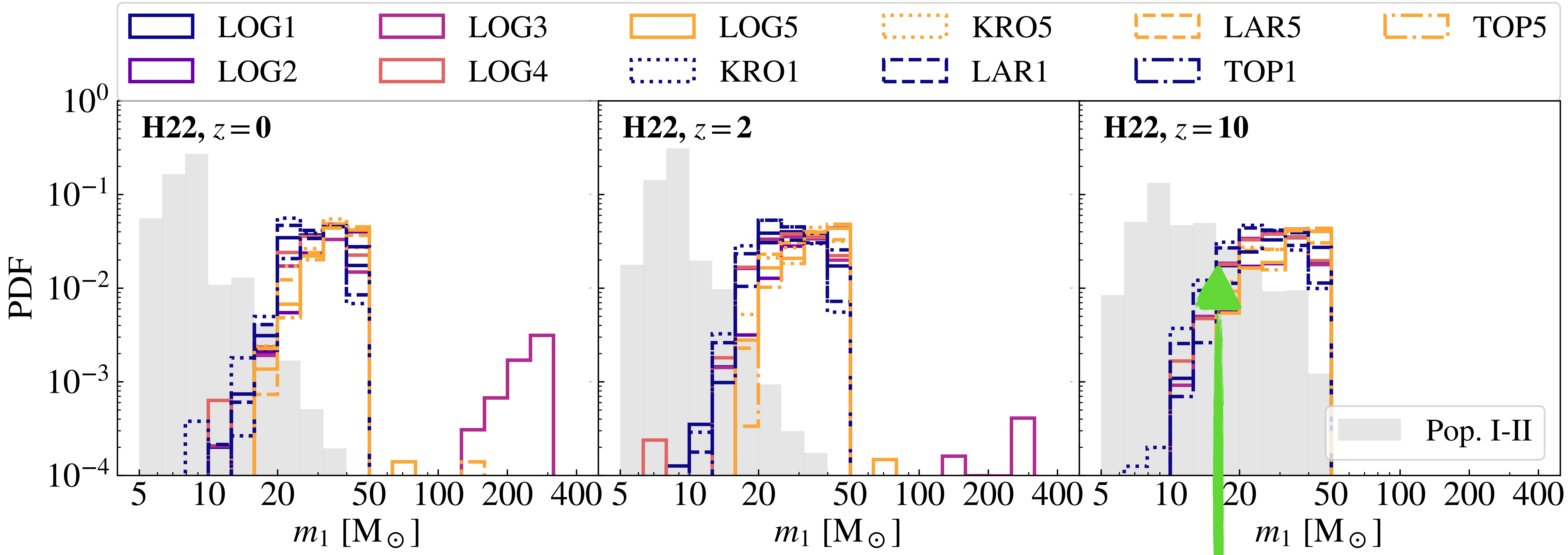
At $z = 0$, **Pop. I-II** BBHs show a **main peak at 8 – 10** $\mathrm{M_\odot}$





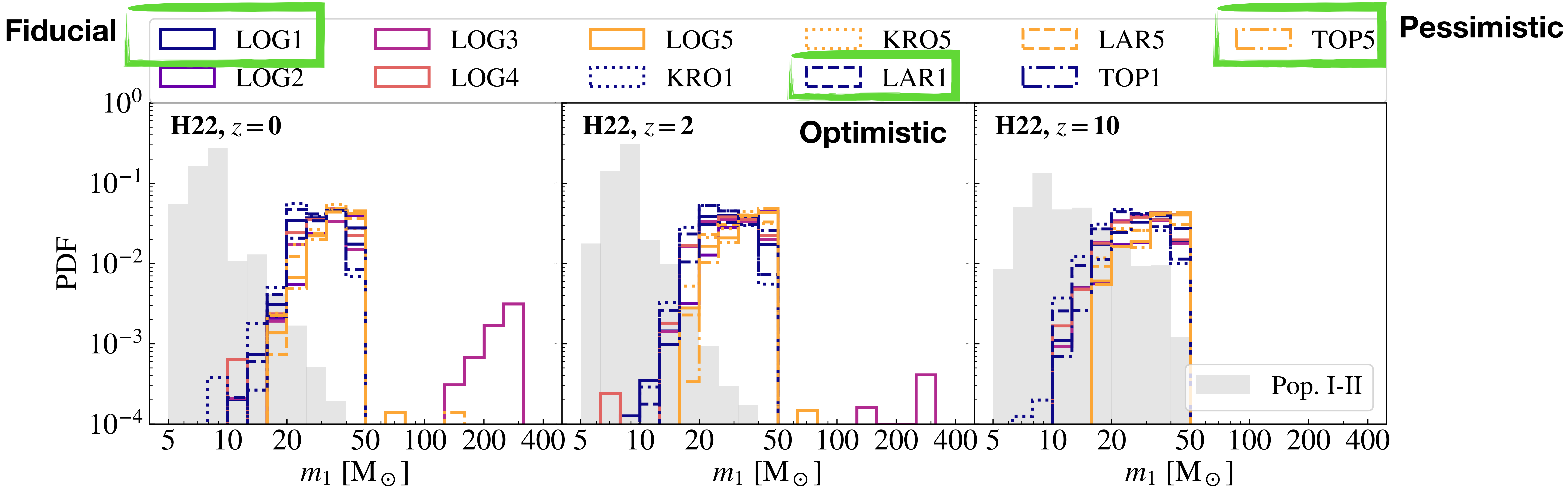
Pop. III BBHs show a **main peak at 30 – 35** $\mathrm{M_\odot}$

Can we identify Pop. III BBHs?



At high redshift, overlap increases

Goal: simulation-based classification



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Classification

This is the probability that the event j is a Pop. III BBH

$$p(j \in k \,|\, d_i, \{\beta\}) = \int p(j \in k \,|\, x, d_j, \{\beta\})\; p(x \,|\, d_j, \{\beta\})$$

Mixing fraction

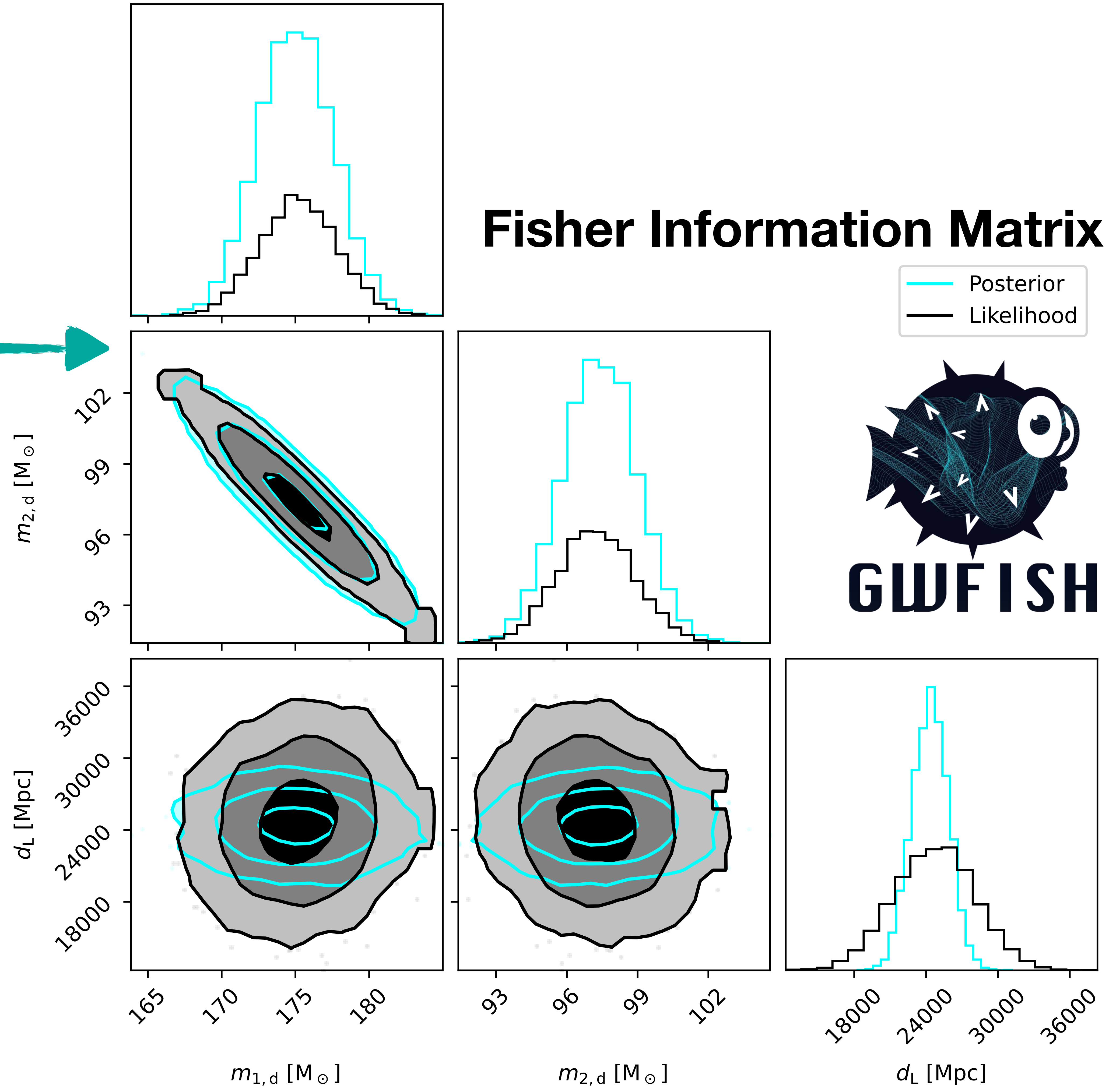
Fiducial ~4% $\beta_{III} \propto N_{\text{Pop. III}} \sim 400$

$$\beta_{I-II} \propto N_{\text{Pop. I–II}} \sim 10^4$$

Classification

$$p(j \in k \,|\, d_i, \{\beta\}) = \int p(j \in k \,|\, x, d_j, \{\beta\})\, p(x \,|\, d_j, \{\beta\})$$

This is the posterior of waveform parameters ➡️ parameter estimation **performance of ET**



Classification

$$p(j \in k \,|\, d_i, \{\beta\}) = \int p(j \in k \,|\, x, d_j, \{\beta\}) \; p(x \,|\, d_j, \{\beta\})$$

This is the probability that links waveform parameters to Pop. III BBHs

➡️ easy to consider a fix threshold

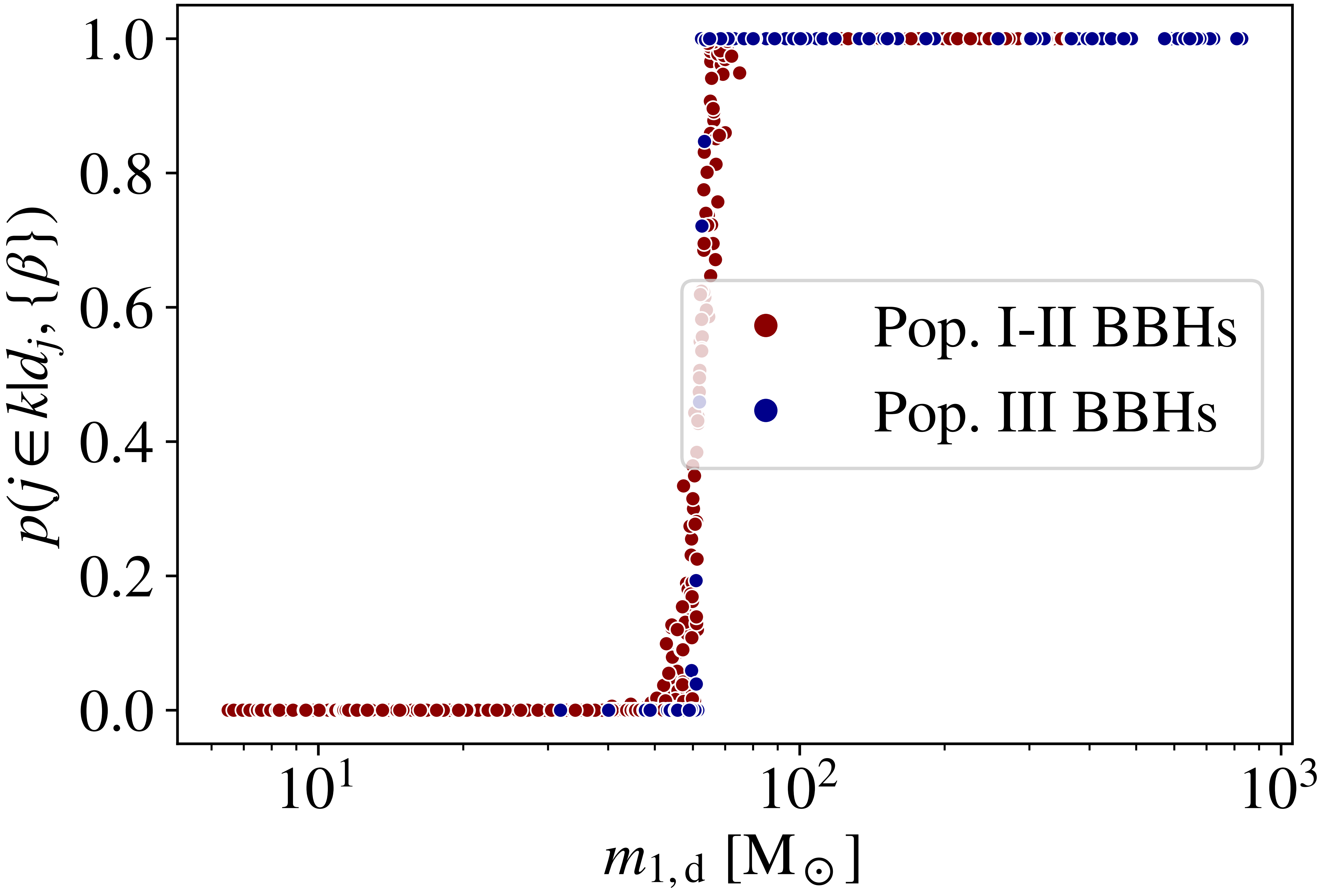
$$p(j \in k \,|\, d_i, \{\beta\}) = \int p(j \in k \,|\, x, d_j, \{\beta\})\, p(x \,|\, d_j, \{\beta\})$$

$$= 1 \quad \text{if} \quad m_{1,\mathrm{d}} \gtrsim 60\ \mathrm{M}_\odot$$

$$p(j \in k \,|\, d_i, \{\beta\}) = \int p(j \in k \,|\, x, d_j, \{\beta\}) \, p(x \,|\, d_j, \{\beta\})$$

$= 1$ if $m_{1,\mathrm{d}} \gtrsim 60\ \mathrm{M}_\odot$

manual classifier - fiducial



⚠️ low performances: precision is ~ 0.16

$$p(j \in k \,|\, d_i, \{\beta\}) = \int p(j \in k \,|\, x, d_j, \{\beta\}) \, p(x \,|\, d_j, \{\beta\})$$

we can use Machine Learning

XGBoost

supervised ML based on decision trees

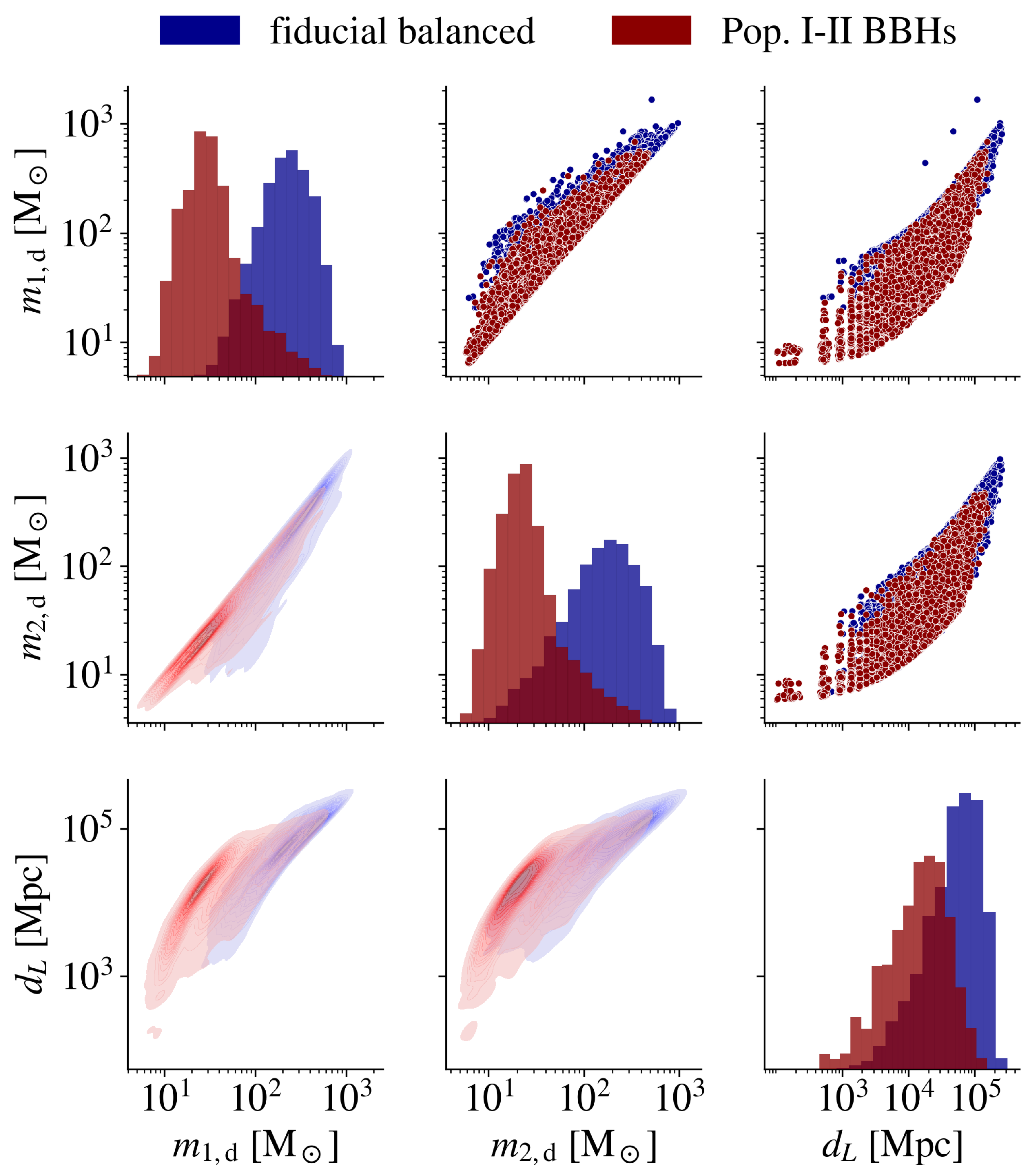
Ref. ***Santoliquido et al. 2024***, ***Chen et al. 2016***, ***Pedregosa et al. 2012***, ***Antonelli et. al 2023***

$$p(j \in k \,|\, d_i, \{\beta\}) = \int p(j \in k \,|\, x, d_j, \{\beta\}) \, p(x \,|\, d_j, \{\beta\})$$

Using Machine Learning

* trained and tested on balanced classes + re-balancing

* instances: > 10^4

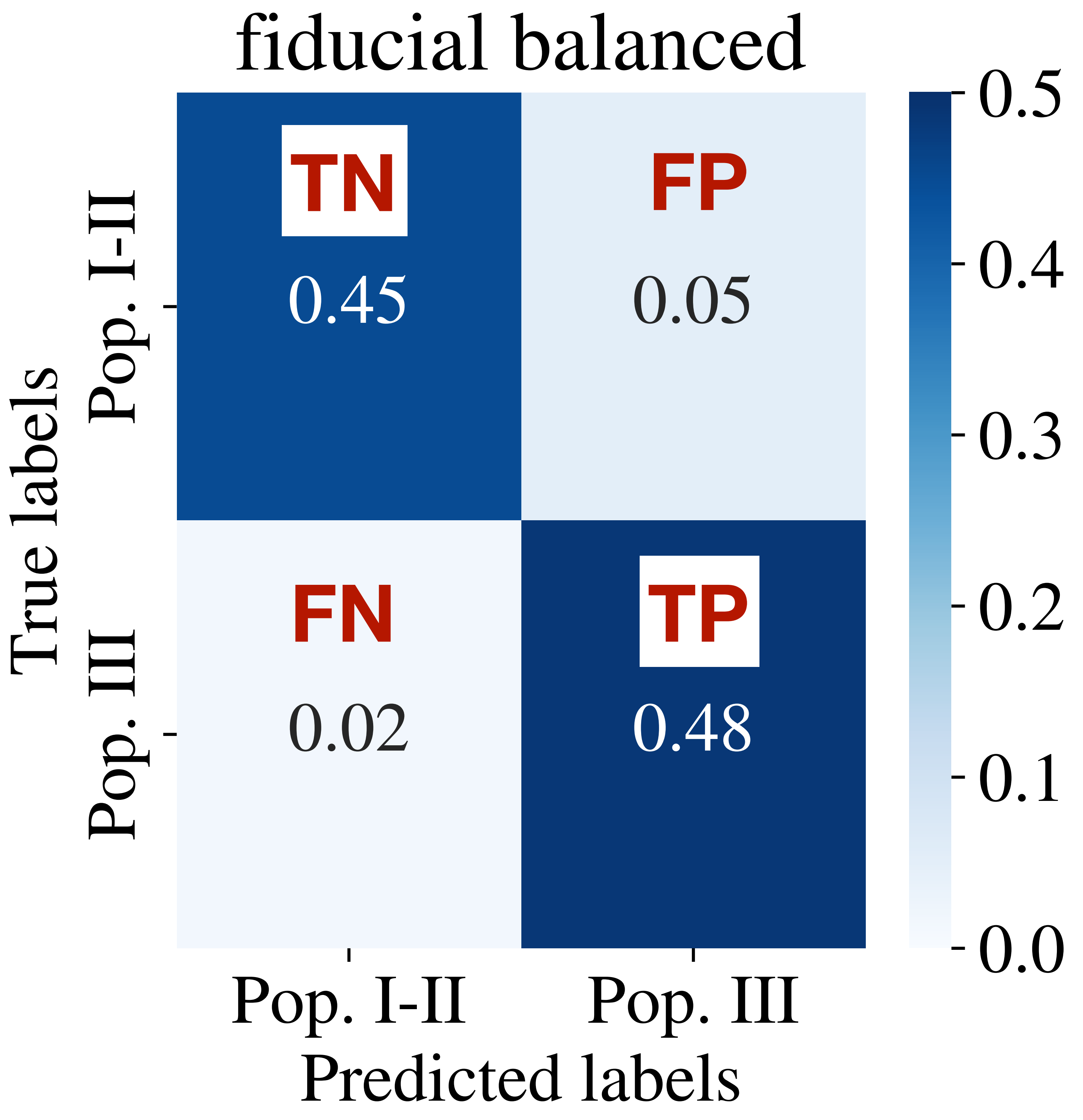


$$p(j \in k \mid d_i, \{\beta\}) = \int p(j \in k \mid x, d_j, \{\beta\})\, p(x \mid d_j, \{\beta\})$$

Using Machine Learning

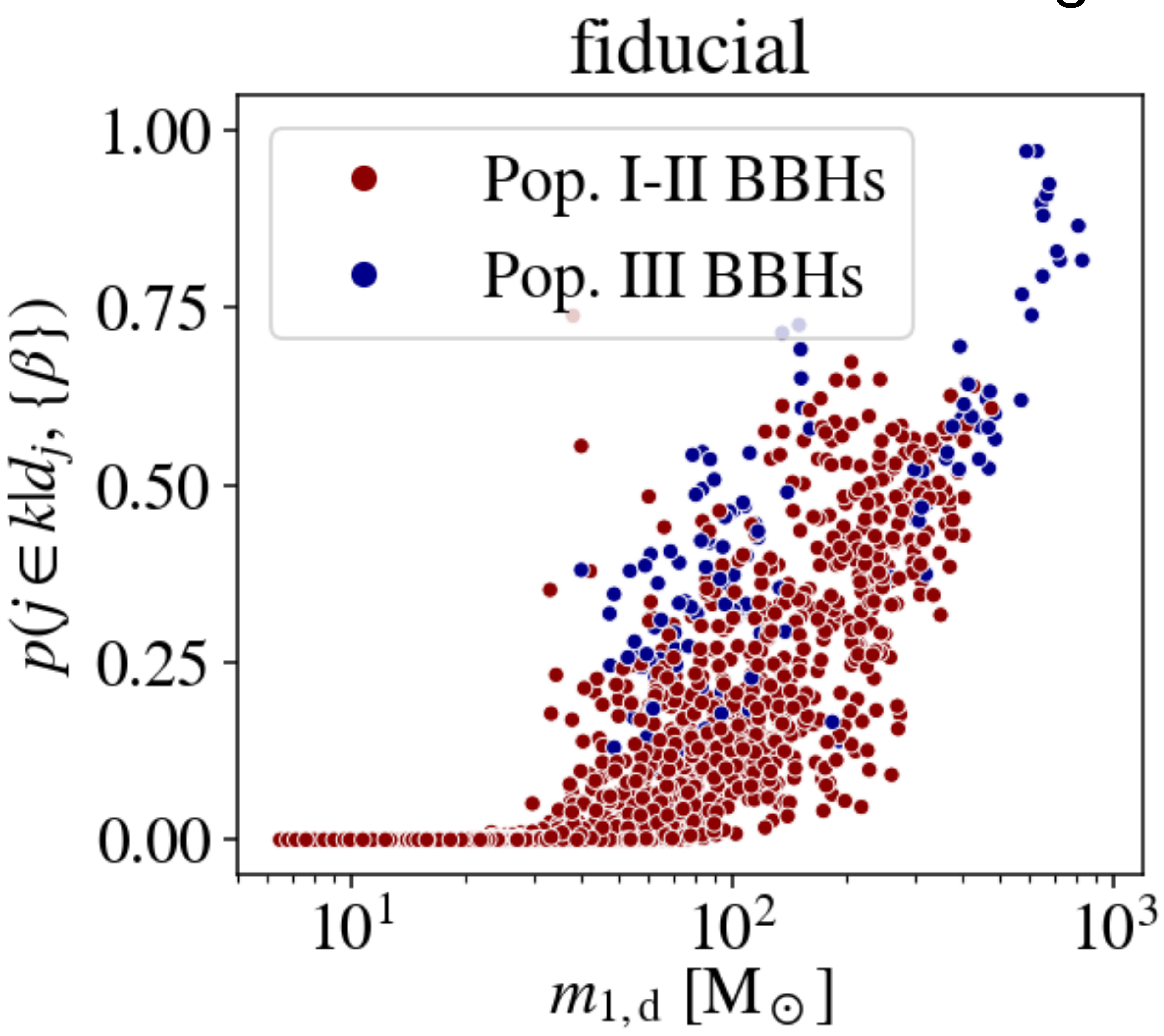
precision = TP/(TP+FP)

high precision > 0.90



$$p(j \in k \,|\, d_i, \{\beta\}) = \int p(j \in k \,|\, x, d_j, \{\beta\})\, p(x \,|\, d_j, \{\beta\})$$

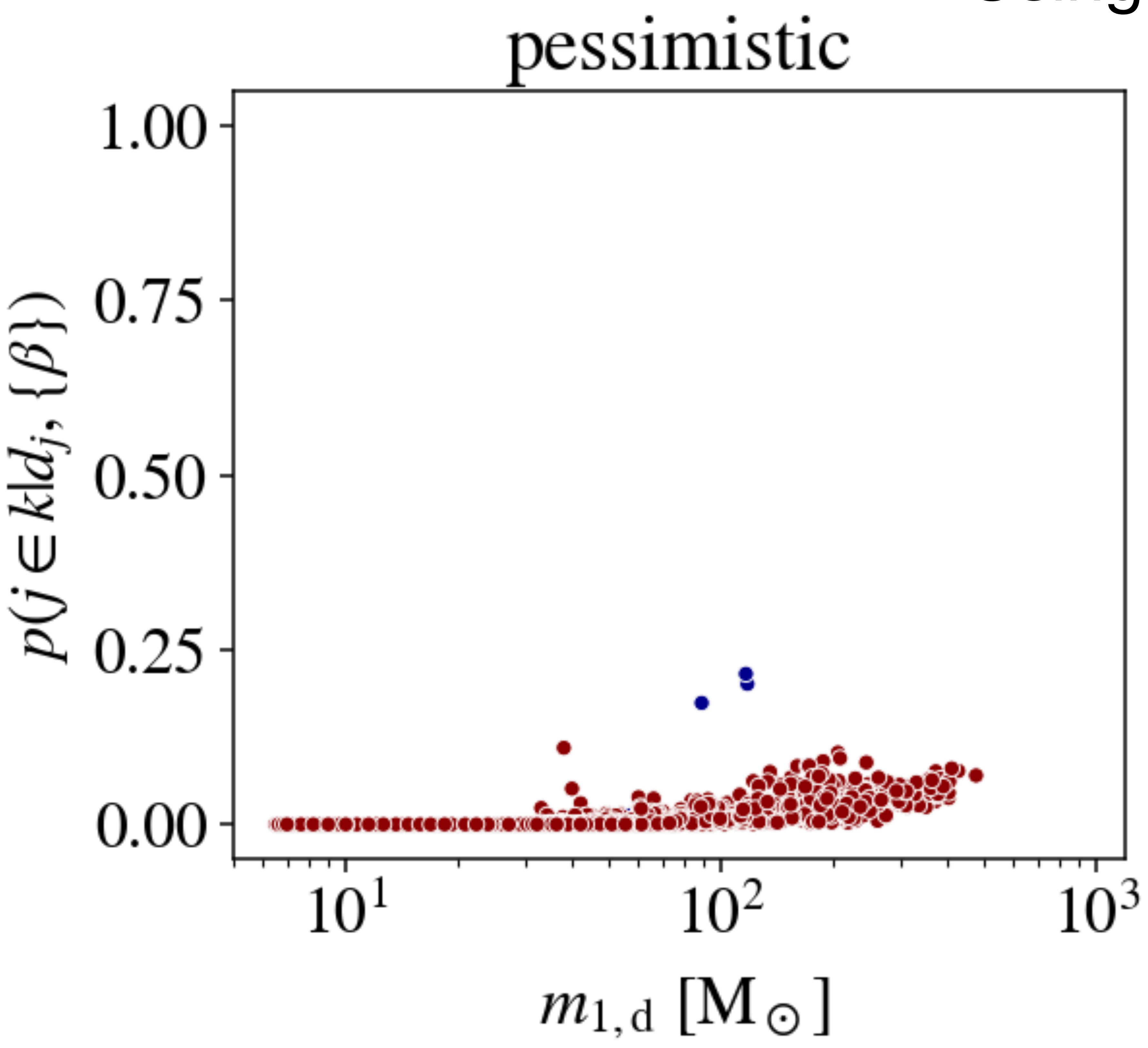
Using Machine Learning



~10% of detected sources are classified with precision > 0.90

$$p(j \in k \,|\, d_i, \{\beta\}) = \int p(j \in k \,|\, x, d_j, \{\beta\})\; p(x \,|\, d_j, \{\beta\})$$

Using Machine Learning

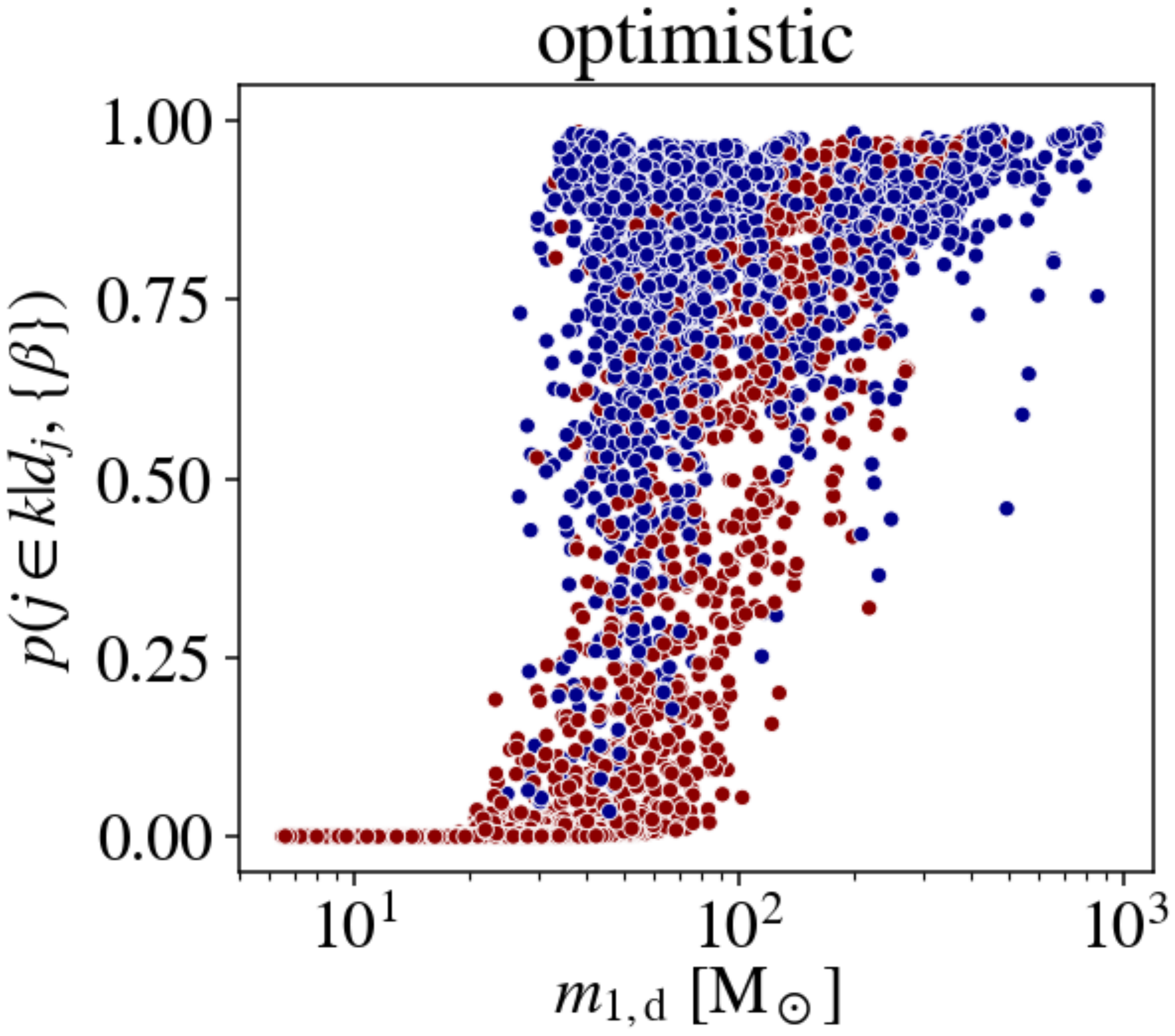


~30% of detected sources are classified with precision > 0.90

Ref. ***Santoliquido et al. 2024***

$$p(j \in k \,|\, d_i, \{\beta\}) = \int p(j \in k \,|\, x, d_j, \{\beta\}) \; p(x \,|\, d_j, \{\beta\})$$

Using Machine Learning



~45% of detected sources are classified with precision > 0.90

Contributions

- First large parameter exploration of Pop. III BBHs
  - SFRD affects normalisation and shape of merger rate density
  - primary mass of Pop. III BHs is substantially larger
- ET will detect Pop. III BBHs and machine learning increases our ability to identify them

Ref. ***Costa et al. 2023***, ***Santoliquido et al. 2023***, ***Santoliquido et al. 2024***

Backup slides

αλ formalism for modelling the common envelope

- $\Delta E = \alpha(E_{\mathrm{b,f}} - E_{\mathrm{b,i}}) = \alpha \frac{G m_{\mathrm{c1}} m_{\mathrm{c2}}}{2} \left(\frac{1}{a_{\mathrm{f}}} - \frac{1}{a_{\mathrm{i}}} \right)$ This is the orbital energy before and after the common envelope phase
- $E_{\mathrm{env}} = \frac{G}{\lambda} \left[\frac{m_{\mathrm{env,1}} m_1}{R_1} + \frac{m_{\mathrm{env,2}} m_2}{R_2} \right]$ This is the binding energy of the envelope
- By imposing $\Delta E = E_{\mathrm{env}}$, $\frac{1}{a_{\mathrm{f}}} = \frac{1}{\alpha\lambda} \frac{2}{m_{\mathrm{c1}} m_{\mathrm{c2}}} \left[\frac{m_{\mathrm{env,1}} m_1}{R_1} + \frac{m_{\mathrm{env,2}} m_2}{R_2} \right] + \frac{1}{a_i}$
- If α is larger, a_{f} is larger, following $a_{\mathrm{f}} \sim \frac{\alpha}{1+\alpha}$. Therefore larger α gets wider binaries
- Where λ is the parameter which measures the concentration of the envelope (the smaller λ is, the more concentrated is the envelope).
- The $\alpha\lambda$ formalism is a simplified prescription. When $\alpha > 1$, we account for other sources of energy that make the envelope less bind, for instance recombination energy. Recent works (e.g. *Fragos et al. 2019*) suggest that $\alpha > 1$ is necessary to reproduce the final orbital separation obtained with hydrodynamical simulations.

Initial conditions

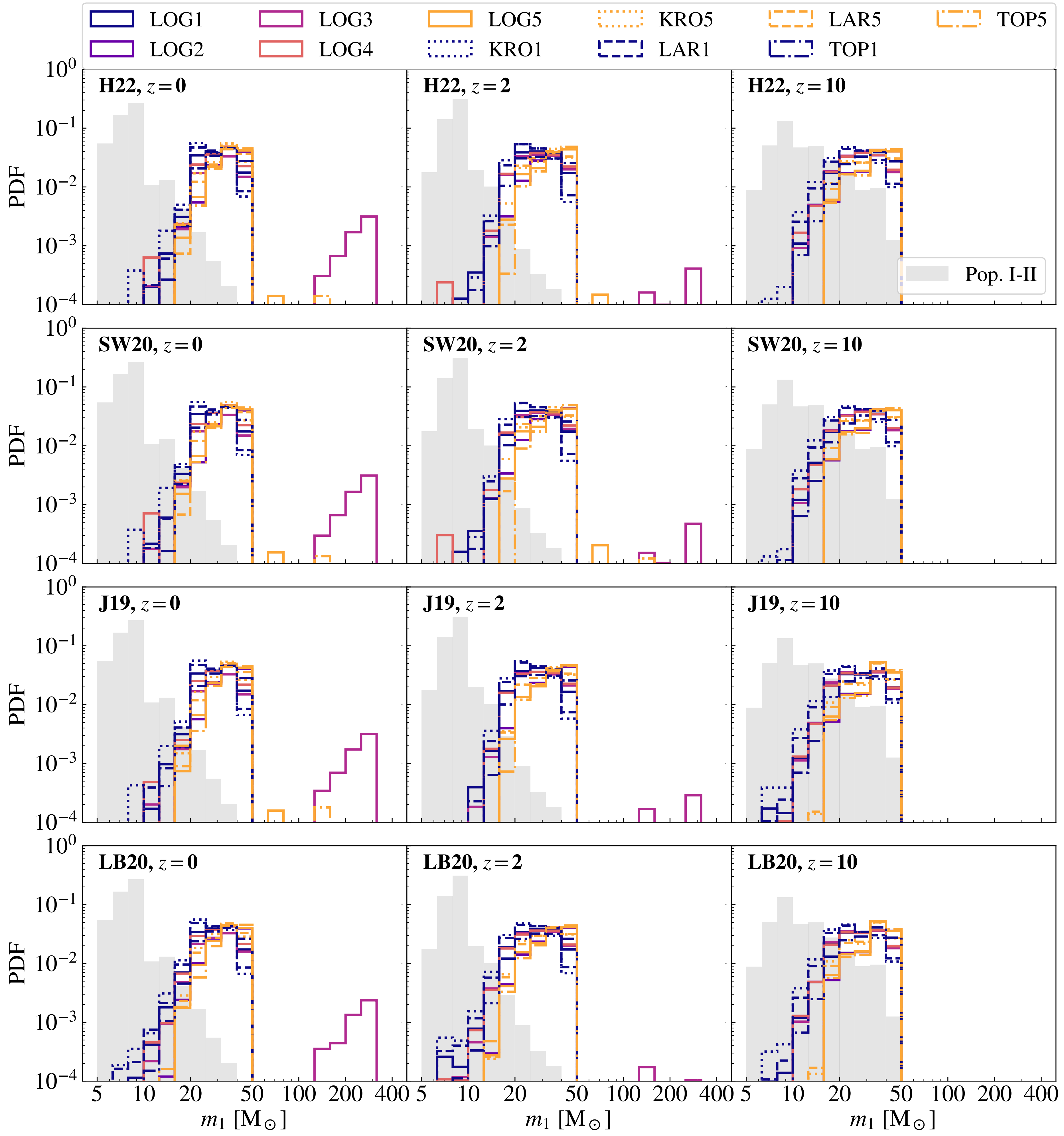
Table 1. Initial conditions.

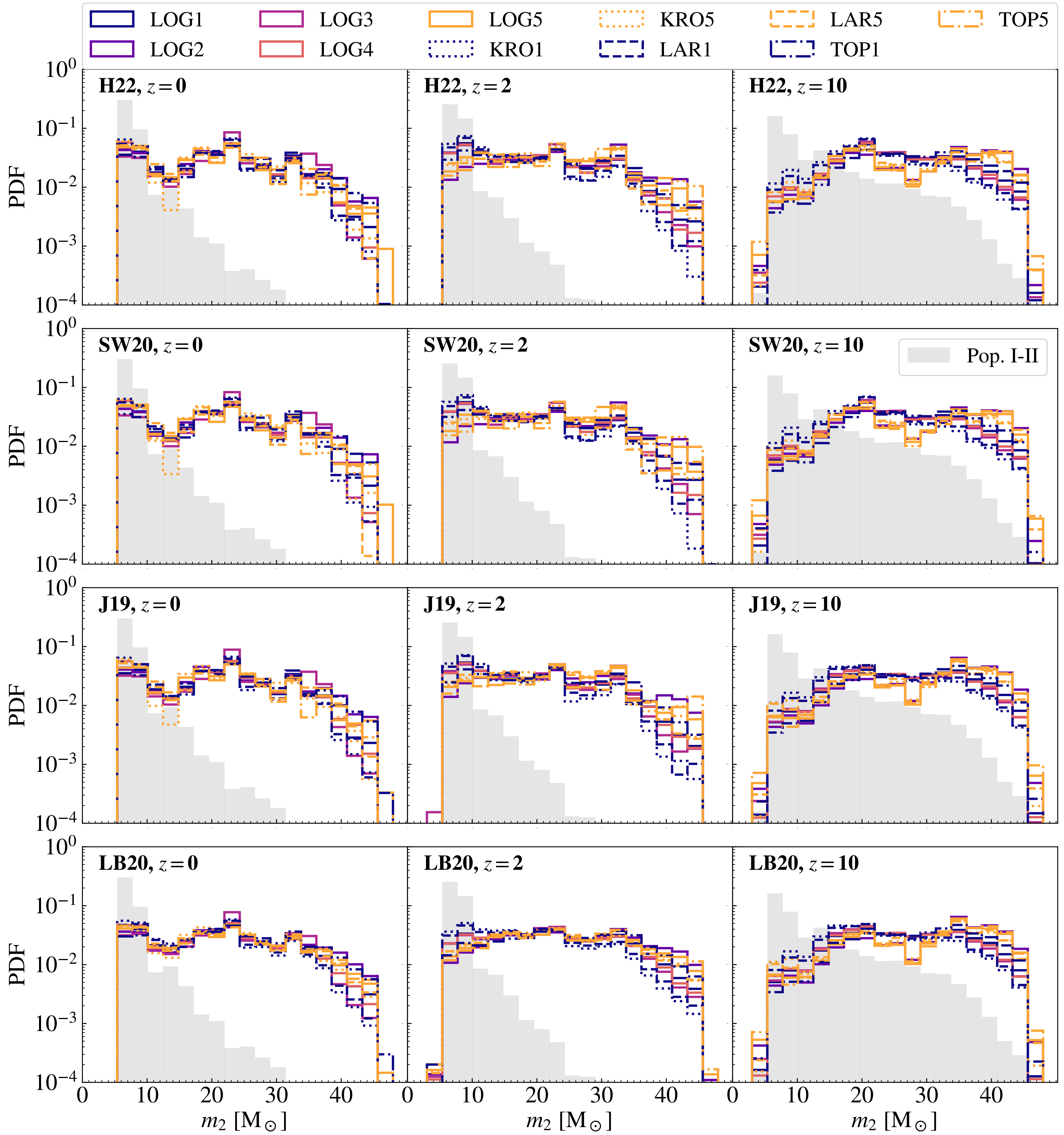
Model	$M_{ZAMS,1}$	M_{ZAMS}	q	P	e
LOG1	Flat in log	–	S12	S12	S12
LOG2	Flat in log	–	S12	SB13	Thermal
LOG3	–	Flat in log	Sorted	S12	S12
LOG4	Flat in log	–	SB13	S12	Thermal
LOG5	Flat in log	–	SB13	SB13	Thermal
KRO1	K01	–	S12	S12	S12
KRO5	K01	–	SB13	SB13	Thermal
LAR1	L98	–	S12	S12	S12
LAR5	L98	–	SB13	SB13	Thermal
TOP1	Top heavy	–	S12	S12	S12
TOP5	Top heavy	–	SB13	SB13	Thermal

Column 1 reports the model name. Column 2 describes how we generate the ZAMS mass of the primary star (i.e., the most massive of the two members of the binary system). Column 3 describes how we generate the ZAMS mass of the overall stellar population (without differentiating between primary and secondary stars). We follow this procedure only for model LOG3 (see the text for details). Columns 4, 5, and 6 specify the distributions we used to generate the mass ratios q, the orbital periods P and the orbital eccentricity e. See Section 2.2 for a detailed description of these distributions.

Santoliquido et al. 2023:
https://arxiv.org/pdf/2303.15515.pdf

Pop. III BBHs: mass evolution





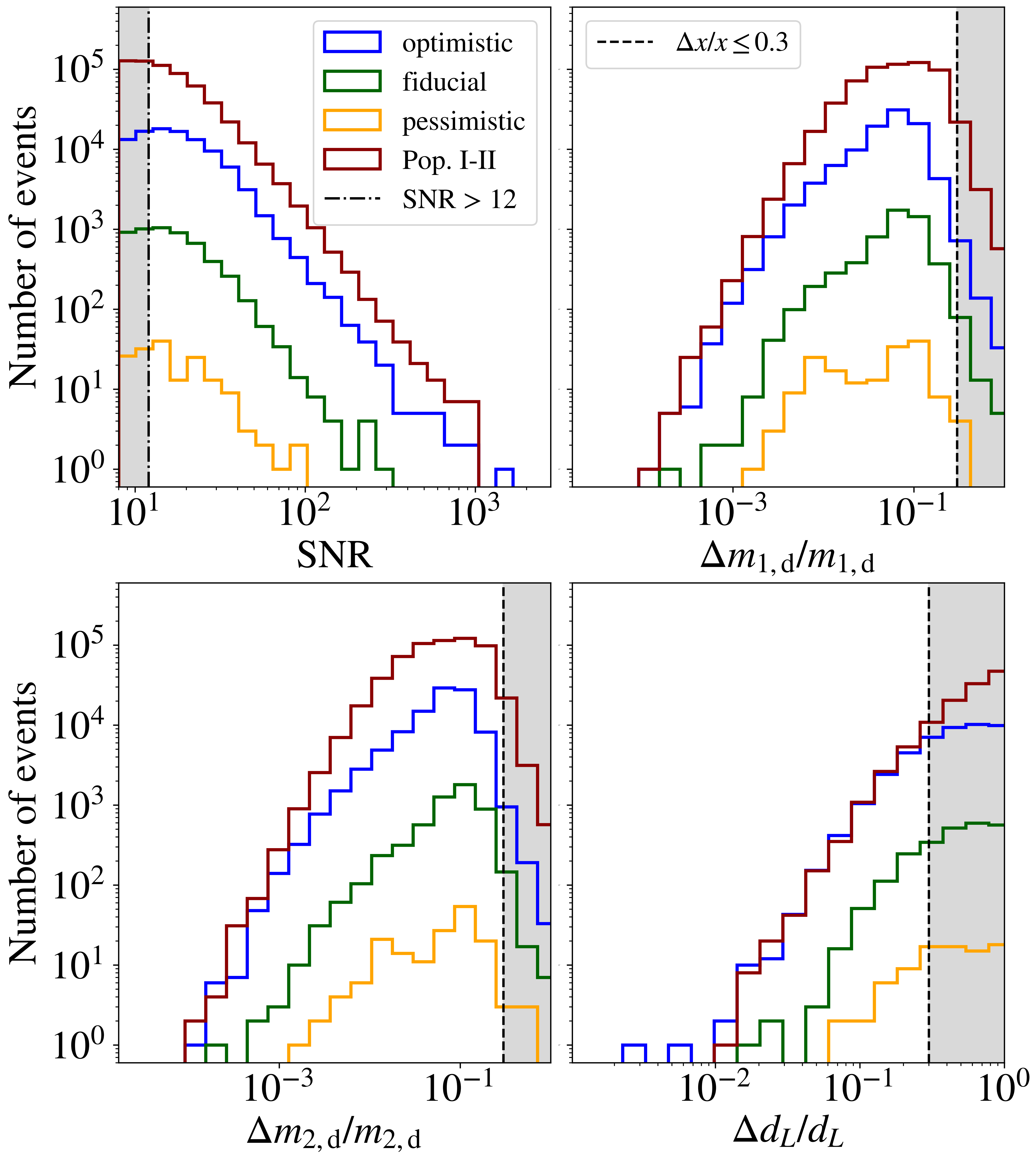
detection rate

$$\mathcal{R}_{\rm det} = \int \frac{{\rm d}^2\mathcal{R}(m_1, m_2, z)}{{\rm d}m_1{\rm d}m_2} \frac{1}{(1+z)} \frac{{\rm d}V_c}{{\rm d}z}\, p_{\rm det}(m_1, m_2, z)\, {\rm d}m_1\, {\rm d}m_2\, {\rm d}z.$$

$$\frac{{\rm d}^2\mathcal{R}(m_1, m_2, z)}{{\rm d}m_1{\rm d}m_2} = \mathcal{R}(z)\, p(m_1, m_2|z).$$

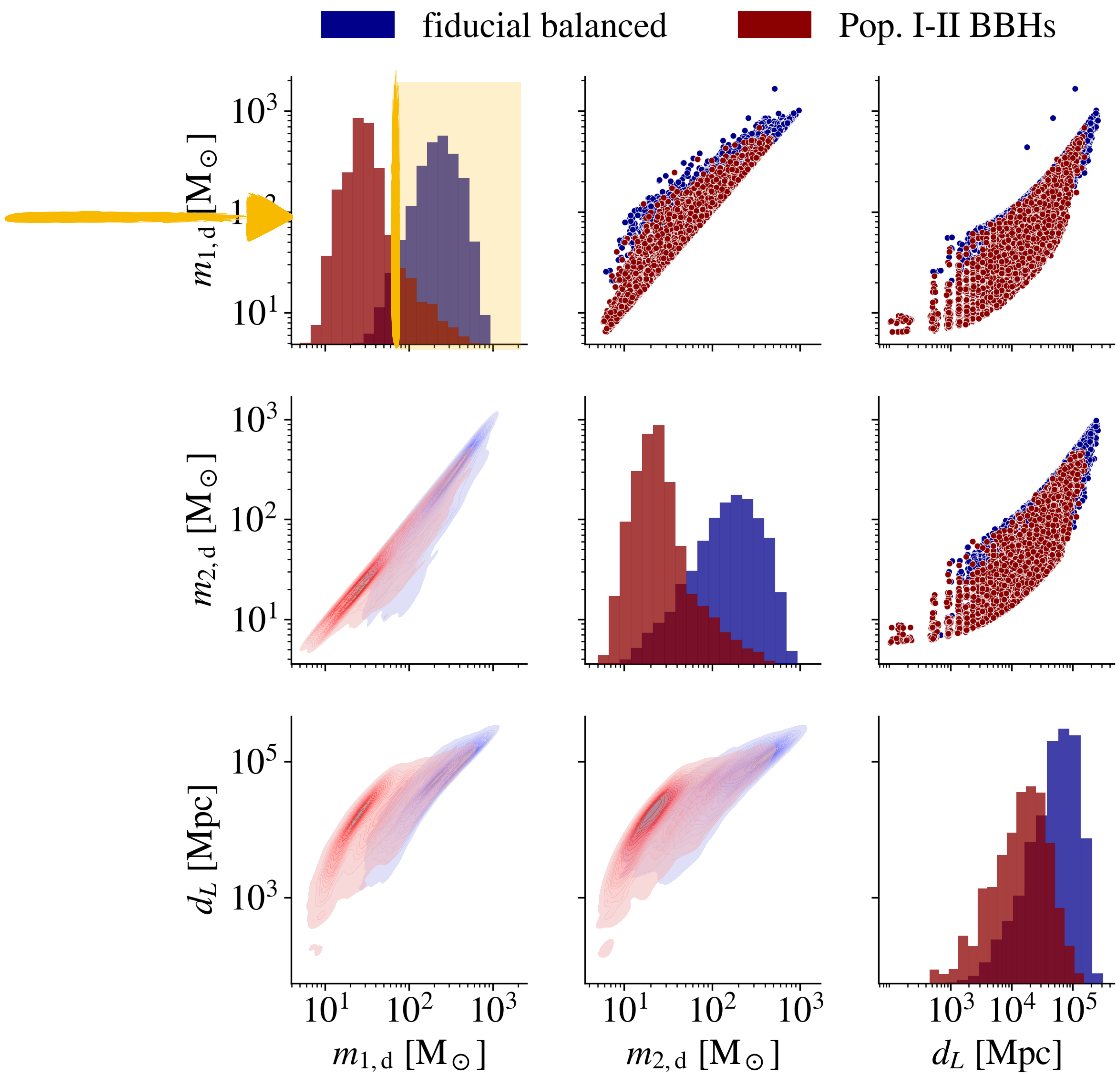
$$\rho = \rho_{\rm opt}\sqrt{\omega_0^2 + \omega_1^2 + \omega_2^2}$$

$$\rho_{\rm opt}^2 = 4\int_{f_{\rm low}}^{f_{\rm high}} {\rm d}f\, \frac{|\tilde{h}(f)|^2}{S_n(f)}$$

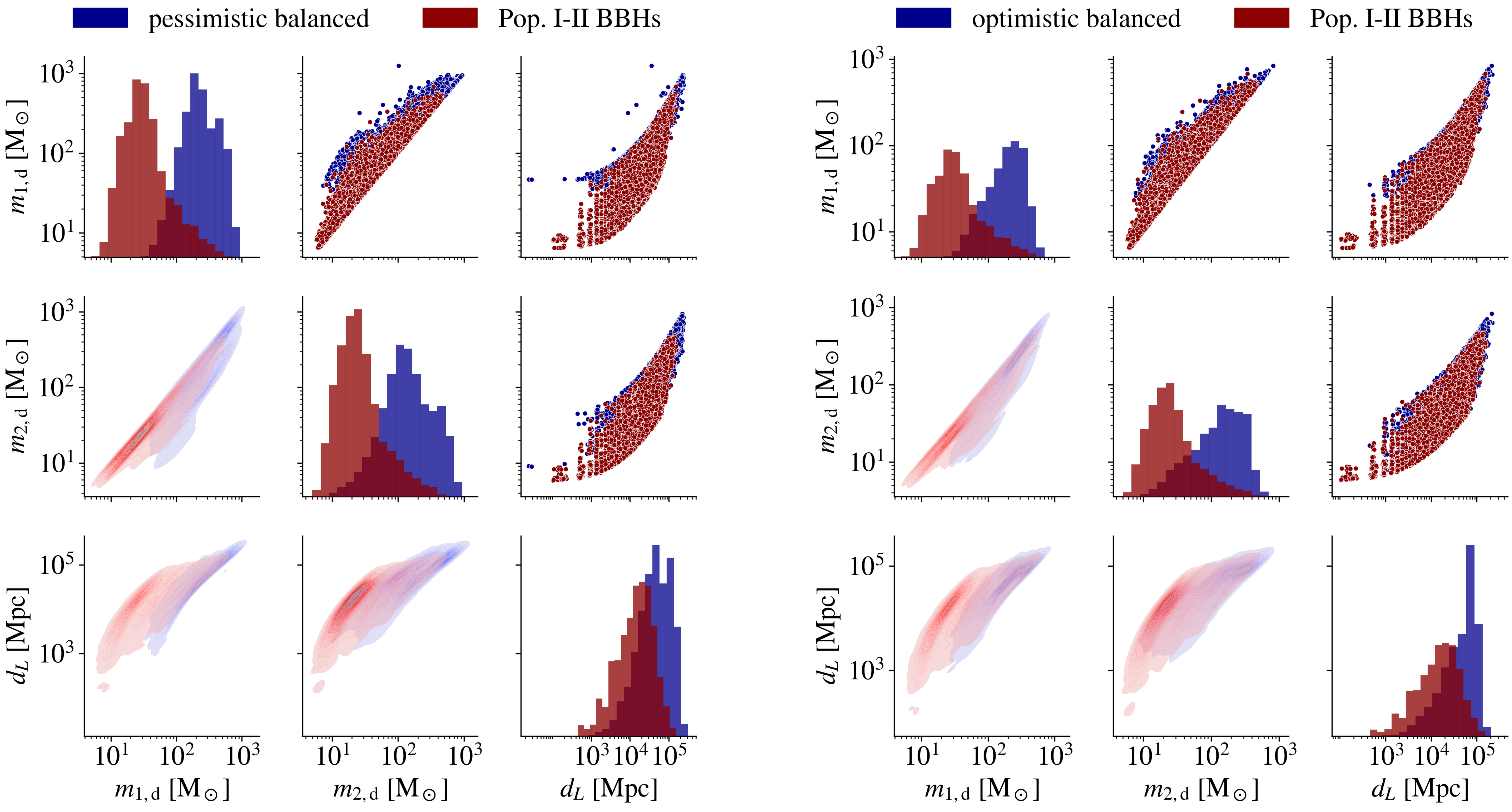


optimistic
fiducial
pessimistic
Pop. I-II
SNR > 12
$\Delta x/x \leq 0.3$
Number of events
SNR
$\Delta m_{1,\mathrm{d}}/m_{1,\mathrm{d}}$
$\Delta m_{2,\mathrm{d}}/m_{2,\mathrm{d}}$
$\Delta d_L/d_L$

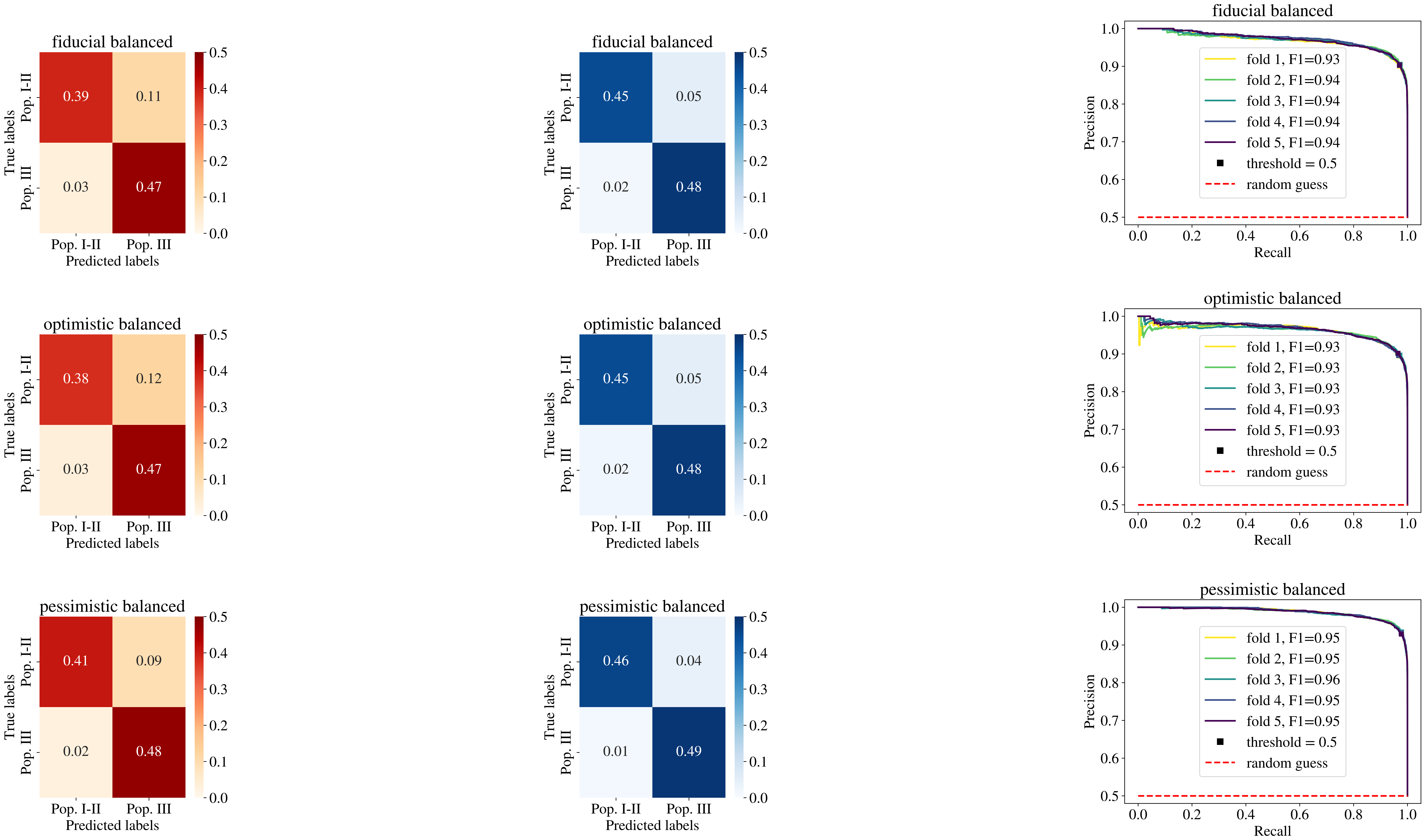
$$p(j \in k \,|\, x, d_j, \{\beta\}) = 1 \quad \text{if} \quad m_{1,\mathrm{d}} \gtrsim 60\ \mathrm{M}_\odot$$

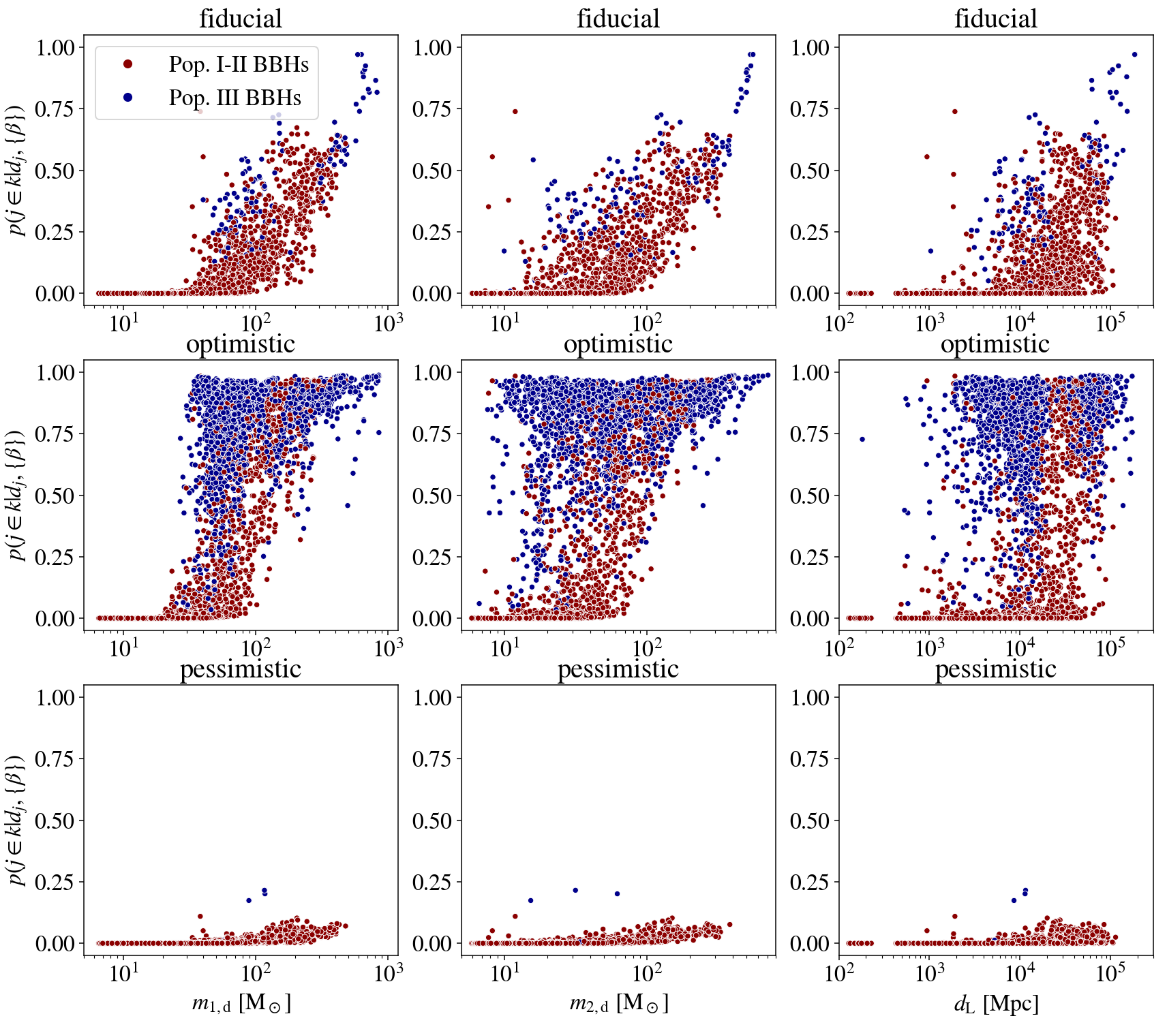


Ref. *Santoliquido et al. 2024*



pessimistic balanced
Pop. I-II BBHs
optimistic balanced
Pop. I-II BBHs
$m_{1,\mathrm{d}}$ [M$_\odot$]
$m_{2,\mathrm{d}}$ [M$_\odot$]
d_L [Mpc]
10^1
10^2
10^3
10^4
10^5


fiducial balanced
True labels
Pop. I-II
Pop. III
0.39
0.11
0.03
0.47
Predicted labels
0.5
0.4
0.3
0.2
0.1
0.0
fiducial balanced
0.45
0.05
0.02
0.48
fiducial balanced
Precision
Recall
fold 1, F1=0.93
fold 2, F1=0.94
fold 3, F1=0.94
fold 4, F1=0.94
fold 5, F1=0.94
threshold = 0.5
random guess
optimistic balanced
0.38
0.12
0.03
0.47
optimistic balanced
0.45
0.05
0.02
0.48
optimistic balanced
fold 1, F1=0.93
fold 2, F1=0.93
fold 3, F1=0.93
fold 4, F1=0.93
fold 5, F1=0.93
threshold = 0.5
random guess
pessimistic balanced
0.41
0.09
0.02
0.48
pessimistic balanced
0.46
0.04
0.01
0.49
pessimistic balanced
fold 1, F1=0.95
fold 2, F1=0.95
fold 3, F1=0.96
fold 4, F1=0.95
fold 5, F1=0.95
threshold = 0.5
random guess



Fiducial

Thr.	%TP	%TN	%FP	%FN	Precision	Recall
0.1	96	85	15	4	0.20	0.96
0.2	86	90	10	14	0.26	0.86
0.5	33	98	2	67	0.43	0.33
0.7	11	100	0	89	0.94	0.11
0.9	3	100	0	97	1.00	0.03

Optimistic

Thr.	%TP	%TN	%FP	%FN	Precision	Recall
0.1	100	77	23	0	0.80	1.00
0.2	99	80	20	1	0.81	0.99
0.5	95	85	15	5	0.85	0.95
0.7	87	89	11	13	0.88	0.87
0.9	46	96	4	54	0.91	0.46

Pessimistic

Thr.	%TP	%TN	%FP	%FN	Precision	Recall
0.1	50	100	0	50	0.60	0.50
0.2	33	100	0	67	1.00	0.33
0.5	0	100	0	100	0	0
0.7	0	100	0	100	0	0
0.9	0	100	0	100	0	0